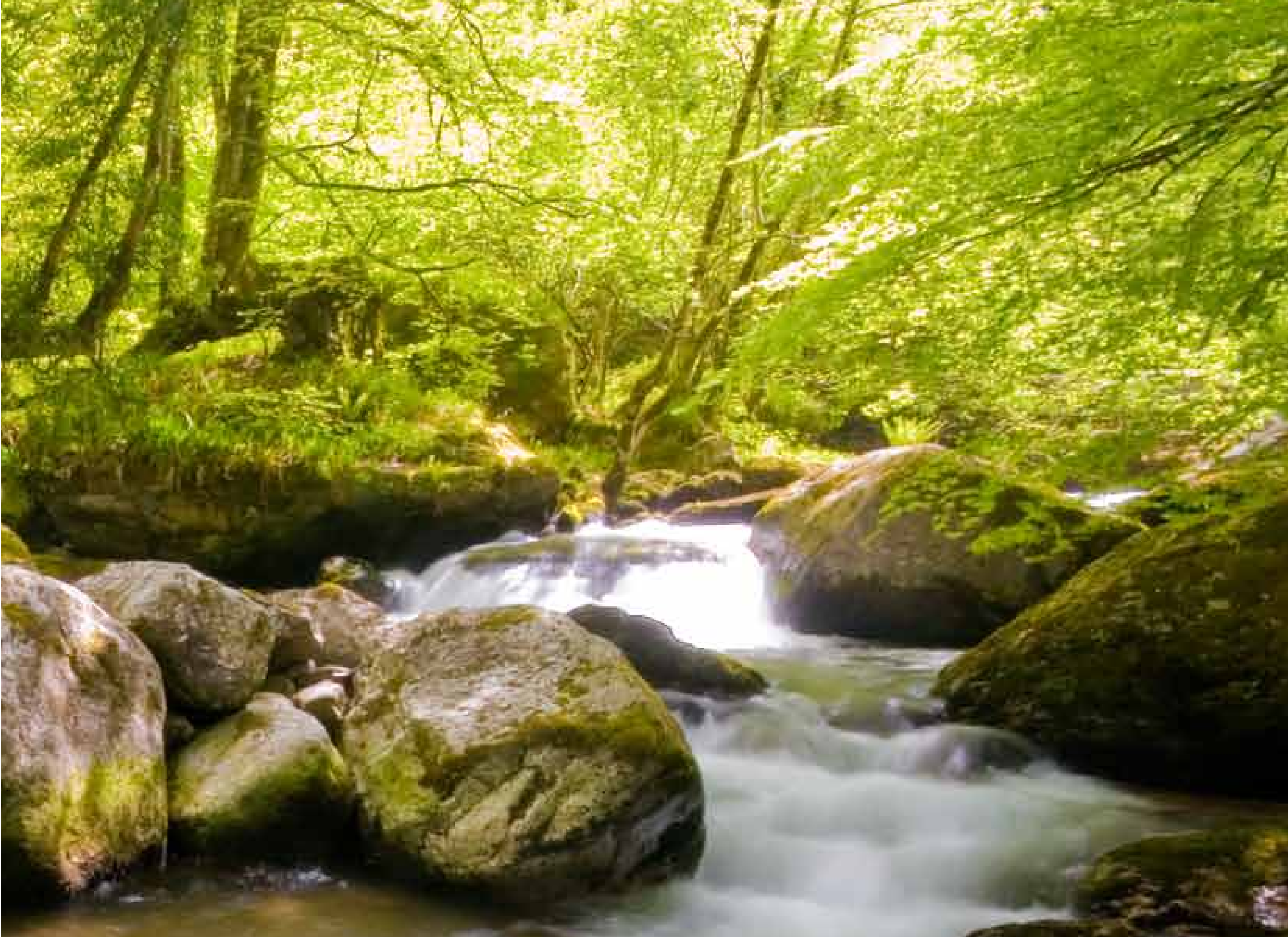

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del Agua y del Medio Ambiente

CLASIFICACIÓN DEL RÉGIMEN HIDROLÓGICO NATURAL Y PREDICCIÓN DE CARACTERÍSTICAS HIDROECOLÓGICAS EN EL TERCIO NORTE DE LA PENÍNSULA IBÉRICA

Classification of the natural flow regime and prediction of hydroecological characteristics in the northern third of the Iberian Peninsula

UNIVERSIDAD DE CANTABRIA

E.T.S. INGENIEROS DE CAMINOS, CANALES Y PUERTOS

DPTO. DE CIENCIAS Y TÉCNICAS DEL AGUA Y DEL MEDIO AMBIENTE

T E S I S   D O C T O R A L

CLASIFICACIÓN DEL RÉGIMEN HIDROLÓGICO NATURAL Y PREDICCIÓN DE CARACTERÍSTICAS HIDROECOLÓGICAS EN EL TERCIO NORTE DE LA PENÍNSULA IBÉRICA

PhD   D I S S E R T A T I O N

CLASSIFICATION OF THE NATURAL FLOW REGIME AND PREDICTION OF HYDROECOLOGICAL CHARACTERISTICS IN THE NORTHERN THIRD OF THE IBERIAN PENINSULA

Presentada por: FRANCISCO J. PEÑAS SILVA

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CESAR ÁLVAREZ DÍAZ

Santander, Febrero de 2014

A mis padres

A Miguela

“Listen, Lad. I've built this kingdom up from nothing. When I started here, all there was, was swamp. All the kings said I was daft to build a castle in a swamp, but I built it all the same, just to show 'em. It sank into the swamp. So, I built a second one. That sank into the swamp. So I built a third one. That burned down, fell over, then sank into the swamp. But the fourth one stayed up. And that's what you’re gonna get, Lad, the strongest castle in these islands.”

Monty Python and the Holy Grail

Agradecimientos

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So long and thanks for all the...inspiration!

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Resumen en Castellano

RESUMEN

De acuerdo con la normativa de estudios de doctorado de la Universidad de Cantabria en relación a los requerimientos exigidos para aquellas tesis redactadas en un idioma diferente al español, aprobada por Junta de Gobierno de 12 de marzo de 1999 y actualizada a 17 de diciembre de 2012, a continuación se presenta un resumen “suficientemente extenso” del documento original redactado en inglés.

1. Introducción

1.1 El régimen natural de caudales

El régimen natural de caudales influye decisivamente en la composición biótica, estructura, función y diversidad de los ecosistemas fluviales (Richter *et al.*, 1996) y actúa en todas las escalas temporales y espaciales (Lytle and Poff, 2004). De acuerdo con Bunn y Arthington (2002), existen tres mecanismos principales a través de los cuales se establecen los vínculos entre el régimen hidrológico y las comunidades biológicas: (1) El caudal es el principal determinante del hábitat, (2) las especies fluviales han desarrollado estrategias para adaptarse a la variabilidad natural del régimen hidrológico y (3) los patrones de conectividad longitudinal y transversal, esenciales para mantener las poblaciones acuáticas, están determinados por procesos hidrológicos. Además, la capacidad de establecimiento de especies invasoras es más efectiva en ríos cuyo régimen hidrológico se encuentra alterado.

El régimen de caudales puede ser descrito a través de cinco atributos fundamentales que influyen directamente en multitud de procesos ecológicos (Richter *et al.*, 1996; Poff *et al.*, 1997): La magnitud, duración, frecuencia, estacionalidad y predictabilidad y tasa de cambio. Uno de los principales retos en el ámbito de la hidroecología es establecer las interacciones y nexos entre los procesos hidrológicos y la dinámica ecológica de los ecosistemas fluviales. Por ello, el carácter hidrológico de las redes fluviales definido a través de los cinco atributos expuestos anteriormente debe ser analizado en paralelo a datos ecológicos lo que permitirá establecer y testar hipótesis concretas sobre las relaciones entre estos dos elementos (Monk *et al.*, 2007). Sin embargo, las interrelaciones tanto entre diferentes atributos del régimen como con otros factores ambientales (Snelder and Lamouroux, 2010) dificultan la definición y cuantificación de relaciones directas entre la condición del caudal y respuestas concretas en el ecosistema.

1.2 La alteración del régimen natural de caudales

Los ecosistemas fluviales proporcionan recursos naturales y numerosos servicios ecológicos y sociales que son básicos para el mantenimiento y desarrollo de la sociedad (Naiman *et al.*, 2002). Desafortunadamente, el aprovechamiento de todos esos recursos y servicios se ha llevado a cabo ignorando como estos sistemas se autoregulan y mantienen sus procesos (Gleick, 1998). Esto ha provocado un descenso de la biodiversidad en torno al 50% en los últimos 40 años (Millenium Ecosystem Assessment, 2005) y la pérdida de muchos procesos indispensables para el mantenimiento de los servicios ecosistémicos (Postel and Ritcher, 2003). La alteración del régimen hidrológico es un factor de amenaza importante en estos ecosistemas, la cual interactúa además con otras fuentes de degradación ambiental (Arthington *et al.*, 2010). El régimen natural de caudales puede ser modificado a través de diferentes presiones, tales como la construcción de embalses (Poff *et al.*, 2007), la extracción de agua superficial (Döll *et al.*, 2009) y sobreexplotación de los acuíferos (Carlisle *et al.*, 2011), los grandes trasvases intercuenca (Jackson *et al.*, 2001) y la modificación de los usos del suelo (Martinez-Fernandez *et al.*, 2013), cuyos impactos pueden verse agravados por los efectos derivados del cambio climático (Schneider *et al.*, 2013).

La construcción y gestión de embalses constituye la forma de alteración hidrológica más frecuente y en muchos casos con efectos más perniciosos (Vitousek, 1994). En la actualidad existen más de 40000 grandes presas que afectan directamente a más del 60% de los grades ríos en todo el mundo (Nilsson *et al.*, 2005). Teniendo en consideración los graves problemas ambientales y sociales asociados a la actividad de los embalses, uno de los objetivos principales de esta tesis pretende investigar la forma más eficaz de evaluar la alteración hidrológica producida por estas infraestructuras y generar herramientas capaces de reducir la incertidumbre asociada a este proceso de evaluación.

Los embalses muestran una gran diversidad en cuanto a su tamaño, capacidad, usos y modos de gestión por lo que predecir la alteración hidrológica potencial no se plantea como un problema de fácil solución. Además, no sólo el grado sino la dirección de la alteración pueden depender en muchos casos de las propias características del río impactado (McManamay *et al.*, 2013). Teniendo en cuenta esta variabilidad, las consecuencias derivadas de la actividad de los embalses pueden manifestarse a través de una gran cantidad de impactos sobre el ecosistema. Además, la actividad de un embalse suele traer asociada la alteración de más de un atributo del régimen hidrológico que actúan sinérgicamente sobre el ecosistema (Poff *et al.*, 2007) y más aún, en combinación con otras fuentes de deterioro ambiental (Poff and Zimmerman, 2010). Todo esto dificulta la definición de relaciones directas causa-efecto entre la alteración hidrológica y las consecuencias ecológicas.

1.3 La definición de un régimen de caudales naturalizado

De acuerdo a todo lo expuesto hasta ahora, se considera que el restablecimiento de un régimen de caudales seminatural, es decir, un régimen ambiental de caudales, es una de las actuaciones de restauración fluvial más efectiva (Roni *et al.*, 2008). La Declaración de Brisbane (2007) define los caudales ambientales como “la cantidad, recurrencia, duración, frecuencia y calidad de caudales requerida para mantener los ecosistemas de agua dulce y estuarios y el sustento y bienestar humanos que dependen de estos ecosistemas”. Es necesario, por tanto, que desde el ámbito científico se desarrollen herramientas capaces de abordar este objetivo, lo cual viene haciéndose desde hace más de 40 años y ha dado como resultado la definición de más de 200 métodos (Jowett, 1997; Tharme, 2003). Estos pueden diferenciarse en tres grupos bien definidos: Métodos hidrológicos, métodos hidráulicos y métodos de simulación del hábitat. Dentro de estos grupos las aproximaciones más simples han ido evolucionado hacia otras más robustas que incluyen los aspectos hidrológicos más relevantes desde el punto de vista ambiental. No obstante, muchos de ellos aún presentan ciertos inconvenientes que ponen en tela de juicio su utilidad a la hora de formular políticas de gestión efectivas.

En la actualidad se considera que un adecuado funcionamiento de los ecosistemas fluviales únicamente es posible si se mantiene cierto grado de similitud con las diversas combinaciones de magnitud, frecuencia, duración, temporalidad y tasa de cambio que tenían lugar antes de la perturbación del régimen de caudales (Arthington *et al.*, 2006). En este sentido, un cuarto tipo de métodos denominados métodos holísticos, identifican las condiciones y eventos de caudal más relevantes, modelan las relaciones entre el caudal y las respuestas ecológicas, analizan las implicaciones sociales y definen grupos de expertos interdisciplinares para establecer las recomendaciones finales. Dentro de este tipo de métodos se enmarca la aproximación denominada "Límites Ecológicos de Alteración Hidrológica" (ELOHA de sus siglas en inglés; Poff *et al.*, 2010). La aplicación de este marco metodológico se fundamenta en el uso de información hidrológica y biológica existente y en la experiencia y conocimiento adquiridos en casos de estudio desarrollados en todo el mundo. El proceso científico de ELOHA comprende cuatro pasos (Figura 1): (1) creación de una base de datos de caudal en la cuenca objetivo, (2) clasificación de los ríos de acuerdo a sus características hidrológicas, (3) análisis de la alteración hidrológica y (4) desarrollo de relaciones entre caudal natural, régimen alterado y funcionamiento ecológico asociado a cada tipo de rio, que finalmente permiten la definición de un régimen ambiental de caudales. La presente tesis se centra en los tres primeros pasos de ELOHA con el objetivo principal de evaluar fuentes de incertidumbre potenciales asociados a cada uno de los pasos. Las conclusiones derivadas de este estudio serán útiles para abordar el resto de pasos y completar las futuras aplicaciones de este marco metodológico.

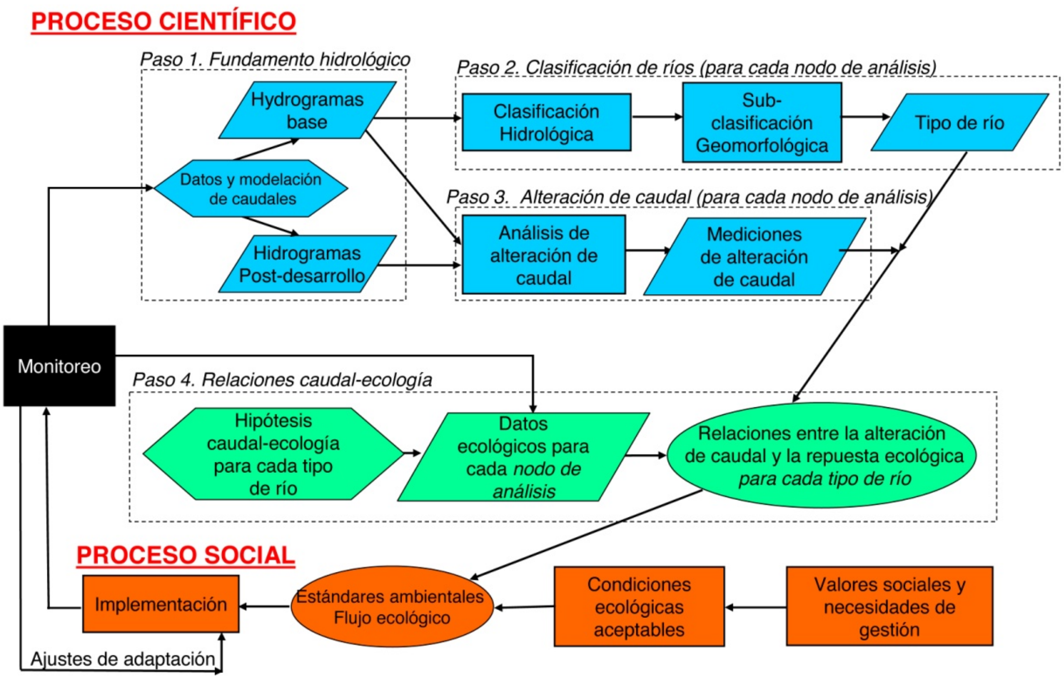

Figura 1 - Diagrama indicando los principales pasos de ELOHA (Fuente: Poff et al, 2010).

1.4 De la teoría a la práctica

1.4.1 Desarrollo de una base de datos hidrológica

El primer paso de ELOHA consiste en la estimación del régimen de caudales en toda la red fluvial. Es un paso esencial dentro de la metodología, ya que supone la base sobre la que se fundamenta el resto de pasos. Los modelos de precipitación-escorrentía han sido ampliamente utilizados para cubrir esta necesidad (Kennen *et al.*, 2007) y han demostrado ser una herramienta fundamental en cuencas muy intervenidas (Belmar *et al.*, 2011). Sin embargo, la fiabilidad de las series modeladas está condicionada por diversos factores (Sauquet, 2006). Alternativamente, cuando la red de aforos en el área de estudio es suficientemente extensa y los datos cuentan con una calidad adecuada, está información puede constituir la base de datos inicial. A partir de las series de caudales medidos en estaciones de aforo inalteradas se pueden calcular índices hidrológicos, los cuales contienen la información ecológicamente significativa del régimen natural de caudales. Esta información junto con aquellos atributos de cuenca que tengan influencia sobre el régimen hidrológico supone el punto de partida para desarrollar clasificaciones hidrológicas (Snelder *et al.*, 2009) y predecir el carácter hidrológico a tramos no aforados de una red fluvial (Carlisle *et al.*, 2010).

1.4.2 Clasificación hidrológica: Un tarea esencial en la hidroecología

Actualmente, se considera que los ríos con un carácter hidrológico similar presentarán una variabilidad ecológica similar. Por lo tanto, las clasificaciones hidrológicas constituyen un marco de organización y una herramienta indispensable en los ámbitos de la investigación y de la gestión de los recursos hídricos (Olden *et al.*, 2012). En la actualidad existe una considerable variedad de aproximaciones y técnicas estadísticas para clasificar redes fluviales, muchas de las cuales coinciden en los conceptos y criterios generales pero difieren significativamente en los procesos específicos. En este sentido, la aplicación de diferentes aproximaciones puede conducir a clasificaciones muy diferentes que condicionaran las conclusiones que se extraigan. Por lo tanto, el proceso de clasificación es un aspecto realmente crítico que debe ser investigado en detalle. Los Capítulos III y IV de esta tesis versan sobre los efectos de aplicar diferentes métodos para realizar un clasificación hidrológica.

Dentro de la variedad de procedimientos de clasificación hidrológica surgidos en las últimas décadas, los procedimientos inductivos son aquellos que identifican y caracterizan la similitud entre ríos de acuerdo a una serie de índices hidrológicos que varían espacialmente a lo largo de la red fluvial (Olden *et al.*, 2012). Los procedimientos para desarrollar una clasificación de este tipo pueden variar significativamente dependiendo de los objetivos de la misma y de los datos hidrológicos disponibles. Por ejemplo, dentro del procedimiento, se puede optar por diversas vías en relación al tratamiento inicial de los datos, la selección de índices hidrológicos, el nivel de detalle de la clasificación o la estrategia para predecir la clase de todos los segmentos de la red fluvial (Snelder and Booker, 2013).

Por otro lado, se considera que las series de caudales diarias cuentan con una escala temporal adecuada para el desarrollo de clasificaciones hidrológicas. Sin embargo, cuando los datos a escala diaria son escasos o no cuentan con una calidad apropiada varios autores han abogado por el uso de series a escala mensual (Harris *et al.*, 2000; Belmar *et al.*, 2011; Belmar *et al.*, 2013). El uso de series de caudales con escalas temporales insuficientes para describir todos los atributos del régimen puede derivar en clasificaciones que no cumplan los objetivos para los que fueron diseñadas.

Por último, como se ha introducido previamente muchas de las clasificaciones desarrolladas en diferentes partes del mundo pueden ser consideradas robustas y defendibles desde un punto de vista científico ya que están basadas en métodos objetivos, transparentes, interpretables y repetibles. Es más, cuando el proceso de clasificación no se basa en procedimientos y criterios objetivos sino en los establecidos de acuerdo al criterio de experto, las clasificaciones pueden variar significativamente de un autor a otro con la consecuente influencia en las futuras aplicaciones de la clasificación.

1.4.3 Predicción del carácter hidrológico de las redes fluviales

La aplicación de ELOHA requiere, además de la segregación en tipos hidrológicos de acuerdo a una clasificación, la estimación de toda la información hidrológica relevante, es decir los índices hidrológicos, a toda la red fluvial. El propio marco metodológico reconoce el uso de técnicas estadísticos como una herramienta apropiada para este fin. A pesar de las ventajas de este método sobre otras aproximaciones, su aplicación para la predicción de índices hidrológicos ha sido limitada (Knight *et al.*, 2011). Por otro lado, la técnica estadística más utilizada para predecir esta información hidrológica ha sido las de modelos lineales (Yadav *et al.*, 2007; Knight *et al.*, 2011), si bien, es ampliamente reconocida la falta de linealidad de muchos de los procesos hidrológicos (Snelder *et al.*, 2009). Por ello, el uso de modelos enmarcados en el campo del aprendizaje automático (Carlisle *et al.*, 2010) o la segregación de los aforos previamente al desarrollo de los modelos (Sanborn and Bledsoe, 2006), podrían suponer una mejora significativa frente a aproximaciones más clásicas. Estos aspectos se analizan en el capitulo V de la presente tesis.

1.4.4 Evaluación de la alteración hidrológica generada por embalses

Una vez desarrollada la base de datos hidrológica para toda la red fluvial a través de los procedimientos expuestos anteriormente, uno de los aspectos más importantes en la investigación hidroecológica y un paso esencial en ELOHA, es la definición del grado de desviación del régimen alterado frente al régimen natural de caudales. Sin embargo, la correcta cuantificación de la alteración hidrológica puede estar influenciada por diversos factores que pueden conducir a conclusiones equivocadas. En el Capítulo VI de esta tesis, se ha desarrollado y valorado un protocolo que incluye cinco diseños alternativos para evaluar la alteración hidrológica causada por embalses dependiendo del tipo de datos disponibles. Habitualmente, la evaluación de la alteración hidrológica se ha llevado a cabo mediante la comparación directa de las series hidrológicas de los periodos anteriores y posteriores a la implantación de la construcción del embalse (Richter *et al.*, 1996) o bien, mediante la comparación de las series en la estación impactada con las de otra estación no impactada en el mismo periodo de tiempo (Zhao *et al.*, 2012). En ambos casos, únicamente es posible determinar si existe una variación hidrológica pero no se puede discernir si este cambio se debe a la presencia del embalse o la influencia de otros elementos (Downes *et al.*, 2002). Por otro lado, la falta de información hidrológica en los puntos de interés, especialmente de series anteriores a la perturbación, es una situación muy habitual. En muchas ocasiones esta carencia se ha solventado mediante la estimación de la información hidrológica disponible en otros puntos de la red (p.e. a través de la predicción de índices hidrológicos; Carlisle *et al.*, 2010), o reconociendo la similitud de los ríos impactados con otros ríos del mismo tipo hidrológico, es decir, mediante el uso de una clasificación hidrológica (Arthington *et al.*, 2006). La aplicación de estos métodos alternativos requiere una evaluación meticulosa del grado de fiabilidad de las valoraciones de modo que permita establecer el alcance y efectividad de las medidas de gestión propuestas a partir de dichos análisis.

El análisis en profundidad de estos tres elementos, la clasificación hidrológica, la predicción de índices hidrológicos y la valoración de la alteración hidrológica, es una cuestión fundamental que permitirá establecer hipótesis más rigurosas sobre las relaciones entre la variabilidad hidrológica y las respuestas del ecosistema, así como definir con un menor grado de incertidumbre el impacto que la alteración del régimen tendrá sobre estas relaciones. Todo ello dotará a científicos y gestores de las herramientas oportunas para definir regímenes de caudales ecológicos y establecer hipótesis sobre los potenciales efectos que la restauración del régimen de caudales tendrá sobre los ecosistemas.

1.5 Objetivos

El objetivo general de esta tesis es avanzar en el conocimiento de tres aspectos críticos dentro del campo de la hidroecología y la gestión de los recursos hídricos: La clasificación hidrológica, la caracterización hidrológica de redes fluviales completas y la valoración de la alteración del régimen natural de caudales. Estos tres aspectos representan pasos esenciales en el marco de gestión ELOHA, por lo que los resultados de la tesis serán especialmente valiosos para definir regímenes ambientales de caudales con mayor rigor.

El objetivo general puede disgregarse en cinco objetivos parciales:

1. Investigar como la normalización de las series hidrológicas y la aplicación de dos procedimientos de clasificación opuestos influyen en (1) el rendimiento de las clasificaciones, (2) la interpretación hidrológica de las clasificaciones, (3) su capacidad para reducir el sesgo asociado a las partes infra-representadas del espacio hidrológico y (4) la disposición espacial de las clases.
2. Investigar como la escala de tiempo (datos diarios contra datos mensuales), el origen (datos medidos contra datos modelados) y el procedimiento de clasificación (clasificación inductiva contra criterio de experto) influyen en (1) el

rendimiento de las clasificaciones, (2) la interpretación hidrológica de las clasificaciones y (3) la disposición espacial de las clases.

3. Evaluar la capacidad de diferentes técnicas estadísticas para predecir índices hidrológicos a toda una red fluvial y examinar las ventajas de la Aproximación de Regresión Regional al modelado de dichos índices.
4. Diseñar un protocolo para valorar el grado de alteración hidrológica que incluye diferentes diseño de acuerdo al tipo de datos hidrológicos disponibles.
5. Evaluar el grado de incertidumbre asociado a cada uno de los diseños incluidos en el protocolo de evaluación de la alteración hidrológica.

2 Área de estudio y compilación de datos

2.1 Área de estudio

El área de estudio abarca el tercio norte de la península Ibérica (Figura 2) ocupando una extensión total de más de 124000 km^2.

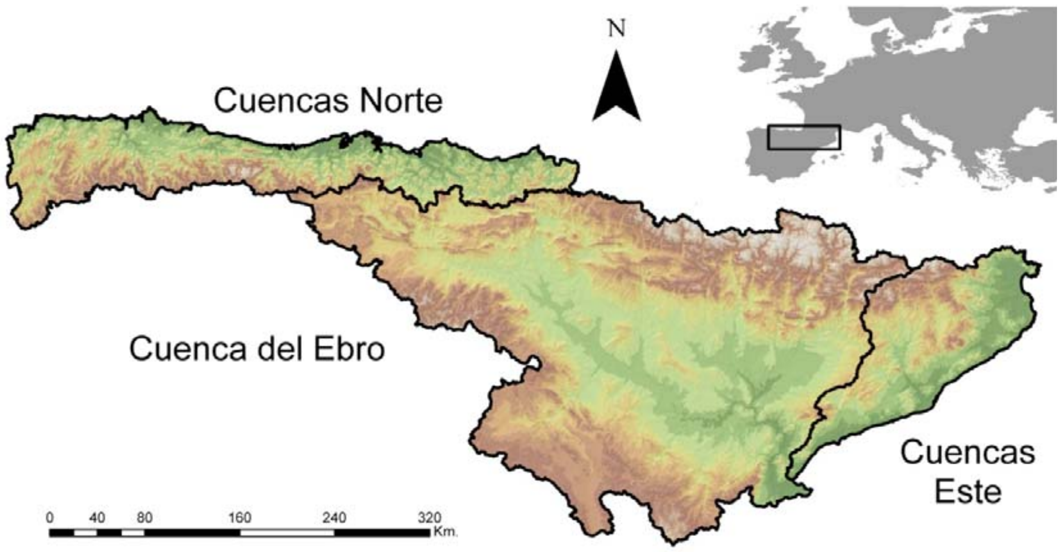

Figura 2 - Área de estudio: Tercio norte de la Península Ibérica.

Presenta condiciones ambientales heterogéneas y se divide en tres áreas principales. Por un lado, la vertiente norte, que incluye una serie de cuencas con áreas comprendidas entre 30 km^2 y 4907 km^2, ocupando en total, un área de más de 22000 km^2. Los ríos nacen en la Cordillera Cantábrica, una cadena montañosa que se dispone de manera paralela al Océano Atlántico y que alcanza alturas de más de 2600 msnm. Estos ríos se caracterizan por presentar pendientes pronunciadas y corto recorrido desde su nacimiento hasta su desembocadura. El clima en esta región es oceánico templado (Rivas-Martínez *et al.*, 2004). La temperatura media anual es de 14 ºC y las precipitaciones son abundantes a lo largo de todo el año, con valores medios de 1300 mm $año^{-1}$. Las máximas precipitaciones tienen lugar entre Diciembre y Febrero y las mínimas entre Julio y Septiembre. No obstante, la intensidad y distribución de las precipitaciones varía significativamente en función de la orografía local. Las precipitaciones en forma de nieve son frecuentes por encima de los 1000 msnm. Más del 50% de la superficie está ocupada por vegetación caducifolia, matorrales y pastos, mientras que un 10% está dedicado a la agricultura. Tiene una población cercana a los 3500000 habitantes, con una densidad de población de 175 habitantes por km^2, aunque hay diferencias importantes entre regiones.

Por otro lado, el área mediterránea está principalmente ocupada por la cuenca del Ebro junto con otras cuencas de tamaño intermedio localizadas en la zona este. La cuenca del Ebro ocupa una extensión total de 85530 km^2. Ésta se encuentra delimitada por las cordillera Cantábrica y los Pirineos (3400 msnm) en el norte, la Cordillera Costero-Catalana (1712 msnm) en el este y el Macizo Ibérico (2300 msnm), que bordea la cuenca por el sur en dirección noroeste-sudeste. Esta configuración crea una red fluvial densa en las zonas montañosas de la cuenca y una extensa llanura en el interior. La cuenca del Ebro tiene influencias tanto del clima templado como del clima mediterráneo. El área Pirenaica (noroeste) y la parte norte del Macizo Ibérico tienen clima oceánico, que va cambiando a clima mediterráneo hacia la zona central de la depresión del Ebro. La precipitación es de 656 mm $año^{-1}$ aunque varía significativamente desde 330 mm $año^{-1}$ en el centro hasta 1700 mm $año^{-1}$ en las montañas más altas (Bejarano *et al.*, 2010), donde la precipitación en forma de nieve es habitual en los meses de invierno. En la región mediterránea, el régimen de lluvias alcanza máximos en otoño y primavera y mínimos en verano e invierno. La temperatura presenta también importantes oscilaciones a lo largo del año, con valores por encima de los 30 ºC en verano y por debajo de 5 ºC en invierno. La densidad de población es inferior a 35 habitantes km^{-2}. Sin embargo, más del 40% de la superficie está ocupada por explotaciones agrícolas, lo que ha generado un intenso control del recurso hidráulico mediante más de 216 presas y otras infraestructuras hidráulicas.

La zona Este del área de estudio contiene varias cuencas medianas con superficies entre 72 y 5000 km^2, ocupando una extensión total de 16500 km^2. Estas cuencas drenan directamente dese los Pirineos o la cordillera Catalana al mar Mediterráneo. Presentan clima mediterráneo oceánico en la costa y templado en las montañas. Las precipitaciones oscilan entre los 1200 mm año^{-1} en las cabecera situadas en la región septentrional y menos de 500 mm año^{-1} en las cuencas del sur. Los bosques de coníferas, matorrales y pastos ocupan más del 60 % de la superficie en las cuencas del norte, que son progresivamente sustituidas por tierras de cultivo en el sur. En estas cuencas se concentran alrededor de 6600000 habitantes, principalmente en la ciudad de Barcelona y su área metropolitana. Por tanto, una parte importante de los recursos hídricos son destinados a usos urbanos e industriales.

2.2 Desarrollo de una red fluvial teórica

Las Redes Fluviales Sintéticas (RFSs) desarrollados a partir de Modelos Digitales de Elevación (MDE; Figura 3) proporcionan el marco espacial y la organización jerárquica adecuados para articular la información hidrológica y ambiental.

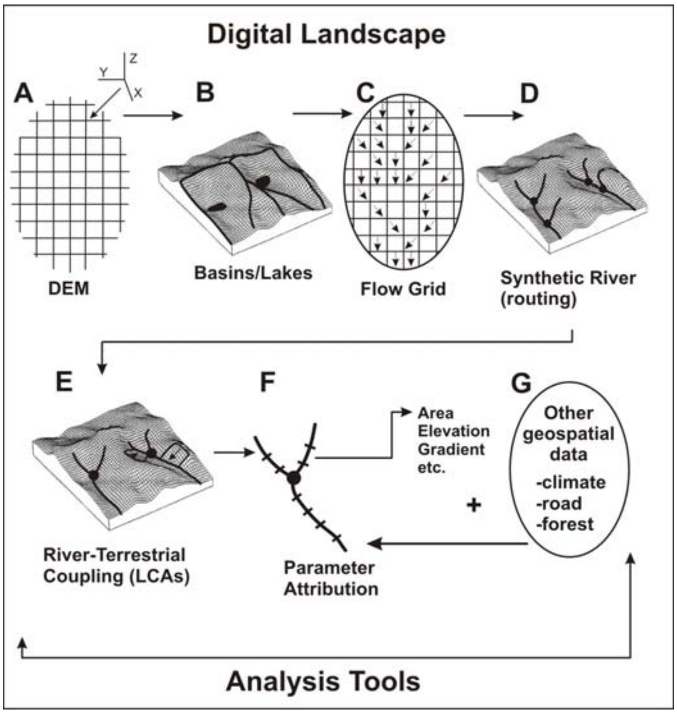

Figura 3 - Representación esquemática de la extracción de las Redes Fluviales Sintéticas (RFSs) a partir de los Modelos Digitales de Elevación (MDEs). Figura extraída de Benda et al. (in prep.)

Para obtener las RFSs del área de estudio se utilizaron paquetes informáticos específicos (Buildgrids y Netrace) proveniente de la plataforma de modelado 'NetMap' (Miller, 2002; www.terrainworks.com). La red fluvial se delineó utilizando direcciones de flujo inferidos a partir de un MDE con 30 m de resolución espacial, usando los algoritmos descritos por Clarke et al. (2008). Hemos aplicado un drenaje forzado en las zonas de bajo relieve (pendiente inferior al 30%) mediante la reducción de dos metros la elevación de las celdas de la corriente en el MDT usando datos GIS con ubicaciones reales de los cauces. La localización real de los canales fluviales se extrajo de la red hidrográfica oficial. La red fluvial se dividió en tramos de entre 100 y 500 m de longitud.

2.3 Datos hidrológicos

2.3.1 Medición de series fluviales

Los datos hidrológicos de partida consistieron en series de caudales medios diarios medidos en 428 estaciones de aforo gestionadas por diferentes confederaciones, agencias del agua y gobiernos regionales. Se descartaron todas las estaciones de aforo afectadas por obras hidráulicas ni por tomas de agua. Posteriormente, se seleccionaron únicamente aquellos aforos que tenían información en el periodo 1976-2010 y cuyas series contaban con la calidad óptima. Los criterios para la eliminación de años con datos de baja calidad han sido la presencia de (1) periodos largos de caudales constantes, (2) tasas de cambio de caudal extremadamente altas durante cortos periodos de tiempo (3) periodos con caudales nulos en ríos no intermitentes y (4) diferencias significativas entre dos periodos, probablemente debidas al cambio de método de aforo o reajuste de las curvas de gasto. Además, se eliminaron del análisis aquellos años que presentaron más de 30 días consecutivos sin datos. En el último paso se eliminaron todas las series con duraciones inferiores a 8 años. Tras aplicar estas restricciones, se seleccionaron 156 estaciones de aforo con una media de 17 años de registro (Figura 4; Tabla 1).

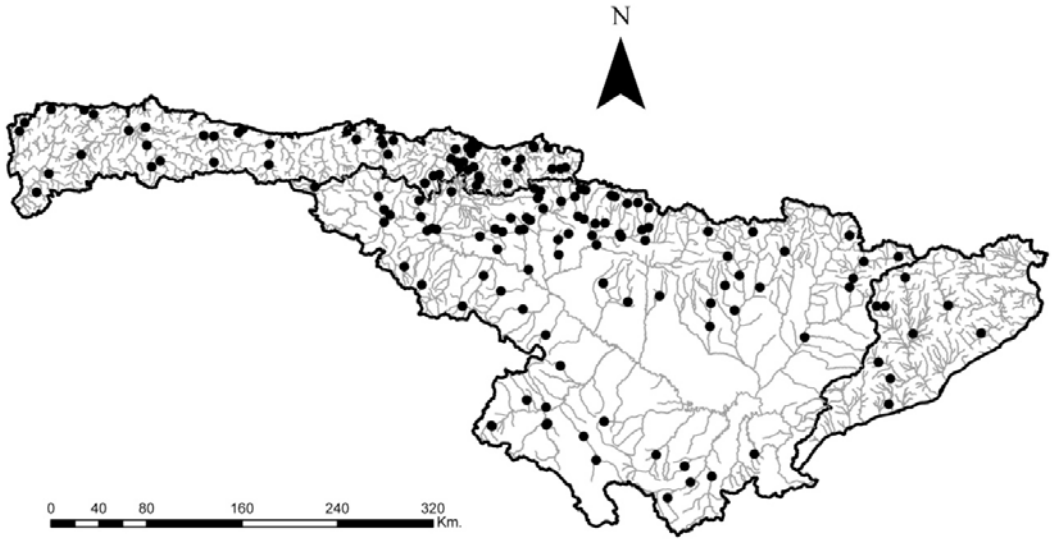

Figura 4 - Mapa de las estaciones de aforo no alteradas (●; n=156) en el área de estudio. La línea negra separa las cuencas Cantábrica, la del Ebro y las cuencas internas de Cataluña.

N. años	N. medidas	Frecuencia	Frec. Acum.
>19	52	33.3	33.3
19	3	1.9	35.3
18	7	4.5	39.7
17	6	3.8	43.6
16	16	10.3	53.8
15	7	4.5	58.3
14	8	5.1	63.5
13	8	5.1	68.6
12	11	7.1	75.6
11	9	5.8	81.4
10	9	5.8	87.2
9	9	5.8	92.9
8	11	7.1	100.0

Tabla 1 - Número de años de series de caudal utilizados para el análisis.

2.3.2 Modelado de series fluviales

Se obtuvieron series de caudal medio mensual para cada estación de aforo considerada en la sección previa utilizando los resultados del modelo SIMPA (Sistema Integrado de Modelización del proceso de Precipitación-Aportación; Alvarez *et al.*, 2005). SIMPA lleva a cabo una modelación distribuida de los componentes básicos del ciclo hidrológico con periodo temporal mensual y a la escala global de todo el territorio nacional. Se simula el proceso de generación de la escorrentía a partir de información meteorológica y de las características de las cuencas, permitiendo estimar los caudales medios mensuales en régimen natural en cualquier punto de la red hidrográfica de una cuenca. Trabaja con celdas de 1 km^2, lo que supone que en cada paso de tiempo se simulan los distintos componentes del ciclo hidrológico en más de 500000 celdas (Estrela and Quintas, 1996; Alvarez et al., 2005). Basado en la escorrentía mensual específica para cada cuadrícula de 1 x 1 km y el mapa de direcciones utilizado para el desarrollo de la RFS, se obtuvieron los datos de caudal acumulado mensual para el período 1980/81-2005/06 en cada tramo de la RFS, los cuales fueron a su vez, normalizados.

2.4 Características ambientales

El clima, la topografía, la cobertura y la geología de la cuenca se consideran factores con una influencia significativa sobre el régimen hidrológico, independientemente de la situación geográfica. Variables predictoras de clima, topografía, cobertura y geología fueron proporcionadas por varias organizaciones regionales y nacionales a partir de bases de datos existentes. Las variables en cada segmento de la RFS representan la media de la variable en la cuenca aguas arriba del segmento. Se seleccionó un conjunto inicial de 50 variables ambientales con potencial influencia en los diferentes índices hidrológicos. Posteriormente se realizo un test de correlación de Pearson para cada par de variables y las variables con correlaciones superiores a 0.7 se descartaron de los análisis posteriores. Finalmente se seleccionó un conjunto de 18 y 17 variables para predecir las clases hidrológicas (Capítulo III y IV) y los índices hidrológicos (Capítulo V), respectivamente (Tabla 2):

1. Clima: Se derivaron variables relacionadas con precipitación, temperatura y evapotranspiración a partir de variables climáticas mensuales calculadas en mapas con tamaño de celda de 1 km^2. Los mapas de clima utilizados fueron generados originalmente por el centro de estudios hidrográficos CEDEX para ser incorporados en el modelo SIMPA.
2. Topografía: El área de cuenca, pendiente, elevación, densidad de confluencias y densidad de drenaje se derivaron del MDE de 30 m.
3. Cobertura del suelo: el porcentaje de superficie ocupada por bosques de coníferas y caducifolias, pastos, tierras de cultivo, roquedos y áreas urbanas se obtuvo del Sistema de Información de Ocupación del Suelo en España (SIOSE) desarrollado por el Instituto Geográfico Nacional. SIOSE presenta una escala 1:25000 e integra imágenes de satélite e imágenes aéreas.
4. Geología: La dureza media y la permeabilidad del terreno se obtuvieron del mapa litoestratigráfico y de permeabilidad a escala 1:200000 desarrollado por el Instituto Geológico y Minero del Gobierno de España. Estas variables se calcularon utilizando procedimientos descritos en otros trabajos a partir de datos geológicos y edafológicos (Snelder *et al.*, 2008; Fernández *et al.*, 2012).

Variable	Tipo	Unidades	Descripción	Fuente
[1,2]Precipitación anual	CL	mm	Precipitación anual media	SIMPA
[2]Precipitación Abril	CL	mm	Precipitación media en Abril	SIMPA
[2]Precipitación verano	CL	mm	Precipitacion media de verano (Julio-Septiembre)	SIMPA
[2]Precipitación máxima	CL	mm	Precipitación máxima mensual	SIMPA
[2] Precipitación mínima	CL	mm	Precipitación mínima mensual	SIMPA
[2]Mes mínimo	CL	Mes	Mes de precipitación mínima	SIMPA
[1,2]Rango de precipitación mensual	CL	-	Precipitación mínima mensual/ Precipitación máxima mensual	SIMPA
[1,2] Rango de precipitación trimestral	CL	-	Precipitación mínima trimestral/ Precipitación máxima trimestral	SIMPA
[1,2]Temperatura	CL	ºC	Temperatura anual media	SIMPA
[2]Temperatura de verano	CL	ºC	Temperatura media de verano (Julio-Septiembre)	SIMPA
[1,2]Evapotranspiración	CL	mm	Evapotranspiración anual de la cuenca	SIMPA
[2]Evapotranspiración máxima	CL	mm	Evapotranspiración máxima mensual	SIMPA
[1, 2]Área cuenca	TG	Km^2	Área total cuenca	MDE
[1, 2]Pendiente	TG	%	Pendiente media de la cuenca	MDE
[1, 2]Elevación	TG	m	Elevación media de la cuenca	MDE
[1]Densidad de confluencia	TG	-	Número de confluencias por área de la cuenca	MDE
[1]Densidad de drenaje	TG	-	Número de segmentos por área de la cuenca	MDE
[1]Permeabilidad	GL	-	Permeabilidad del terreno	IGM
[1]Dureza	GL	-	Dureza del terreno	IGM

Tabla 2 - Variables ambientales utilizadas para predecir clases hidrológicas (Capítulo III y IV) e índices hidrológicos (Capítulo V) para toda la red fluvial (CL: Climáticas; TG: Topográficas; GL: Geológicas; CS: cobertura de suelo). [1]Variables seleccionadas para predecir clases hidrológicas en los Capítulos III y IV. [2]Variables seleccionadas para predecir índices hidrológicos en el Capítulo V. La cobertura de bosques de coníferas y caducifolios se unificaron en el Capítulo V en una única variable (bosque).

Variable	Tipo	Unidades	Descripción	Fuente
[1, 2]Bosque caducifolio	CS	%	Superficie ocupada por bosque caducifolio	SIOSE
[1, 2]Bosque coníferas	CS	%	Superficie ocupada por coníferas	SIOSE
[1]Pastos	CS	%	Superficie ocupada por pastos	SIOSE
[1, 2]Agricultura	CS	%	Superficie ocupada por campos agrícolas	SIOSE
[1,]Desnudo	CS	%	Superficie ocupada por áreas desnudas	SIOSE
[1]Urbano	CS	%	Superficie ocupada por áreas urbanas	SIOSE

Tabla 2 - (*continuación*)

3 La influencia de los procedimientos metodológicos en el desarrollo de clasificaciones hidrológicas.

Este capítulo ha dado lugar al artículo: "The influence of methodological procedures on hydrological classification performance" de Peñas, F.J., Barquín, J., Snelder, T.H, Booker, D.J. y Álvarez, C. Este artículo se ha enviado para su publicación a la revista: Hydrology and Earth Systems Science.

Las clasificaciones hidrológicas han surgido como un procedimiento adecuado para discriminar, en grupos homogéneos, la compleja variabilidad hidrológica asociada a los ecosistemas fluviales. En este sentido, se considera que representan una herramienta útil para investigar y entender las relaciones biofísicas clave en los ecosistemas fluviales así como los efectos derivados de la modificación del caudal. Por este motivo, en las últimas décadas se han desarrollado numerosas aproximaciones que, si bien convergen en conceptos generales, difieren ampliamente en sus procedimientos específicos. Por tanto, clasificaciones para una misma región pueden presentar patrones espaciales y grados de incertidumbre asociados con la realidad de esas clases muy diferentes. Sin embargo, en la actualidad existen muy pocos estudios que hayan comparado clasificaciones hidrológicas obtenidas a partir de la misma información hidrológica pero utilizando diferentes estrategias. En el presente capítulo se ha clasificado la red fluvial del tercio norte de la península Ibérica utilizando cuatro aproximaciones diferentes. Las clasificaciones desarrolladas varían en el tratamiento de los datos hidrológicos iniciales, el nivel de detalle, es decir, el número de clases y la estrategia utilizada para la modelización de las clases a toda la red fluvial. Concretamente, se han desarrollado clasificaciones con diferentes niveles de desratización, de 2 a 20 clases, basados tanto en las series hidrológicas brutas como en las series normalizados (Figura 5). Además, se han aplicado dos aproximaciones que contrastan en la estrategia para extrapolar una clasificación a toda la red fluvial: Clasificar-después-Predecir (ClasF) y Predecir-después-Clasificar (PredF).

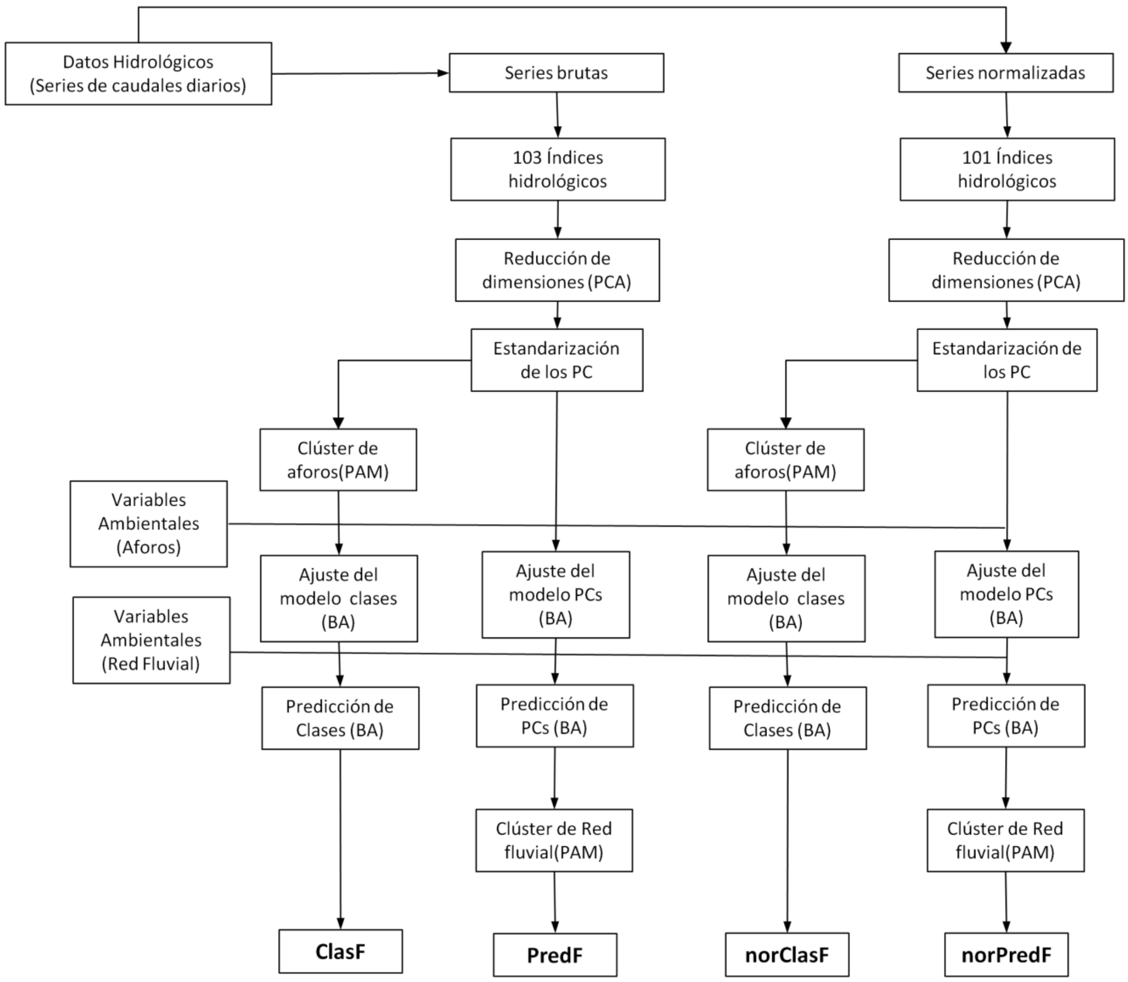

Figura 5 - Esquema en el que se resumen las cuatro estrategias de clasificación utilizadas en este estudio.

Las clasificaciones se compararon en base a su (1) robustez estadística, (2) interpretación hidrológica, (3) habilidad para reducir el sesgo asociado a las partes infra-representadas del espacio hidrológico y (4) la correspondencia espacial entre ellas. Los resultados indicaron que tanto el tratamiento inicial de los datos hidrológicos como la estrategia de clasificación y modelado influyen en las propiedades de las clasificaciones y en la distribución espacial de las clases.

Las clasificaciones basadas en datos no normalizados segregaron los ríos atendiendo, casi exclusivamente, a la magnitud de los caudales y el tamaño del rio. Además, los resultados pusieron de manifiesto que estas clasificaciones no fueron capaces de explicar la variabilidad espacial de algunos atributos muy importantes para los ecosistemas fluviales mediterráneos, tales como la severidad de los eventos de sequia. Por el contrario, la normalización de los datos hidrológicos eliminó la influencia del tamaño del río en la clasificación y además, generó clasificaciones en las que un rango más amplio de características hidrológicas pudo ser considerado. La utilización posterior de las clasificaciones depende en gran medida de los atributos hidrológicos que sean considerados en las mismas, por lo tanto, aquellas clasificaciones hidrológicas que tengan en cuenta un número reducido de atributos estarán limitadas respecto a sus futuras aplicaciones.

La aplicación de la estrategia PredF produjo, en la mayoría de los casos, clasificaciones con mayor poder de discriminación, especialmente cuando las comparaciones fueron realizadas entre clasificaciones basadas en datos no normalizados. No obstante, las diferencias estadísticas no fueron significativas en todos los casos (Figura 6).

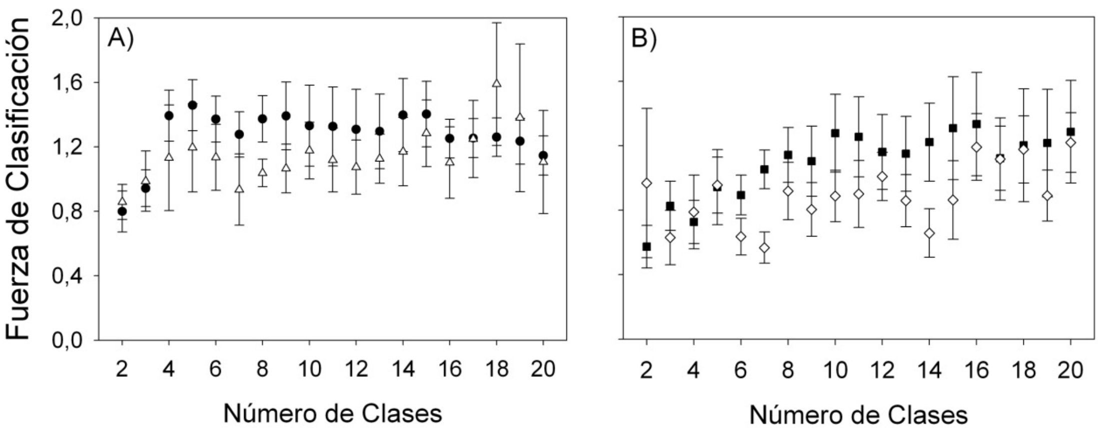

Figura 6 - Rendimiento de las clasificaciones hidrológicas obtenidas a partir de 4 estrategias diferentes. A) Clasificaciones derivas de los series sin normalizar (●: PredF; △: ClasF) B) Clasificaciones derivadas de las series normalizadas (■: norPredF; ◇: norClasF).

La capacidad de PredF para generar clasificaciones más robustas se fundamenta en sus principios conceptuales. En este sentido, ClasF establece los límites de las clases únicamente atendiendo al dominio hidrológico observado, es decir, las estaciones de aforo. Posteriormente impone esa estructura de clases a toda la red, lo cual es un proceso sujeto a un mayor nivel de incertidumbre. Por el contrario, la predicción de las características hidrológicas previamente a la segregación en clases consigue que, en este segundo paso, se elimine el sesgo debido a la localización de las estaciones de aforo. Es decir, la red fluvial se segrega de acuerdo a un patrón espacial hidrológico que probablemente se acomode más al patrón real, si bien esto no puede ser analizado debido a la ausencia de datos. Además, PredF presentó una mayor capacidad para reducir el sesgo asociado a la presencia de estaciones de aforo con características hidrológicas poco frecuentes en el resto de estaciones. Así, las clases en las que estas características hidrológicas quedaron representadas fueron más homogéneas y robustas en comparación con aquellas derivadas mediante ClasF. Asimismo, estas clases presentaron una distribución espacial más equitativa (Figure 7). La generación de clasificaciones sujetas a un menor grado de incertidumbre y con mayor capacidad para afrontar los sesgos impuestos por la falta de información hidrológica es una cualidad deseable para su posterior aplicación. Por lo tanto, la segregación de clases de acuerdo a la aproximación PredF nos permitirá determinar con mayor certeza cuándo la variación del régimen hidrológico se debe a una perturbación humana o a los patrones hidrológicos naturales.

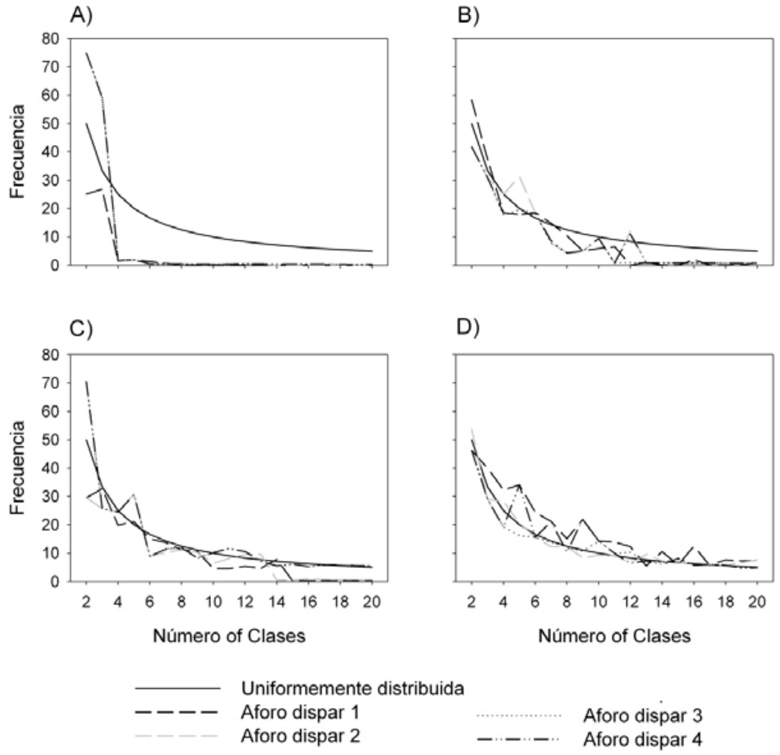

Figura 7 - Frecuencia (%) del número de segmentos incluidos en las clases a las que fueron asignadas las 4 estaciones de aforo con unas características hidrológicas más dispares respecto al número total de segmentos. A) ClasF; B) PredF; C) norClasF; D) norPredF.

4 Fuentes de variación en las clasificaciones hidrológicas: Escala de tiempo, origen de las series hidrológicas y proceso de clasificación

Este capítulo ha dado lugar al artículo: "Sources of variation in hydrological classifications: Time scale, flow series origin and classification procedure" de Peñas, F.J., Barquín, J., y Álvarez, C. Este artículo se ha enviado para su publicación a la revista: Water Resources Research.

En los últimos años se ha producido un incremento significativo en el desarrollo de clasificaciones hidrológicas debido, en gran medida, a su utilidad para la gestión de recursos hídricos y en el ámbito de la investigación hidroecológica. Sin embargo, dependiendo de los datos hidrológicos iniciales y del propio procedimiento de clasificación, es posible que aparezcan, para una misma zona de estudio, clasificaciones con diferentes características y diversos patrones espaciales. En este estudio se han desarrollado, para la red fluvial del tercio norte de la península ibérica, clasificaciones hidrológicas con un número creciente de clases (2 a 26 clases) utilizando cuatro estrategias diferentes. Tres de ellas se basan en un procedimiento inductivo pero difieren en el origen y la escala temporal de datos de partida, mientras que la cuarta se ha desarrollado utilizando un procedimiento basado en criterio de experto (Figura 8).

La Clasificación 1 se desarrolló a partir de series de caudal diarios registrados en 156 estaciones de aforo en régimen natural, mientras que las Clasificaciones 2 y 3 partieron de datos mensuales, usando tanto series aforadas como series modelados. La Clasificación 4 se basó en el procedimiento utilizado para el desarrollo del mapa de hidroregiones a escala nacional (Figura 9). Este mapa ha sido utilizado posteriormente en la determinación de caudales ecológicos dentro de los Planes Hidrológicos 2010-2015 de las diferentes demarcaciones hidrográficas españolas.

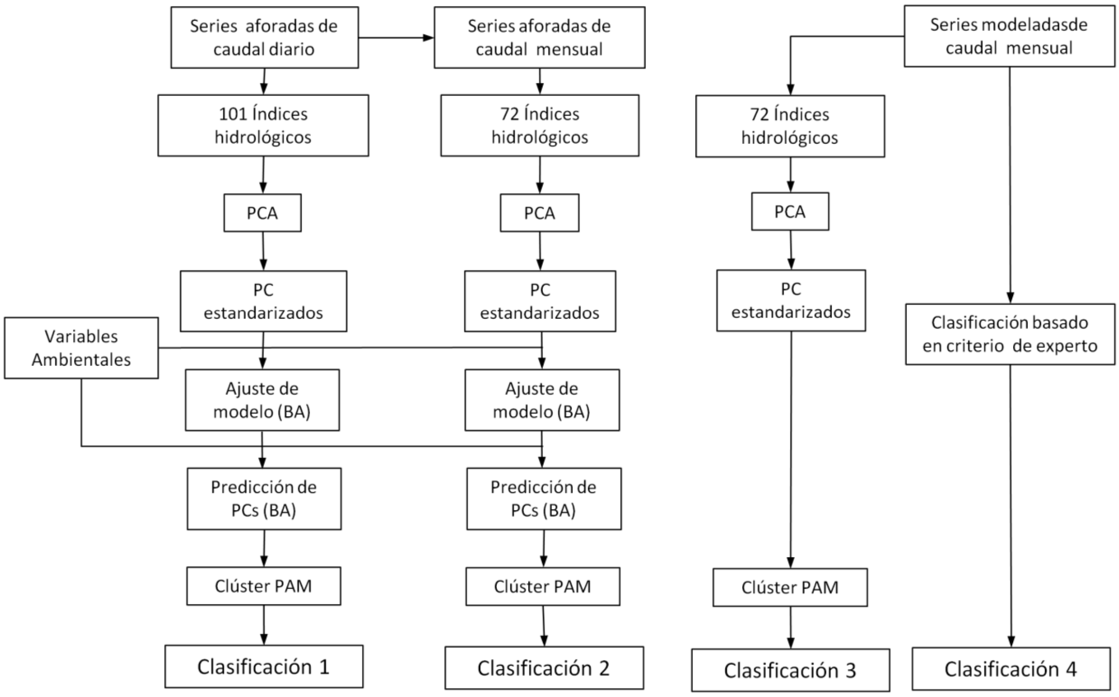

Figura 8 - Esquema en el que se resumen las cuatro estrategias de clasificación utilizadas en este estudio.

Las cuatro clasificaciones se han comparado de acuerdo a su (1) interpretación hidrológica, (2) su rendimiento estadístico y (3) su correspondencia espacial. La Clasificación 2 explicó la mayor parte de la variabilidad hidrológica del área de estudio y produjo una distribución espacial comparable a la Clasificación 1. No obstante, aún presenta limitaciones para representar ciertos atributos relevantes desde el punto de vista hidroecológico, p.e. la frecuencia de los eventos de crecida de corta duración.

El paso de una escala temporal diaria a una mensual no afecto significativamente a las propiedades de la clasificación, sin embargo, la clasificación 2 no fue capaz de explicar la variabilidad hidrológica de determinados atributos hidrológicos y fue menos robusta que la clasificación 1 (Figura 10). El rendimiento de la Clasificación 3 fue menor que el de clasificaciones 1 y 2 (Figura 10), es decir, las estaciones de aforo asociadas a una misma clase presentaron menor homogeneidad entre ellas y menor heterogeneidad en relación a las estaciones de otras clases. Así mismo, la clasificación 3 presentó un patrón espacial de clases relativamente diferente al de las clasificaciones 1 y 2. Por lo tanto, el uso de clasificaciones basadas en series de caudal modeladas debería limitarse a cuencas con un reducido número de aforos en las que la mayor parte de clases no estén representadas por los aforos. Su uso debería restringirse a la delimitación de la distribución espacial de clases hidrológicas y al asesoramiento general en la gestión de los recursos hídricos.

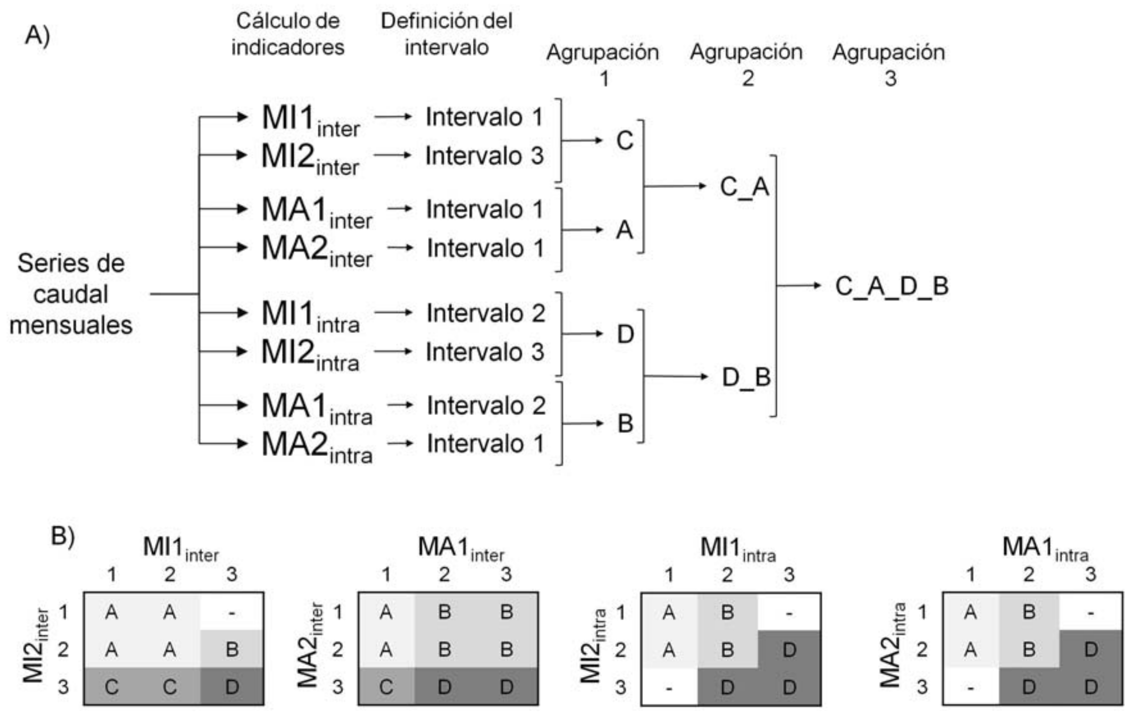

Figura 9 - A) Diagrama en el que se resumen los índices hidrológicos y los principales pasos seguidos en el proceso de agregación para el desarrollo de la Clasificación 4. B) Proceso de combinación de cada par de indicadores para obtener el nivel de Agrupación 1. Es importante señalar que de acuerdo al procedimiento de clasificación original, la tabla de agregación utilizada para cada par de indicadores es diferente.

Por último, los resultados han demostrado que la clasificación 4 posee un rendimiento significativamente inferior al de las clases 1 y 2 (Figura 10), generando clases muy heterogéneas y con un amplio solape entre ellas en cuanto a sus características hidrológicas. Así mismo, se ha puesto en evidencia que los indicadores y el procedimiento utilizado en esta clasificación generaron una distribución de clases muy desigual, en la que una sola clase abarcó la mayor parte del territorio. Este estudio demuestra que la selección de los datos iniciales y especialmente el procedimiento de clasificación generaron clasificaciones dispares en relación a los tres elementos analizados. Por tanto, la selección de la estrategia más adecuada puede tener importantes implicaciones para las futuras aplicaciones de la clasificación. Es recomendable analizar los resultados detenidamente, especialmente si los resultados clasificaciones se van a aplicar en un marco legislativo. En este sentido, principal objetivo el mapa de hidroregiones a nivel nacional (Clasificación 4) es ser la base para los procesos posteriores de estimación de caudales ambientales planteados en la Instrucción de Planificación Hidrológica. El uso de clasificaciones basadas en criterios menos objetivos puede generar un grado de incertidumbre significativo en el proceso de determinación de dichos caudales que ha de ser considerado previamente al establecimiento de los mismos.

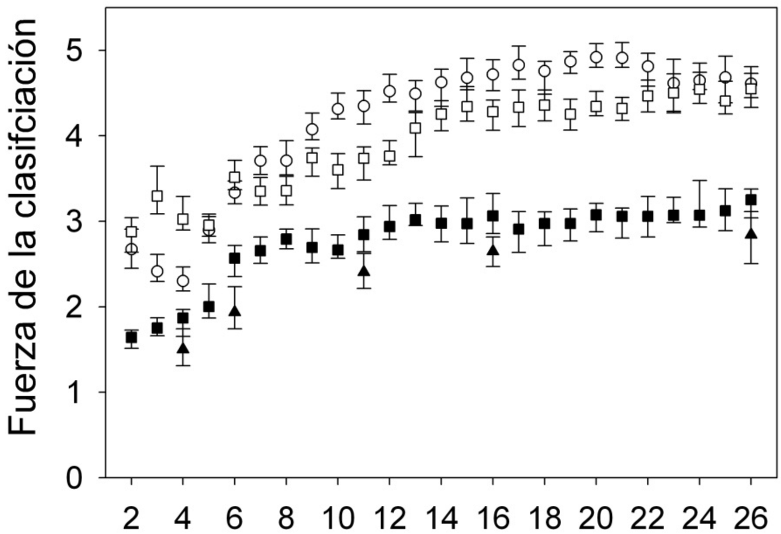

Figura 10 - Rendimiento de las clasificaciones hidrológicas con diferente grado de detalle obtenidas a partir de 4 estrategias diferentes. Los símbolos representan el valor medio de la fuerza de la clasificación y los bigotes los intervalos de confianza a un nivel del 95% (○: Clasificación 1; □: Clasificación 2; ■ : Clasificación 3; ▲: Clasificación 4).

5 Comparación de técnicas estadísticas y estrategias para el modelado de índices hidrológicos en ríos no aforados.

Este capítulo ha dado lugar al artículo: "A comparison of statistical techniques and strategies to model hydrological indices to ungauged rivers" de Peñas, F.J., Barquín, J., y Álvarez, C. Este artículo se ha enviado para su publicación a la revista: Water Resources Research.

La predicción del régimen natural de caudales en ríos no aforados representa un aspecto clave para poder asumir los nuevos retos que se plantean dentro de la gestión de los recursos hídricos y en el campo de la hidroecología. Este ejercicio se ha llevado a cabo normalmente mediante modelos de precipitación-escorrentía ya que permiten extraer cualquier tipo de información hidrológica. Sin embargo, el desarrollo de estos modelos presenta una serie de limitaciones asociadas a la complejidad en la estimación de los parámetros del modelo, la gran cantidad de información requerida para el calibrado y validado, los errores conceptuales y la cuantificación del error del modelo. Por otro lado, el establecimiento de relaciones empíricas entre índices hidrológicos concretos y variables de cuenca (p.e. climáticas, geológicas, topográficas y de usos del suelo) mediante técnicas estadísticas representa una de las alternativas más extendías para la predicción del régimen de caudales. Sin embargo, este procedimiento se ha utilizado principalmente para predecir un número limitado de índices relacionados con la gestión del recurso o la protección frente a inundaciones. Además, en la mayoría de los casos las técnicas estadísticas empleadas no han ido más allá de las regresiones múltiples, si bien, como se ha mencionado anteriormente, diferentes estudios han puesto de manifiesto que muchas de los procesos hidrológicos no presentan relaciones lineales. En el presente trabajo se han desarrollado modelos estadísticos para predecir 16 índices hidrológicos del régimen de caudales para toda una red fluvial. El conjunto de índices seleccionado aborda los 5 atributos del régimen natural de caudales considerados relevantes desde un punto de vista hidroecológico. Así mismo, se ha comparado la capacidad de diferentes técnicas estadísticas incluyendo Modelos de Regresión Múltiple (MRM), Modelos Aditivos Generalizados

(MAG), Bosques Aleatorios (BA), Redes Neuronales Artificiales (RNA) y Sistemas adaptativos de inferencia por lógica difusa (SAILD). Finalmente, se han analizado las ventajas asociadas a la Aproximación de Regresión Regional (ARR). Esta aproximación requiere el desarrollo de MRM específicos para distintas clases de una clasificación hidrológica (desarrollada en el Capítulo III). Los resultados han puesto en evidencia que la capacidad predictiva de los modelos depende en gran medida del tipo de índice modelado (Figura 11). Así, los modelos de los índices relacionados con la magnitud y frecuencia obtuvieron R^2-ajustados superiores a 0.7. En cambio, los índices relacionados con la estacionalidad, duración y tasa de cambio fueron predichos con menor exactitud, normalmente con R^2-ajustados inferiores a 0.5. Esto indica la necesidad de recopilar y generar la información necesaria que permita incluir en los modelos otras variables predictoras capaces de explicar la variabilidad espacial de estos índices. Por otro lado, los resultados han demostrado que las técnicas estadísticas más complejas no siempre superan a los MRMs y que ninguna de las técnicas utilizadas en el presente estudio resulta óptima para modelar todos los índices hidrológicos (Figura 11). Es probable que la discrepancia entre nuestros resultados y los obtenidos en diversos estudios en los que técnicas más complejas han aumentado la capacidad predictiva respecto a modelos lineales sea una consecuencia de la limitada base de datos hidrológica utilizada para desarrollar los modelos. En este sentido, las aptitudes de los modelos más complejos se maximizan cuento mayor son las bases de datos iniciales. Por lo tanto, el proceso de selección de la técnica más adecuada debe estar supeditado, además de a la capacidad predictiva del modelo, a otros elementos críticos, tales como a la interpretabilidad de los resultados y a la capacidad para afrontar relaciones no lineales entre variables dependientes y predictoras e interacciones complejas entre varias predictoras. En cuanto a los resultados obtenidos mediante la ARR, esta sólo ha mejorado los MRM globales en aquellas clases dominadas por los patrones climáticos más predecibles. En estas clases la precipitación en forma de lluvia es la principal fuente de caudal y además es patente durante todo el año. Contrariamente, los análisis han puesto de relieve que la capacidad predictora en muchas clases se ve mermada debido a la reducción del número de aforos con los que ajustar y validar el modelo. Esta es una de las principales desventajas de la ARR en zonas en las que la disponibilidad de datos hidrológicos es limitada.

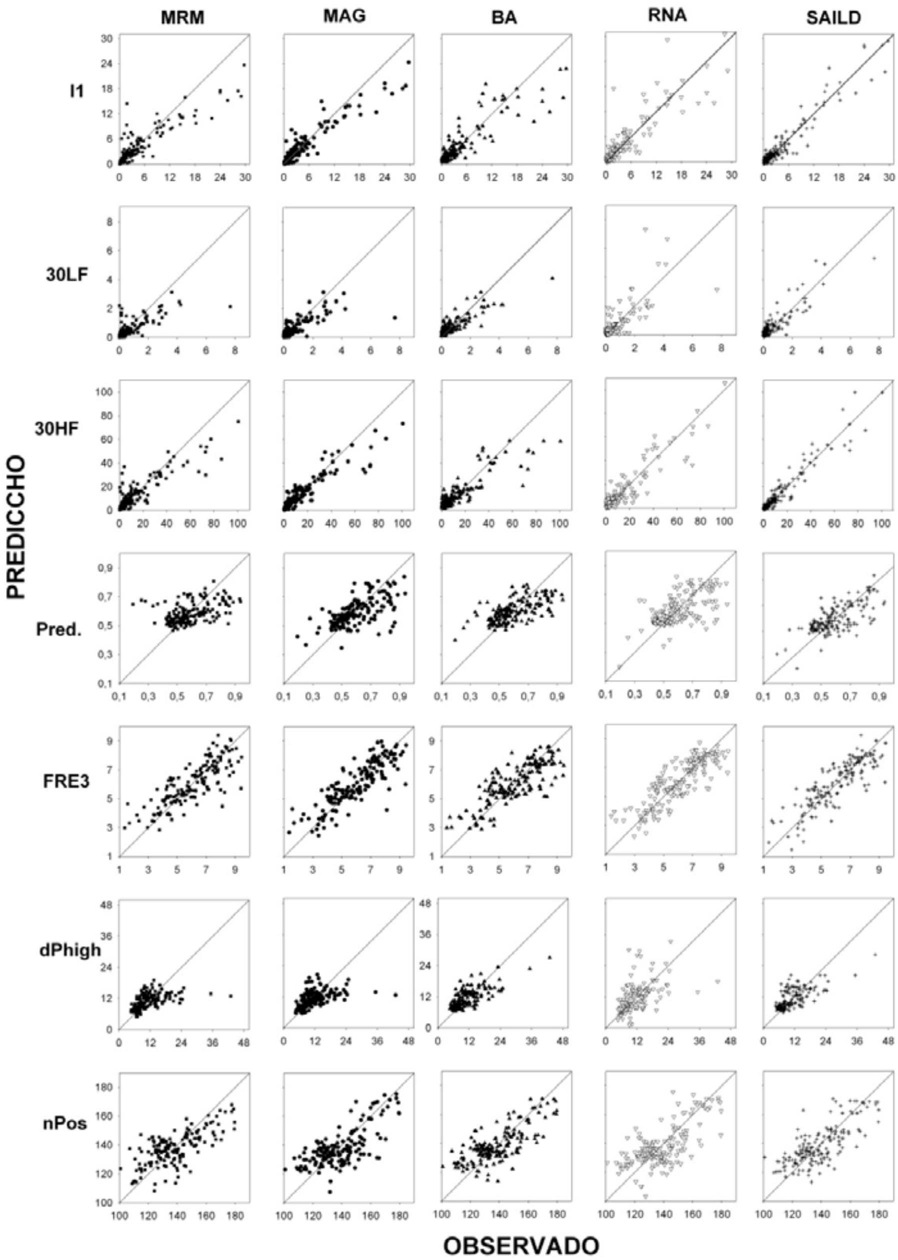

Figura 11 - Valores observados y predichos para 7 índices hidrológicos incluidos en uno de los 5 atributos del régimen natural de caudales: Magnitud (I1; 30LF; 30HF); Temporalidad (Pred), Frecuencia (FRE3); Duración (dPHigh); Tasa de cambio (nPos).

6 Evaluación de la alteración hidrológica: Análisis de diferentes alternativas de acuerdo a la disponibilidad de datos.

Este capítulo se encuentra en proceso de preparación para ser enviado para su publicación.

El régimen natural de caudales ha sido ampliamente modificado en muchos ríos del mundo. La adecuada evaluación de la alteración hidrológica es un proceso crítico en la gestión de los recursos hídricos y requiere que se haga con la mayor certeza posible. Sin embargo, los métodos aplicados hasta el momento en la mayor parte de evaluaciones están sujetos a cierto grado de arbitrariedad, lo que podría generar un error en la valoración y por lo tanto el establecimiento de medidas de restauración inefectivas frente a esa alteración. Por lo tanto, es esencial dotar a los gestores de herramientas capaces de discernir con el menor grado de incertidumbre posible aquellos efectos asociados a una perturbación humana de aquellos debidos a la variabilidad natural de los sistemas hídricos. En este sentido, se considera actualmente que los "Indicadores de Alteración Hidrológica" son una de las herramientas más adecuadas para valorar la alteración hidrológica y su aplicación ha sido la más extendida alrededor del mundo. Sin embargo, existen una serie de factores, tales como la variabilidad climática entre los periodos pre y post-impacto o la escasez de datos hidrológicos, que pueden influir significativamente en la valoración. Por lo tanto, estos elementos deben ser considerados durante el proceso de evaluación. En este capítulo se presenta un protocolo de evaluación de la alteración hidrológica que incluye cinco diseños alternativos de acuerdo a la disponibilidad de datos que presumiblemente presentarán diferentes grados de incertidumbre (Figura 12): Antes-Después-Control-Impacto-Pareado (ADCIP); Antes-Después (AD); Control-Impacto (CI); Clasificación Hidrológica (CH) y Predicción de Índices Hidrológicos (PH).

En el diseño ADCIP y en el diseño CI, el principal criterio para la selección de los controles fue que tanto el aforo impactado como el control perteneciesen a la misma clase hidrológica. Por otro lado, el diseño ADCIP permitió comparar el estado de una estación de aforo antes y después del inicio de la perturbación teniendo en cuenta, además, la variabilidad climática natural entre los dos periodos. Por lo tanto, en el presente estudio se ha considerado que este diseño representa el punto de referencia con el que comparar todos los demás diseños incluidos en el protocolo.

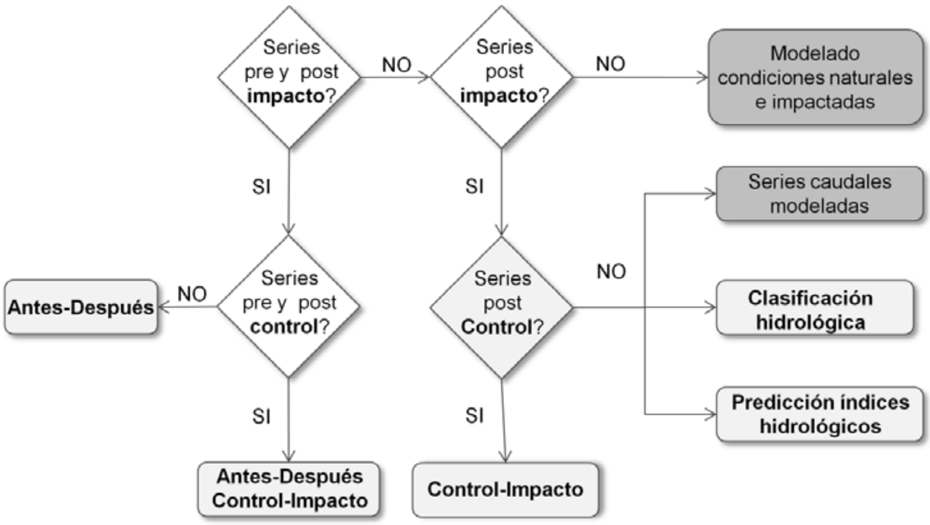

Figura 12 - Diagrama de flujo en el que se representa el protocolo para la evaluación de la alteración hidrológica.

La capacidad de los diferentes diseños para evaluar el grado de alteración hidrológica se determinó mediante la aplicación del protocolo en 11 embalses situados en el tercio norte de la península ibérica (Figura 13). En este sentido, hay que puntualizar que tanto para la selección de controles como para la aplicación del diseño CH se utilizó la clasificación hidrológica desarrollada en el Capítulo III mientras que para la aplicación del diseño PH se utilizaron los índices modelados mediante la técnica de bosques aleatorios en el capítulo V.

AD evaluó correctamente el 75% de las alteraciones hidrológicas en comparación con ADCIP. Esto es indicativo de que los patrones climáticos en periodos pre y post-impacto fueron relativamente homogéneos y que la variación de las condiciones hidrológicas se debe principalmente a la influencia de los embalses. Paralelamente, el diseño CI evaluó correctamente el 70% de las alteraciones hidrológicas, lo que pone de manifiesto que el uso de la clase hidrológica como criterio de selección de la estación control resulta adecuado para la estimación de la alteración hidrológica. Sin embargo, es patente que ambos procedimientos presentan un grado de incertidumbre en la valoración que ha de ser considerado.

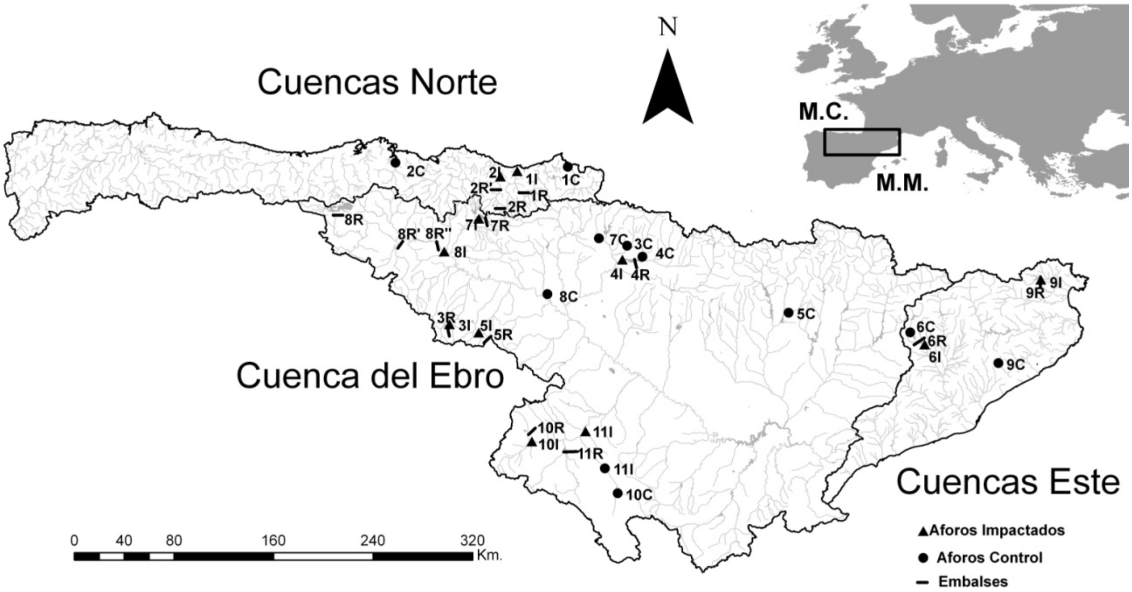

Figura 13 - Área de estudio donde se incluye la situación de los 11 embalses evaluados (R) y de las estaciones de aforo impactadas (I) y controles (C). La información relativa tanto a los embalses como a las estaciones de aforo se incluyen en la Tabla 6.1 del Capítulo VI.

Por otro lado, los análisis de los resultados obtenidos con estos dos diseños AD y CI, han evidenciado que los umbrales a partir de los cuales una alteración hidrológica debería ser considerada significativa varía de acuerdo al índice valorado. Estos umbrales tomaron valores desde 5% para los índices representativos de la tasa de cambio hasta 64% para los índices representativos de la duración de los eventos de sequia. No obstante, hay que puntualizar que normalmente los umbrales obtuvieron valores en torno al 30% (Figura 14). Estos resultados contrastan ampliamente con los criterios establecidos en la mayor parte de estudios encontrados en la literatura, en los que normalmente se establecen umbrales equivalentes independientemente del tipo de índice hidrológico. Así mismo, los umbrales establecidos en estudios previos están, en la mayoría de los casos, por encima de los obtenidos en este capítulo. Mediante este análisis se ha podido determinar el grado de alteración hidrológica que se puede considerar como significativamente diferente a la variabilidad natural. Estos resultados son muy valiosos a la hora de guiar los estudios posteriores cuyo objetivo sea la determinación del grado de impacto de la alteración hidrológica sobre el funcionamiento del ecosistema. La integración de ambos resultados permitirá llevar a cabo una gestión adecuada de los recursos y establecer unos límites de alteración adecuados.

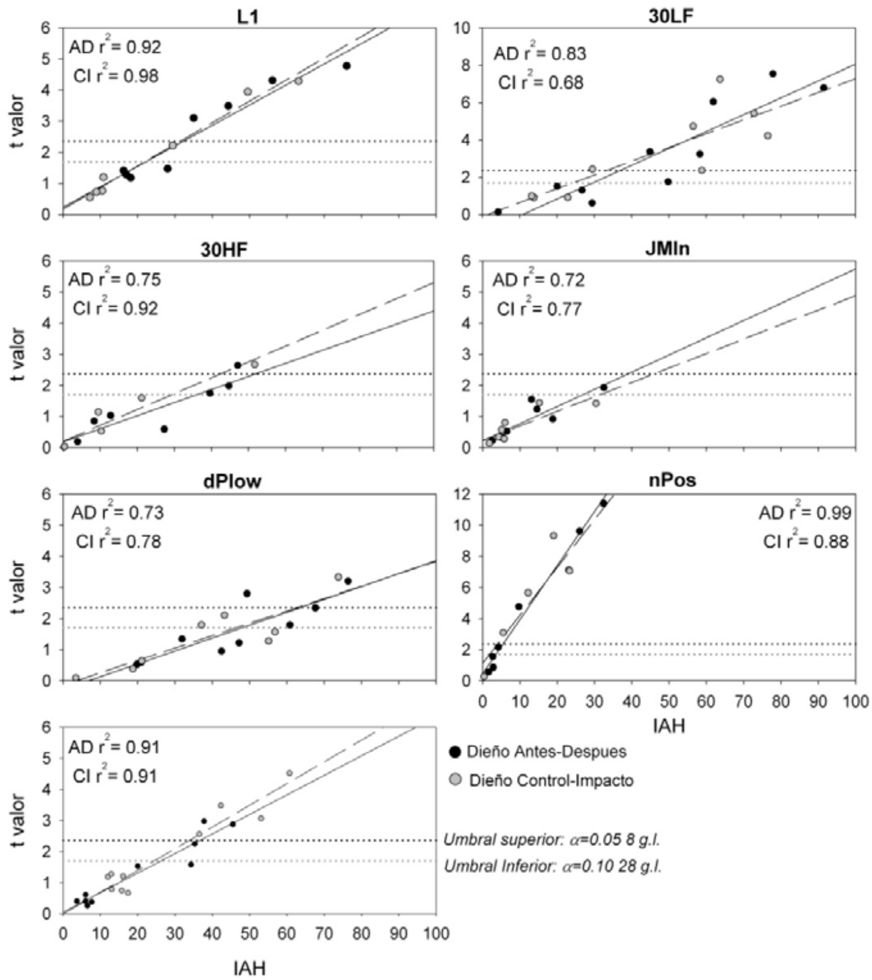

Figura 14 - Grafico de puntos y regresiones lineales obtenidas para 7 IAH frente a los valores de t. Las coordenadas de los puntos son el resultado de los tests de Student para el diseño AD (círculos negros y línea continua) y el diseño CI (círculos blancos y línea discontinua). Las líneas punteadas representan los umbrales calculados a partir de una distribución de la t con $t_{1-0.05/2,g.l.=8-1}$ =2,36 (umbral superior) y $t_{1-0.10/2,d.f.=28-1}$ =1,701 (umbral inferior).

Finalmente, la aplicación de los diseños CH y PH han puesto en evidencia un mayor grado de incertidumbre para valorar la alteración hidrológica en comparación con los otros diseños incluidos en el protocolo. Por ejemplo, de acuerdo a los análisis realizados, el 25% de los casos no pudieron ser analizados con ambos diseños. No obstante, de los casos en los que si se pudo evaluar la alteración hidrológica, tanto CH como PH lo hicieron correctamente más del 75% de las veces (Figura 15). Esto evidencia que ambas técnicas pueden resultar muy útiles cuando la alteración hidrológica ha de ser evaluada en ríos en los que los datos hidrológicos son especialmente escasos y difíciles de conseguir.

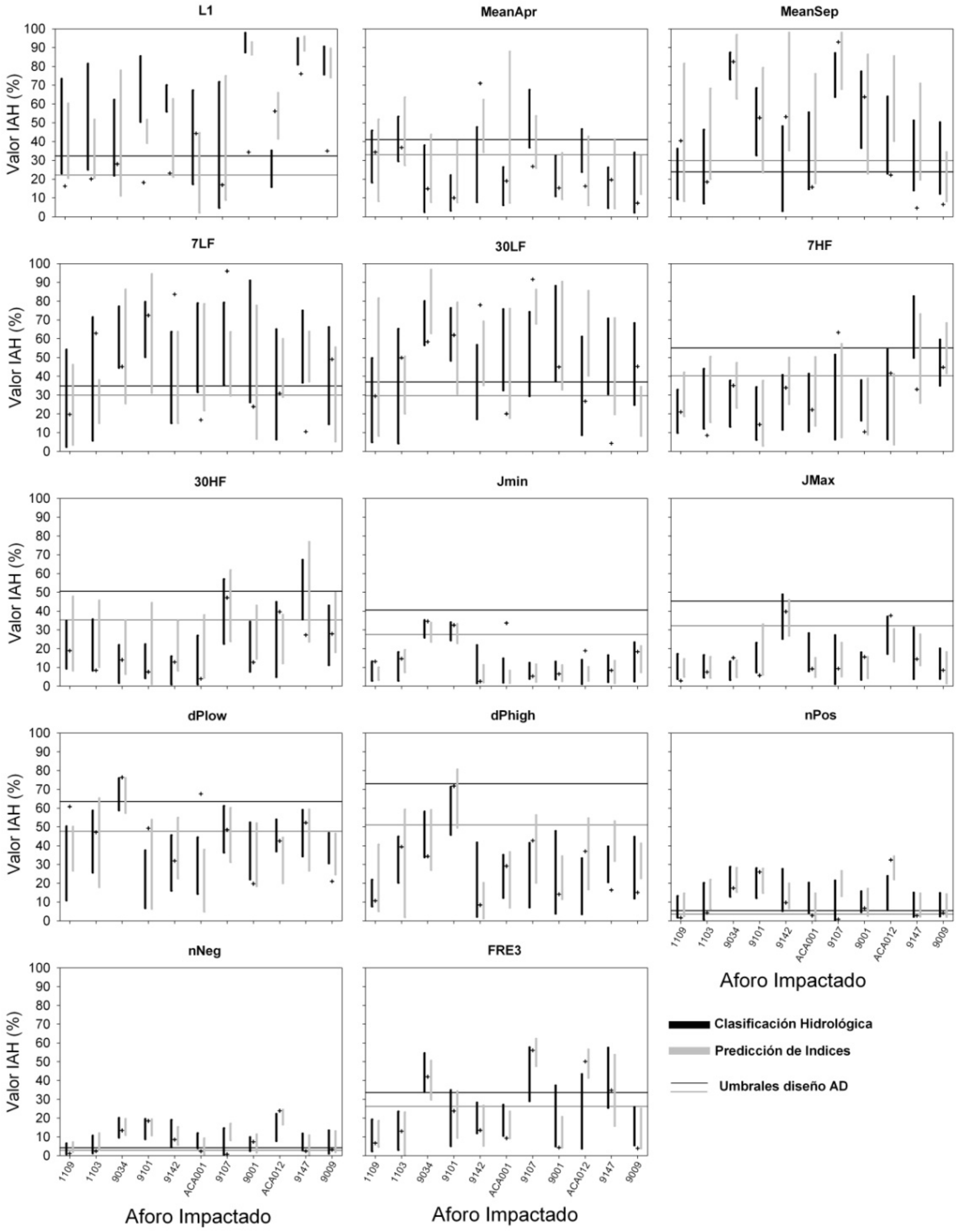

Figura 15 - Resultados de la evaluación de la alteración hidrológica mediante los diseños CH (cajas negras) y PH (cajas grises). Las cruces representan los índices de alteración hidrológica obtenida mediante el método AD para los diferentes índices y estaciones de aforo impactadas. Las líneas horizontales representan los umbrales superior e inferior calculados previamente a partir de los resultados del diseño AD.

7 Conclusiones generales y futuras líneas de investigación

7.1 Conclusiones Generales

Las clasificaciones, regresiones y modelos hidrológicos representan herramientas que nos permiten discernir la variabilidad espacio-temporal natural del régimen de caudales de aquella producida por alteraciones humanas. Tal como se ha expuesto previamente, todos estos procesos están sometidos a un importante grado de incertidumbre. Esto puede influir significativamente en la valoración final de la alteración del régimen de caudales y en muchas otras cuestiones relacionadas con la gestión de los recursos hídricos. Además, el proceso de valoración de la alteración del régimen hidrológico está expuesto a otras fuentes de variabilidad que únicamente pueden ser controladas mediante la aplicación de diseños estadísticos adecuados, lo que contrasta en gran medida con los procedimientos más utilizados hasta la fecha. Debido a la importancia social, económica y ecológica de los recursos hídricos, su gestión y los procesos de toma de decisiones deben presentar el menor grado de incertidumbre posible. Dotar a los gestores de herramientas que les permitan cuantificar rigurosamente el efecto que determinadas presiones ejercen sobre el régimen hidrológico así como el impacto que estas puedan suponer sobre laos ecosistemas fluviales, es sin lugar de dudas, un importante reto científico.

En esta tesis, se han comparado una serie de fuentes de incertidumbre asociadas al proceso de valoración de la alteración hidrológica, utilizado datos iniciales de distinta naturaleza y diferentes procedimientos sobre un mismo área de estudio. Las conclusiones extraídas de cada capítulo, y que se presentan a continuación, introducen elementos clave que se deberían considerarse a la hora de analizar los patrones de variabilidad hidrológica natural y evaluar la alteración hidrológica causada por impactos antropogénicos:

Capítulo III. La influencia de los procedimientos metodológicos en el desarrollo de clasificaciones hidrológicas.

- El tratamiento inicial de las series de caudal fue decisivo en la interpretación de las clasificaciones hidrológicas. El uso de las series no transformadas dividió la red fluvial atendiendo, casi exclusivamente, a la magnitud de los caudales y al tamaño del rio. Por el contrario, la normalización previa de los datos hidrológicos generó clasificaciones en las que fueron consideradas una gama más amplia de características hidrológicas.
- La caracterización y segregación de la red fluvial atendiendo únicamente a la magnitud de los caudales se traduce en una importante pérdida de información. Esto limita el uso de esas clasificaciones para valorar la alteración hidrológica y para investigar las relaciones caudal-respuesta ecológica a aquellos elementos dependientes de la magnitud de los caudales, tales como la disponibilidad de hábitat. Opuestamente, las clasificaciones que incluyen un mayor número de atributos hidrológicos poseen un mayor alcance en relación a las alteraciones potencialmente evaluables. La valoración del régimen hidrológico en diferentes ríos del mundo ha puesto de manifiesto que muchos otros atributos, además de de la magnitud, pueden ser modificados por perturbaciones antrópicas. Por lo tanto la normalización previa de las series hidrológicas representa un procedimiento adecuado que permitirá realizar una valoración desde una perspectiva más completa.
- La aproximación Predecir-después-Clasificar generó clasificaciones con mayor robustez y mayor capacidad para discriminar índices hidrológicos entre clases. Es decir, las clases generadas mediante esta aproximación presentaron mayor homogeneidad dentro de la clase y mayor heterogeneidad respecto a las otras clases. Teniendo en cuenta estas propiedades se puede concluir que las clasificaciones basadas en la aproximación Predecir-después-Clasificar presentan una capacidad superior para discretizar el cambio hidrológico

asociado a una perturbación. Además, considerando los principios en los que se fundamentan las clasificaciones inductivas, una mayor diferenciación hidrológica de las clases supone un mayor distanciamiento en cuanto a sus características ecológicas. Por tanto, las clasificaciones basadas en la aproximación Predecir-después-Clasificar representan una alternativa más adecuada no sólo para valorar el grado de alteración hidrológica, sino también para detectar el cambio ecológico producido por esa alteración.

- La aproximación Predecir-después-Clasificar genero divisiones de la red fluvial con una frecuencia de clases más uniforme. Es más, este procedimiento superó con mayor efectividad las limitaciones asociadas al sesgo generado por la distribución de la red de estaciones de aforo. Ambas son características muy positivas ya que, por un lado, aumenta la probabilidad de que el régimen real de un río se corresponda con el régimen medio de la clase en la que fue incluido. Además, genera que las estaciones control estén equitativamente distribuidas por todas las clases, maximizando el número potencial de controles que pueden ser posteriormente utilizados en un diseño antes-después-control-impacto.
- La selección del número apropiado de clases es un proceso que difícilmente se puede llevar a cabo desde un punto de vista totalmente objetivo, ya que, en muchas ocasiones, clasificaciones con distinto grado de detalle presentaron un rendimiento estadístico similar. Atendiendo a análisis posteriores, se recomienda el uso de clasificaciones con un número relativamente reducido de clases, lo que permitirá dar una visión general de los patrones hidrológicos espaciales en el área de estudio. En este sentido, en las clasificaciones con un número reducido de clases se aumenta el número de controles potenciales para utilizar posteriormente, sin que ello signifique una reducción del grado de homogeneidad entre estos y los tramos fluviales a evaluar. Además, debido al procedimiento de clasificación utilizado, el número de clases se puede adaptar y refinar posteriormente de acuerdo a las necesidades del estudio.

Capítulo IV. Fuentes de variación en las clasificaciones hidrológicas: Escala de tiempo, origen de las series hidrológicas y proceso de clasificación

- Contrariamente a lo esperado, la reducción del grado de detalle temporal, pasando de datos diarios a mensuales, no comprometió significativamente las propiedades de la clasificación. Por lo tanto, aquellas regiones en la que los datos hidrológicos a nivel diario no cuenten con una calidad adecuada, el uso de clasificaciones basadas en series mensuales representa una alternativa eficaz para la valoración de la alteración hidrológica y el establecimiento de grupos ecológicamente similares. Sin embargo, también hay que poner de relieve que las clasificaciones mensuales no integran todos los elementos del régimen de caudales.

- El uso de series de caudal simuladas a partir de modelos precipitación-escorrentía generó clasificaciones con un rendimiento estadístico significativamente menor y con una distribución espacial de clases relativamente diferente a las derivadas de series aforadas. En conclusión, el uso de clasificaciones basadas en series modeladas supone un aumento significativo del grado de incertidumbre en la evaluación la alteración hidrológica. En este sentido, el uso de clases más heterogéneas dificultará la selección de controles, que en algunos casos dejarían de comportarse como controles verdaderos pero, sobre todo, impedirá discernir, en muchos casos, entre el efecto de una perturbación y la variabilidad natural del rio. Por lo tanto, el uso de esta aproximación debe estar limitado a aquellas áreas de estudio en las que no exista información hidrológica para la mayor parte de a clases potencialmente presentes. Aún así, si el uso de clases modeladas es la única alternativa posible para desarrollar clasificaciones, las propuestas de gestión derivadas de la misma deberían ser analizadas cautelosamente.

- Los resultados obtenidos en este capítulo han demostrado, por último, que la selección de índices hidrológicos, los criterios y los procedimientos utilizados para generar las clasificaciones son los factores más importantes que determinan las propiedades de la misma. Las clasificaciones basadas en criterio de experto generaron un bajo rendimiento estadístico, una desproporcionada distribución espacial de clases y un elevado solape del carácter hidrológico en diferentes clases. Esto plantea importantes limitaciones de cara al uso de estas clasificaciones en la gestión de los recursos hídricos. En este sentido, la clasificación 4 desarrollada en este estudio, se basa en el mapa de hidroregiones a escala nacional. El objetivo de este mapa era servir de base para los procesos posteriores de estimación de caudales ambientales, los cuales deben ser definidos e incluidos en los planes hidrológicos de cuenca. De acurdo a nuestros resultados, creemos que aquellos aspectos del régimen ambiental de caudales definidos a partir de dicha clasificación deberían revisarse y establecer, al menos, el grado de incertidumbre asociada a esa estimación.

Capítulo V. Comparación de técnicas estadísticas y estrategias para el modelado de índices hidrológicos en ríos no aforados.

- Los modelos predictivos desarrollados para los índices hidrológicos de magnitud y frecuencia explicaron la mayor parte de la variabilidad espacial de estos atributos y generaron predicciones precisas. Sin embargo, dado la gran heterogeneidad espacial, los modelos dejaron sin explicar una parte importante de la variabilidad. La precisión de los modelos supone un elemento fundamental que debe tenerse en cuenta para definir la incertidumbre con la que las predicciones se pueden utilizar posteriormente. Sin embargo, este aspecto ha recibido, hasta el momento, un tratamiento relativamente limitado.

- Es necesario mejorar los modelos para aquellos atributos relacionados con la estacionalidad, duración y tasa de cambio, que sean capaces de explicar con mayor exactitud su variabilidad hidrológica espacial. Creemos que en una primera etapa habría que mejorar la resolución espacial de ciertas variables edafológicas y geológicas así como desarrollar otras variables que den cuenta de los patrones de circulación subterránea. Además, la disposición de variables climáticas con un mayor grado de detalle y la inclusión de otros atributos referente al ciclo de innivación y deshielo, aumentaría la capacidad para entender muchas características hidrológicas, tales como la variabilidad del régimen, la estacionalidad o los patrones de sequia y crecida.

- Las cuatro técnicas estadísticas complejas empleadas generaron, normalmente, modelos más precisos que aquellos desarrollados a partir de regresiones lineales si bien, en muchas ocasiones, las diferencias fueron menores a las esperadas. Las técnicas de aprendizaje automático precisan de bases de datos extensas, lo que contrasta con la bases de datos hidrológica utilizada en esta tesis. En este sentido, creemos que la ampliación del número de estaciones de aforo conferiría a estas técnicas un mayor potencial para superar a los modelos lineales.
- El desarrollo de RNA y SAILD requiere un importante nivel de conocimiento para poder tanto definir la estructura óptima de los modelos como establecer las relaciones causa efecto entre los índices hidrológicas y las variables de ambientales. Por otro lado, la aplicación de los MRM y MAG necesita la transformación especifica de las variables que cumplan con los supuestos requeríos por los modelos, lo cual no siempre se ha conseguido. Por lo tanto, más allá de la capacidad predictiva, todos estos factores han de tenerse en cuenta. En este sentido, es importante proporcionar herramientas que permitan entender, más allá de las relaciones estadísticas, las relaciones y procesos físicos entre las variables. Esto permite asociar un rango potencial de respuesta esperado frente a una determinada medida de gestión.
- La segregación previa de las estaciones de aforo de acuerdo a una clasificación hidrológica no generó un aumento en la calidad de los modelos. La limitación en cuanto al número de datos por clase es la causa más probable de que no se haya cumplido la hipótesis inicial. Sin embargo, también cabe señalar que la mejora potencial asociada a esta aproximación no sólo está relacionada con el aumento del número de datos sino con el aumento del nivel

de detalle de las variables predictoras. Es decir, al reducir la variabilidad de los atributos hidrológicos dentro de cada clase se necesitan variables predictoras que respondan tanto a los patrones regionales como locales.

Capítulo VI. Evaluación de la alteración hidrológica: Análisis de diferentes alternativas de acuerdo a la disponibilidad de datos.

- El uso de estaciones de control en combinación con el diseño antes-después para evaluar la alteración hidrológica asegura que los cambios observados en el régimen hidrológico se deban exclusivamente a la influencia de la perturbación, en este caso, la presencia un embalse. Aunque la evaluación llevada a cabo con y sin estaciones controles, es decir mediante el diseño ADCIP y BA, respectivamente, hayan generado resultados similares, la aplicación del protocolo de evaluación también ha puesto de manifiesto que es posible encontrar estaciones control para todo los sitios impactados. Por lo tanto, creemos que el uso de estaciones control debería ser considerado en todos los procesos de evaluación de la alteración hidrológica ya ADCIP que es el único diseño que puede conferir a los gestores la certeza total de que el cambio se debe a elementos antrópicos. La aplicación de este diseño permite establecer medias de restauración y los caudales ecológicos desde una perspectiva defendible científicamente y que elimina mucha parte de la incertidumbre, lo que es indispensable para aminorar confrontaciones entre diversos usuarios de los recursos.

- Los resultados han puesto de manifiesto que el uso de clasificaciones hidrológicas representa una estrategia óptima para la selección de controles. En este sentido, la homogeneidad hidrológica entre dos estaciones de aforo que pertenecen a la misma clase está asegurada. Si esta cualidad se combina con otros criterios que controlen la variabilidad debido a efectos locales se garantiza la capacidad de los controles para detectar cambios en las estaciones impactadas y posiblemente supere a otros procedimientos para la selección de controles. Sin embargo, tal como ha sido puntualizado repetidamente a lo largo de este capítulo, solo se deben utilizar aquellas clasificaciones en las que la heterogeneidad dentro de las clases sea mínima. El uso de clasificaciones inadecuadas para la selección de controles puede desembocar en evaluaciones incorrectas y la aplicación de medidas poco eficaces.

- La definición de umbrales que permitan determinar el grado de alteración hidrológico ha de fundamentarse en criterios objetivos. Se ha demostrado que los umbrales establecidos para diferentes índices hidrológicos muestran un rango de variación importante y que además, se encuentran, generalmente, por debajo de los establecidos en otros muchos estudios. La aplicación de índices subjetivos puede conducir a dos situaciones: Que no se detecten alteraciones significativas cuando realmente existen o que se detecten alteraciones significativas cuando en realidad se deben a la variabilidad natural del río. Esto representa un aspecto crítico en la gestión de los recursos hídricos y especialmente para el establecimiento de un régimen de caudales ambientales.
- Las clasificaciones hidrológicas y los índices predichos a partir de técnicas estadísticas representan alternativas adecuadas para evaluar la alteración hidrológica cuando no existen otras fuentes de datos. Creemos que ser capaces de reconocer la incertidumbre asociada a la variabilidad de las clases hidrológicas o a la precisión de los modelos es un elemento muy importante a considerar en la evaluación de la alteración hidrológica.

7.2 Futuras líneas de investigación

De acuerdo con lo objetivos de esta tesis, se han identificado y valorado diversos elementos críticos dentro del procedimiento ELOHA y se han establecido importantes aspectos a tener en cuenta en la gestión de los recursos hídricos. Además, el desarrollo de los diversos estudios en la tesis nos ha permitido identificar una serie de deficiencias que requieren ser priorizados en futuras líneas de investigación:

- El desarrollo de nuevas variables ambientales relacionadas con procesos de cuenca y procesos climáticos nos permitirá explicar con mayor precisión la variabilidad natural de todos los atributos del régimen hidrológico. Este trabajo es esencial para mejorar los procedimientos de clasificación y la predicción de índices hidrológicos y por tanto, avanzar en el entendimiento de los patrones hidrológicos a escala regional. El aumento de la capacidad predictiva es un aspecto especialmente valioso para minimizar el grado de incertidumbre asociado a los métodos alternativos de valoración de la alteración hidrológica.
- El protocolo de evaluación de la alteración hidrológica ha sido validado únicamente mediante el análisis del cambio generado por la actividad de los embalses. Es esencial incluir y valorar las alteraciones producidas por un rango más amplio de presiones, lo que permitirá determinar con mayor firmeza los beneficios y limitaciones de cada diseño. En este sentido, se debería evaluar el efecto producido por la evolución de los cambios del suelo, el cambio de los patrones climáticos y otras alteraciones hidrológicas directas.
- El protocolo de evaluación de la alteración hidrológica presentada en al Capítulo VI no incluyó ninguna alternativa para evaluar aquellos casos en los que no existe ningún tipo de información hidrológica en el río impactado. Los estudios que se centran en esta cuestión son todavía escasos en la literatura y el desarrollo de metodológicas que permitan valorarla permitiría completar un protocolo en el que todas las posibles situaciones de impacto podrían ser incluidas.
- Los umbrales de alteración hidrológica definidos en esta tesis fueron establecidos de acuerdo a la evaluación, únicamente, de 11 embases. La extensión de este análisis a todas las presiones cuantificables en la red fluvial del área de estudio y en toda la geografía española permitirá definir unos umbrales más robustos que podrían ser la base de la gestión de los recursos

hídricos y el establecimiento de regímenes de caudales ambientales a nivel nacional.

- Finalmente, dos elementos fundamentales que permitirían completar el proceso ELOHA no han sido considerados en la presente tesis: (1) El establecimiento de relaciones entre el régimen hidrológico y la respuesta del ecosistema y (2) la cuantificación del impacto sobre esta respuesta generada por la alteración del régimen. La base de datos generada para el desarrollo de esta tesis, no cuenta sólo con datos referentes al régimen de caudales, sino que se han recopilado datos de configuración del hábitat, condiciones físico-químicas e información biológica en más de 2000 puntos de muestreo. La capacidad para explotar esta base de datos representa una oportunidad inmejorable de cara al avance en el conocimiento de los dos aspectos clave mencionados anteriormente. En consecuencia, esto permitiría desarrollar herramientas imprescindibles con las que científicos y gestores de los recursos hídricos podrían plantear medidas de gestiones objetivas y eficientes para el mantenimiento y recuperación de los ecosistemas fluviales.

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Chapter I

Introduction and background to the research

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1.1 The ecological importance of the natural flow regime

Natural flow regime plays a major role in determining the biotic composition, structure, function and diversity within river ecosystems (Richter et al., 1996). It influences freshwater ecosystems in a variety of temporal and spatial scales, ranging from hours to millennia and from local to global scales (Lytle and Poff, 2004; Biggs et al., 2005). In this regard, Bunn and Arthingthon (2002) introduced three key principles and mechanisms to link hydrology and aquatic biodiversity: (1) flow is a major determinant of the habitat, (2) aquatic species have evolved life-history strategies in response to the natural flow regime and the habitats that are available at different times of the year and in wet and dry years and (3) the natural pattern of the longitudinal and lateral connectivity in the river system is important for supporting populations of aquatic species. In addition, it is recognised that the invasion and success of non-native species is facilitated by alterations to streamflow (Bunn and Arthington, 2002).

It is widely recognized that flow regime can be described by five major ecological relevant attributes: Magnitude, Frequency, Duration, Timing and Rate of Change (Richter et al., 1996; Poff et al., 1997). The magnitude is the amount of water that circulates through a point per unit of time. Frequency is the number of times that a flow event occurs in a defined time interval while duration refers to the period of time associated with a specific flow condition. Timing is an indicative of the regularity with which a flow event occurs, while rate of change or flashiness indicates the velocity and the number of times that flow changes form one stage to another. These flow attributes are highly inter-correlated (Puckridge et al., 1998; Olden and Poff, 2003) which makes separation of the ecological response to each particular aspect difficult. Average flow conditions determine the habitat diversity and availability and the hydraulic conditions trough the year. These features significantly determine the biotic composition given the contrasting preferences of different organisms (Jowett and Duncan, 1990; Clausen and Biggs, 1997). On the other hand, high flow episodes of different magnitudes and frequencies regulate numerous ecological processes (Biggs et al., 2005; Fitzhugh and Vogel, 2011). For instance, high magnitude, low frequency floods are the major driver of channel form (Gordon et al., 2004), structure the floodplain habitats and determine the frequency of habitat turnover (Petts, 2007). Lower magnitude, more frequent floods (or spates) provide other functions such as removing fine sediments and preventing its accumulation in interstitial spaces (Lake, 2007). Moreover, high flows sustain system productivity through the connection of main channel to floodplains (Puckridge et al., 1998) importing woody debris, nutrients and organic matter into the river channel (Lytle, 2000; Hering et al., 2004).

Likewise, droughts and episodes of flow cessation regulate a variety of ecological processes. During low flow episodes longitudinal fragmentation disrupt the transport of nutrients, fine sediment and organic matter (Lake, 2007) and an increment of temperature and rates of deoxygentaion can occur in isolated pools (Dahm et al., 2003). Lotic ambients gradually disappear and fauna adapted to fast current are eliminated (Boulton and Lake, 1990) which can be intensified by the reduction of habitat quantity and quality. Duration modulates the degree of the ecological significance of low flow events, as species are tolerant to specific durations beyond which they are not able to persist. For instance, invertebrate (Boulton, 2003) and fish (Matthews and Marsh-Matthews, 2003) populations could be greatly diminished during long drought events leading to a complete modification of biological communities (Bonada and Resh, 2013).

The life cycles of many aquatic and riparian species have evolved to avoid or exploit the natural timing of different flow conditions (Lytle and Poff, 2004) and the natural seasonality of high and low flow periods prevents the establishment of non-native species (Fausch et al., 2001). For instance, in rivers with highly variable timing of high flows, species present long breeding seasons and flexible reproductive strategies

(Puckridge et al., 1998), while in more predicable rivers reproduction and maturation can be synchronized with specific flow episodes (Lytle and Poff, 2004).

Finally, the flashiness of a single flood event can highly influence the endurance of different organisms according to different behavioural and morphological adaptations (Lytle and Poff, 2004). In addition, seasonal rate of change from high to low or from low to high flow conditions controls the persistence of many aquatic (Stanley et al., 2004) and riparian species (Stanley et al., 1997; Lake, 2007).

One of the main challenges of hydroecology is to unravel the interaction and linkages between hydrological and stream ecosystem dynamics. It has been proposed that the five attributes of the natural flow regime should be examined in association with ecological data to promulgate and test concrete flow-ecology hypothesis and analyse how these relationships change according to flow alteration (Monk *et al.*, 2007; Poff *et al.*, 2010). This information is extremely valuable to guide water management decisions. This need has provided the definition of over 200 ecologically relevant hydrological indices (Olden and Poff, 2003; Monk et al., 2007) describing each of the five attributes of the natural flow. Nonetheless, it should be acknowledge that environmental factors other than flow regime also play an important role in determine ecological attributes of a river (Snelder and Lamouroux, 2010). This hampers the precisely quantification of direct relationships between ecological characteristics and flow regimes.

1.2 The alteration of the natural flow regime

Freshwater systems provide natural resources (e.g. fish, riparian plants and clean water) as well as cultural and ecological services (e.g. transportation, energy, irrigation, recreation and waste assimilation) basic to human societies (Naiman *et al.*, 2002). Unfortunately, the worldwide exploitation of freshwater has occurred without clear understanding of how these systems self sustain their processes (Gleick, 1998; Naiman and Turner, 2000). The direct consequence of this practice is reflected in the decline of freshwater species by 50% from 1970 to 2000, compared to the 30% for marine and terrestrial species (Millenium Ecosystem Assessment, 2005). The loss of freshwater biodiversity is also paralleled with loss of ecosystem functioning and thus, the services they provide to human societies (Postel and Ritcher, 2003). Furthermore, considering the actual predictions under global climatic change scenarios (Millenium Ecosystem Assessment, 2005), losses of freshwater ecosystem services may reach up to 40% of the world's population by 2050. Overexploitation of natural resources, water pollution, fragmentation, habitat degradation and invasion by non-native species are considered the five principal threats to freshwater ecosytem (Malmqvist and Rundle, 2002; Dudgeon *et al.*, 2006). These five aspects are strongly correlated and aggravated by the modification of the natural flow regime (Arthington *et al.*, 2010). In this regard, rivers' flows have been largely altered by impoundments (Poff *et al.*, 2007), surface water withdrawals (Döll *et al.*, 2009), groundwater pumping (Carlisle *et al.*, 2011), interbasin water transfers (Jackson *et al.*, 2001) and land use modifications (Zhao *et al.*, 2012; Martinez-Fernandez *et al.*, 2013). Moreover, the predicted shifts related to climate change (Suen, 2010; IPCC, 2013) might interact and strengthen these hydrological perturbations (Naik and Jay, 2011; Schneider *et al.*, 2013).

Among these flow perturbations, it is widely recognize that the construction and operation of large reservoirs represent the most prevalent form of hydrological alteration (Vitousek *et al.*, 1997; Tharme, 2003). Currently exist more than 40000 large dams (WCD, 2000) which directly affect more than 60% of the large river systems (Nilsson *et al.*, 2005). The presence of dams is especially dramatic in semi-arid and arid regions, where there´s high water demand together with water scarcity (Döll *et al.*, 2009; Bonada and Resh, 2013). The case of Spain is quite significant. It represents the 51^{st} country in terms of extension, but it is identified within the top five dam-building countries (WCD, 2000). Moreover, reservoirs impound almost 60% of the total runoff in some of the country principal basins (Batalla *et al.*, 2004). Considering the serious societal and ecological concerns related to the activity of reservoirs, one of the objectives of the present thesis is to provide useful tools that reduce the uncertainty of assessing the flow alteration caused by this type of perturbation.

Reservoirs vary in size, level of impoundment, function and operational rules so it is not an easy question to predict their potential hydrologic alteration. Furthermore, the degree and direction of alteration might also depend upon the characteristics of the impacted river (McManamay *et al.*, 2012; Belmar *et al.*, 2013). According to this variability, the hydrological alteration caused by reservoirs could manifest also a myriad of ecological adjustments. Even if, the greater the modification of the flow regime, the greater the expected ecological shift (Poff and Hart, 2002), significant ecological responses to small hydrological alterations have also been recorded (Lloyd *et al.*, 2003). In addition, changes on different flow regime attributes act synergistically (Poff *et al.*, 2007) and also in combination with other drivers of environmental degradation (e.g. wastewater, channelization, nutrient enrichment in agricultural catchments, etc; Poff and Zimmerman, 2010). All these factors hinder the definition of straightforward cause-effect relationships between hydrological alterations and ecological consequences.

The dominant alterations caused by reservoirs are related to changes in flow magnitude. Flow regulation normally implies diminished average flow conditions, leading to reduced amplitudes of seasonal variability (Döll *et al.*, 2009); this can even reach, in the most dramatic cases, to inversions of the seasonal patterns (Graf, 2006; Belmar *et al.*, 2013). In general, it is widely accepted that the homogenization of the flow regime through the year may decline biotic heterogeneity as it allows establishment of non-native and generalist species (Fausch *et al.*, 2001; Moyle and Mount, 2007). Alteration of seasonal flow variability has been associated to negative impacts in the habitat diversity and availability. For instance, fish show characteristic preferences to different values of velocity, water depth and particle size (Lamouroux and Capra, 2002) which basically depends on the interaction between discharge and geomorphological configuration (Bovee *et al.*, 1998). Modification of the natural patterns of hydraulic habitats greatly affects the functional organization of fish communities and overall diversity (Bunn and Arthington, 2002).

On the other hand, it has been demonstrated that natural disturbing flow episodes, e.g. flood-pulse cycle (Junk *et al.*, 1989) and recurrent droughts (Lake, 2007) are especially susceptible to be altered by reservoir operation. Minimum flows are normally increased (Black *et al.*, 2005) which facilitate the proliferation of non-native species that are not naturally adapted to severe drought regimes. In contrast, other authors have highlighted significant decreases in low flow magnitudes (Yang *et al.*, 2008; Brown and Bauer, 2010) which intensify the biological effects of drought episodes (Lake, 2007). Unnaturally prolonged droughts and episodes of flow cessation can increment exclusion of native flora via effects on competitive interactions by drought-tolerant species (Magilligan and Nislow, 2001; Maingi and Marsh, 2002) and reduction of plant growth because of the lowering of the floodplain water table (Jolly, 1996). In parallel, numerous recent studies have found consistent decreases in the high flows pattern (Carlisle *et al.*, 2011; Fitzhugh and Vogel, 2011; Caruso, 2013), even if reservoirs were not originally designed for flood protection (Batalla *et al.*, 2004). Many studies demonstrated the geomorphic impact produced by reduced flood flows on the stream channel cross-sectional morphology (Maingi and Marsh, 2002) and river planform (Richter and Richter, 2000). Moreover, the reduction of smaller spates might produce the degradation of other critical components of habitat, such as siltation of spawning gravels and cobble surfaces. This may reduce the quality and quantity of suitable habitats for fish, macroinvertebrates and algae (Lloyd *et al.*, 2003; Magilligan and Nislow, 2005). Likewise, riparian vegetation can suffer important changes due to loss of the normal flood pulse cycle (Small *et al.*, 2009), which is associated with the inhibition of seedling establishment (Caruso, 2006) or proliferation of species intolerant to prolonged submersion periods (Cooper *et al.*, 2003). The modification of droughts and flood patterns implies not only the magnitude, frequency and duration but also, their characteristic timing patterns. For instance, changes in timing of high and low flows has consistently been reported, although in many occasions magnitude and direction of changes depends upon climatic and hydrologic patterns of the altered catchment (Poff *et al.*, 2007). Modification of the annual cycles of floods and droughts would inhibit the compatibility with life history of many organism inhabiting predictable streams (Lytle and Poff, 2004), or by contrast, it would reduce the higher competitiveness of species adapted to more unpredictable flow regimes

There are as well several studies which support a consistent trend associated to the modification of the rate of change. Altered rivers generally increase the number of flow reversals, while the rate of rises and fall normally decreased (Pyron and Neumann, 2008; McManamay *et al.*, 2012). Changes of daily and sub-daily rates downstream hydropower dams may produce a complete transformation of aquatic and riparian communities (Poff *et al.*, 1997), together with episodes of drift or stranding of organism (Perry and Perry, 1986; Parasiewicz *et al.*, 1998; Saltveit *et al.*, 2001). Nonetheless, modification of the flashiness of flow episodes may have different biological effects depending on the time of the year, and would likely be maximized during periods of migration or spawning (Zimmerman *et al.*, 2010).

Alternatively, reservoirs can also indirectly affect river stream communities throughout the modification of natural physico-chemical conditions (Camargo and García de Jalón, 1990), organic matter dynamics (Caruso, 2002; Acuña and Tockner, 2010) and the reduction of nutrient inputs (Doyle *et al.*, 2005).

1.3 Providing a naturalized flow regime

According to what has already been described, the importance of the flow regime to maintain healthy freshwater ecosystems and the goods and services they provide has been widely demonstrated. Taking into account the increasing demand of water resources, it is clear that balancing the water needs for people and those of ecosystems has to become a premier environmental issue (Palmer *et al.*, 2004; Wood *et al.*, 2007). In this regard, establishing a near-natural flow regime (i.e. defining an environmental flow) is considered as one of the most effective approaches to restoration (Roni *et al.*, 2008). The Brisbane Declaration (2007) defined environmental flows as the “quantity, timing and quality of water flows required to sustain freshwater and estuarine ecosystems and the human livelihood and well-being that depend on these ecosystems”. Scientists need to develop and provide tools and models to carry out this objective, however, the methodology used to establish environmental flow regimes is far from being universal (Richter *et al.*, 1997; Tharme, 2003). More than 200 methodologies have been developed and applied worldwide (Jowett, 1997; Annear *et al.*, 2004) which are usually grouped in hydrologic (Tennant, 1976), hydraulic (Collings, 1972) and habitat simulation methods (Bovee, 1982). Briefly, hydrologic methods rely on the use of hydrological series to define, in most cases, minimum environmental flows. In general, this category encompasses simple methods which define fixed percentages of the average annual or monthly flow or other hydrologic parameters. However, there are also more complex hydrologic approaches, such as the Range of Variability Approach (Richter *et al.*, 1997). This method considers a set of hydrological indices covering the five attributes of the flow regime and proposes thresholds which might not be exceeded for each of them. Hydraulic methods use changes in hydraulic variables, usually measured in a limited number of cross-sections, as a surrogate for habitat factors important to the biota (Loar *et al.*, 1986). Habitat simulation methods are a natural extension of hydraulic methods. They integrate hydraulic models to predict flow-related changes in physical microhabitat (velocity and depth) at the reach scale with habitat models to define habitat availability under different flow conditions. Although methods in the three types of approaches have evolved to more complex and complete procedures (e.g. Parasiewicz, 2008; Palau and Alcázar, 2012), they still present several flaws that limit their ability to formulate policy and management actions. For instance, main criticisms focus in that many of them define environmental flows only as a fraction of long term average flows to define just annual or monthly minimum flows. This perspective is considered overly simplistic and inappropriate for protecting ecosystems (Döll *et al.*, 2009) as they obviate all other ecologically relevant attributes of the flow regime (Arthington *et al.*, 2006). On the other hand, methods that optimize water regimes for one or a few aquatic species (such as fish or invertebrates), potentially neglect the need for other species and ecosystem processes (Richter *et al.*, 1996) and would hardly sustain long-term ecosystem functioning (Palau and Alcázar, 2012).

It is now widely accepted that maintaining some degree of similarity to the various pre-impacted combinations of flow magnitude, timing, duration, frequency and rate of change is required to maintain freshwater ecosystems' processes and functions (Galat and Lipkin, 2000; Arthington *et al.*, 2006; Schneider *et al.*, 2013). In this regard, a fourth type of method has been usually considered, namely the holistic methods (King and Louw, 1998). Holistic methods identify important flow events for all major river ecosystem components, model relationships between flow and ecological and social responses, and use interdisciplinary team approaches to recommend environmental flow regimes. Although they can be viewed as the most scientific defensible approach, their actual application can take years to complete for just one river reach (Kendy *et al.*, 2012), while ability to develop environmental flow guidelines needs to meet the current rate of hydrologic change. The Ecological Limits of Hydrological Alteration (ELOHA) framework (Poff *et al.*, 2010) arose in response to this problem. ELOHA has been widely accepted by the scientific community and water managers since its publication and several examples of its application already exist, mainly in the US (Kendy *et al.*, 2012; Buchanan *et al.*, 2013; McManamay *et al.*, 2013). The strengths of the framework to guide the development of environmental flow at the regional scale lie in the use of existing hydrologic and biological information and the knowledge and experience gained from individual case studies. The scientific process of the ELOHA framework encompass four steps: (1) creation of a hydrologic foundation of streamflow data, (2) classification of river types according to the natural hydrologic variability, (3) analysis of flow alteration and (4) development of flow-ecology relationships associated with each river type to propose environmental flow standards (Figure 1.1). This thesis is focused on the first three steps of the ELOHA framework aiming to evaluate potential sources of uncertainty within the procedure. Findings might guide further application of the framework in testing flow-ecology relationships and defining environmental flows.

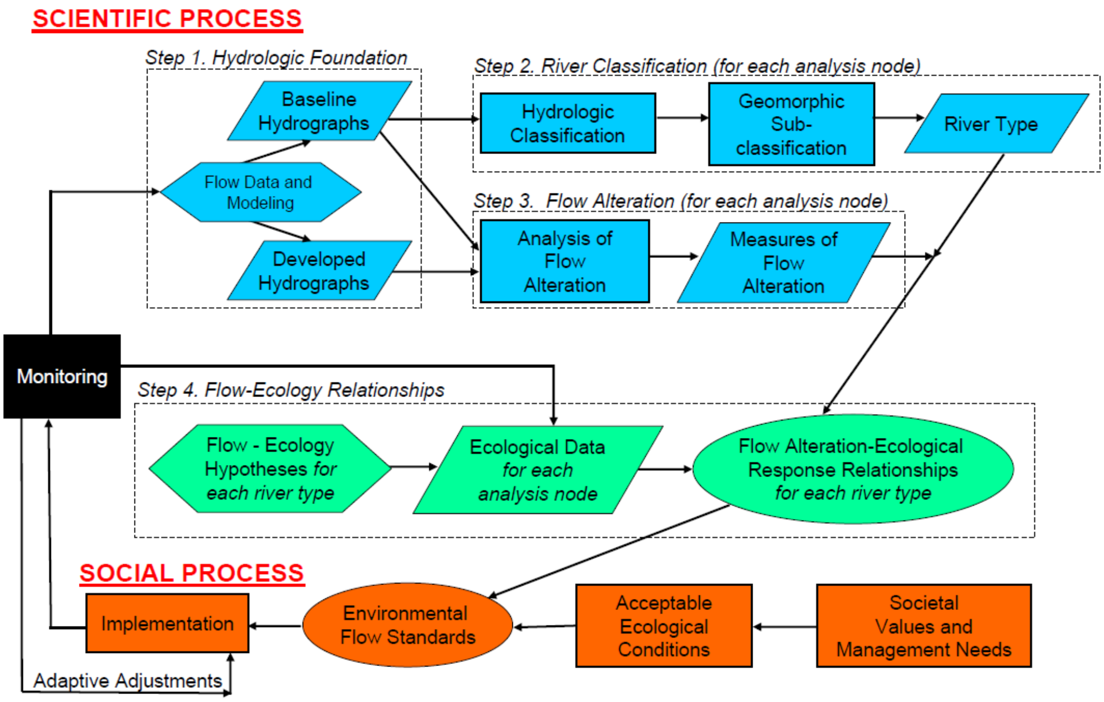

Figure 1.1 - The ELOHA framework (Source: Poff et al, 2010).

1.4 From theory to practice

1.4.1 Defining the hydrological data base

The first step of ELOHA provides estimates of ecologically meaningful streamflows in all the river segments distributed throughout a region. The prediction of natural flow conditions is a key feature as it establishes the baseline for natural classification, hydrologic alteration assessment and development of ecological-flow relationships. Hydrological rainfall-runoff models have been widely used to address this step (Black *et al.*, 2005; Kennen *et al.*, 2008; Murphy *et al.*, 2013) and are specially useful in heavily engineered catchments (Belmar *et al.*, 2011). The extensive application of these models is associated with their flexibility, as any number of hydrologic indices can be calculated from the simulated series without prior knowledge of their ecological relevance (Murphy *et al.*, 2013). However, the reliability of the derived series may be constrained due to the complexity associated to the determination of model parameters (Duan *et al.*, 2006), the large set of gauged basins and spatial coverage of rainfall data required to calibrate models (Sauquet, 2006), conceptual errors in the models (Kirchner, 2006) and inadequate quantification of uncertainty (Beven, 2006; Wagener and Montanari, 2011).

On the other hand, if the gauging monitoring network is large enough to provide a suitable hydrological data base in the targeted region, this information can constitute the hydrological foundation. Thus, flow series recorded at unimpaired gauges coupled with environmental catchment attributes can then be used to develop predictive hydrologic classifications (Snelder *et al.*, 2009; McManamay *et al.*, 2012; Solans and Poff, 2013) and empirical relationships to predict specific hydrologic indices to complete river networks (Sanborn and Bledsoe, 2006; Carlisle *et al.*, 2010; Knight *et al.*, 2011). This approach was followed in the present thesis; however there are still some key methodological aspects in both procedures that can greatly influence the final outcomes as it is outlined below.

1.4.2 Hydrological Classifications: A major task in hydroecology research

It is currently considered that within each river class of a hydrological classification there is an inherent range of natural hydrological and ecological variation (Poff *et al.*, 2010). Hence, hydrological classification provides an organizing framework and scientific tool for river research and management (Olden *et al.*, 2012). In this regard, it represents a critical previous step for the definition of environmental flow through the ELOHA framework (Poff *et al.*, 2010). Nowadays, there exists a plethora of classification approaches, which agree in general concepts but differ largely in specific procedures. The selection of one or another approach may pose significant differences in the final outcome, and hence, influence largely further applications of the classification. We consider that critical aspects influencing hydrological classification should be examined deeply and specific studies are provided in chapters III and IV of this thesis.

Within the variety of classification procedures, inductive classifications are those that identify and characterize similarities among rivers according to a set of hydrologic metrics that vary across the river network (Olden *et al.*, 2012). Normally, inductive classifications (1) use statistical procedures to minimize the redundancy of the hydrological information, (2) use some form of statistical clustering to group similar gauges and (3) predict class membership for the whole fluvial network based on empirical relationships with catchment attributes (Snelder and Booker, 2013). However, procedures and statistical approaches within these three phases can vary largely according to the objectives of the classification and the available data. For instance, different decisions could be taken regarding the treatment of the input variables, the classification detail or the strategy to predict class membership (Snelder and Booker, 2013).

It is generally accepted that daily hydrologic data provide the appropriate temporal resolution for understanding many ecological responses and, thus, develop hydrological classifications. When daily gauged records are scarce or flow series present low quality other strategies must be considered. Several authors have used gauged (Harris *et al.*, 2000) or modelled (Black *et al.*, 2005; Belmar *et al.*, 2013) monthly flow series. Nonetheless, the use of series lacking the appropriate time scale may compromise the accuracy and usefulness of the classification.

Finally, as it was pointed out above, different procedures used in recent literature to develop hydrological classifications worldwide have been demonstrated to be robust and scientifically defensible (Olden *et al.*, 2012) as they are objective, transparent, interpretable and repeatable. However, when classification procedures do not rely on objective but in experts' criteria, they lack, in general, these desirable qualities and depending on the expert, results may differ greatly from one classification to another.

1.4.3 Predicting hydrologic character to river networks

Other approach to generate the hydrological information required in the ELOHA framework is the prediction of hydrological indices to the whole river network from series recorded at unimpaired gauges (Carlisle *et al.*, 2010; McManamay *et al.*, 2013). The framework considers the use of statistical techniques as one of the alternatives to rainfall-runoff models in generating the baseline flow conditions from which further assessing the hydrological alteration and develop flow-ecological response relationships (Poff *et al.*, 2010). In contrast to rainfall-runoff models, through the statistical approach specific models are developed for each targeted hydrological index. This is likely to reduce the noise associated with hydrological data which confers certain advantage to this approach. However, hydrological indices have been widely predicted using statistical techniques for flood insurance and water supply planning, while prediction of ecologically relevant hydrologic indices have received limited attention (Knight *et al.*, 2011). On the other hand, even if the non-linearity of many hydrological processes has been pointed out (Dawson *et al.*, 2006; Snelder *et al.*, 2009), multiple linear regression has been the most extended technique to fulfil this objective (Yadav *et al.*, 2007; Knight *et al.*, 2011). In contrast, other authors have emphasized the potential improvement that machine learning methods (Alcázar *et al.*, 2008; Shu and Ouarda, 2008; Carlisle *et al.*, 2010) and other strategies, such as the development of individual models for specific river types (Sanborn and Bledsoe, 2006), could suppose in model performance. All these aspects are analysed and evaluated in chapter V.

1.4.4 Assessing the hydrological alteration caused by reservoirs

Once the hydrologic baseline is well established trough the approaches described above, one of the most important aspect within hydroecological research is identifying the extend that the flow regime deviates from natural conditions. It represents a critical step previous to adopt appropriate management measures (Black et al., 2005) recognized in the ELOHA framework (Figure 1.1; Poff *et al.*, 2010). However, the correct quantification of the hydrological alteration can be highly influenced by different confounding factors. Hence, in Chapter VI we present and evaluate a protocol that provides five alternative designs to analyse the hydrological alteration caused by reservoirs according to data availability.

As it was previously noticed, generalizations in relation to flow alteration by dams are difficult. So that the assessment of hydrologic alteration has been commonly done trough the comparison between pre and post-development gauged flow series (e.g. Maingi and Marsh, 2002; Magilligan and Nislow, 2005; Yang *et al.*, 2008) or between flow series recorded at impacted and control gauges (Zhao *et al.*, 2012; Caruso, 2013). Comparison of pre- and post-regulation within the same gauge controls for other confounding factors with exception of the temporal shift in the series (McManamay *et al.*, 2012). In contrast, impact-control approach controls for changes in the climate trends but other confounding factor such as the basin size (Assani *et al.*, 2006) or the influence of land uses in flow regimes (Zacharias *et al.*, 2004) may introduce a high level of uncertainty in the assessment. In both cases, the analysis of the hydrological alteration would uniquely indicate whether a hydrologic change has occurred, but it would not allow us to distinguish a change caused by a human perturbation from a change that would have occurred even if the activity had not begun (Downes *et al.*, 2002). Therefore, the application of robust statistical approaches that allow us to discern the true effect of human over other confounding factors is a primary demand to aid water resources management. On the other hand, the application of robust approaches is subjected to the availability of gauged flow series, both in the pre and post-impact periods and in impacted and control gauges. This availability will determine ultimately the degree of confidence regarding the assessment of the hydrologic alteration. In addition, the absolute lack of hydrologic information in many streams (Eng *et al.*, 2013), especially regarding to pre-disturbance flow series, can constrain the application of any method. Hence, it is necessary to provide alternative means and credible approaches to cope with these situations. Many times, the extension of hydrologic information from gauge to ungauged sites (Carlisle *et al.*, 2010) or by the recognition of the homogeneity between river types (Arthington *et al.*, 2006) have been used to carry out this analysis. Likewise, the application of these alternative methods requires determining the reliability with which hydrological alteration can be assessed to support further flow management actions.

Exploring these three fundamental aspects, i.e. hydrological classifications, prediction of hydrological indices and assessment of hydrological alteration, is a previous critical issue to set more rigorous flow-ecology hypothesis and define the degree of uncertainty within flow alteration-ecological response relationships. This will ultimately allow scientists and water managers establishing the potential effects of restoring the natural flow regime.

1.5 Objectives of the thesis

The general objective of the present thesis is to advance in the understanding and of three critical aspects within the hydroecological and water resource management research: Hydrological classification, hydrological characterisation of complete fluvial networks and assessment of hydrological alteration. These three aspects represent critical steps in the ELOHA framework and this thesis will allow defining the uncertainty associated with several sources of variability in the process. Thus, the results of this thesis will be very valuable to the definition of environmental flow regimes at the regional scale.

The specific objectives of this thesis are focused on the following aspects:

1. Investigate how the normalization of flow series data previous to the classification and the use of Classify-then-Predict and Predict-then-Classify procedures influence (1) the classification performance, (2) the hydrological interpretation of the classifications, (3) its ability to reduce the bias associated to the underrepresented parts of the hydrological space and (4) the spatial arrangement of classes.
2. Investigate how time scale (daily versus monthly), flow series origin (gauged versus modelled) and classification procedure (inductive versus expert) influence (1) the classification performance, (2) the hydrological interpretation of the classifications and (3) the spatial arrangement of classes.
3. Evaluate the performance of contrasting statistical techniques to predict hydrological indices to ungauged sites and examine the benefits associated to model hydrological indices when using a “Regional Regression Approach”.
4. Design a protocol to assess the hydrological alteration caused by reservoirs that use alternative designs depending on the available hydrological data
5. Evaluate the uncertainty associated with each of the designs included in the protocol.

1.6 Layout of the thesis

The structure of the thesis is organized as follows:

In Chapter I, a general overview and the background to the research objectives are presented first. At the end of this chapter the general and specific objectives of the thesis are outlined. In Chapter II, a detailed description of the study area and the specific data is presented.

The following four chapters (III, IV, V, VI) address the objectives of the thesis. Each of the chapters includes an abstract, introduction, methods, results, discussion and conclusion section.

A brief synopsis of the investigations conducted in each chapter is described as follows:

Chapter III. The influence of methodological procedures on hydrological classification performance.

In chapter I, the implication of applying different methodological procedures to develop inductive hydrological classifications was analyzed. Classifications of increasing level of detail, ranging from 2 to 20-Class levels, either based on raw and normalized daily flow series and using two contrasting approaches to determine class membership were developed: Classify-Then-Predict (ClasF) and Predict-Then-Classify (PredF). Classifications were compared in terms of their statistical strength, the hydrological interpretation, the ability to reduce the bias associated to the underrepresented parts of the hydrological space and the spatial arrangement of classes.

Chapter IV. Sources of variation in hydrological classifications: Time scale, flow series origin and classification procedure.

In chapter IV, the influence of different source of variation (flow series and classification procedure) on hydrological classification was analyzed. Three inductive classifications derived from different initial flow data and one expert-driven classification were developed. Hence, Classification 1 was derived from daily flow data while Classification 2 and Classification 3 were derived from monthly flow series, using gauged and modelled flow data, respectively. Classification 4 was based on the Spanish nationwide hydrological classification which uses experts' rules as the main classification criteria. Classifications were compared according to their hydrological interpretation, statistical performance and spatial correspondence.

Chapter V. A comparison of statistical techniques and strategies to model hydrological indices to ungauged rivers.

Chapter V explored the ability of statistical models to predict different types of hydrological indices, evaluating and comparing the performance of 5 statistical techniques and examining the benefits associated to model hydrological indices when using a "Regional Regression Approach". Multiple Linear Regression, Generalized Additive Models, Random Forest, Artificial Neural Network and Adaptative Neuro-Fuzzy Inference Systems were applied to predict 16 ecologically meaningful hydrologic indices to the whole river network. In addition, Multiple Linear Regressions were also developed after segregating gauges into different levels of a regional hydrologic classification (developed in Chapter III).

Chapter VI. Assessing hydrologic alteration: Evaluation of different alternatives according to data availability.

In Chapter VI, we introduced and evaluated a protocol that provides 5 alternative designs to assess hydrologic alteration according to the availability of flow data: (1) Paired-Before-After-Control-Impact; (2) Before-After; (3) Control-Impact; (4) Hydrologic Classification (developed in Chapter III) and (5) Predicted Hydrologic Indices (developed in chapter V). Paired-Before-After-Control-Impact design allows comparing the status of the impacted gauge before and after start-up of the perturbation while controlling for natural climatic or other confounding factors. Hence, it has been considered as the reference benchmark for all the other designs. The protocol was applied and evaluated in 11 reservoirs which covered all the hydrologic classes present in the study area.

Finally, general conclusions and future research lines are described in Chapter VII.

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Chapter II

Study Area and data compilation

Chapter II. Study area and data compilation

2.1 Study area

The study area comprises the northern third of the Iberian Peninsula (Figure 2.1) covering a total area greater than 124000 km^2.

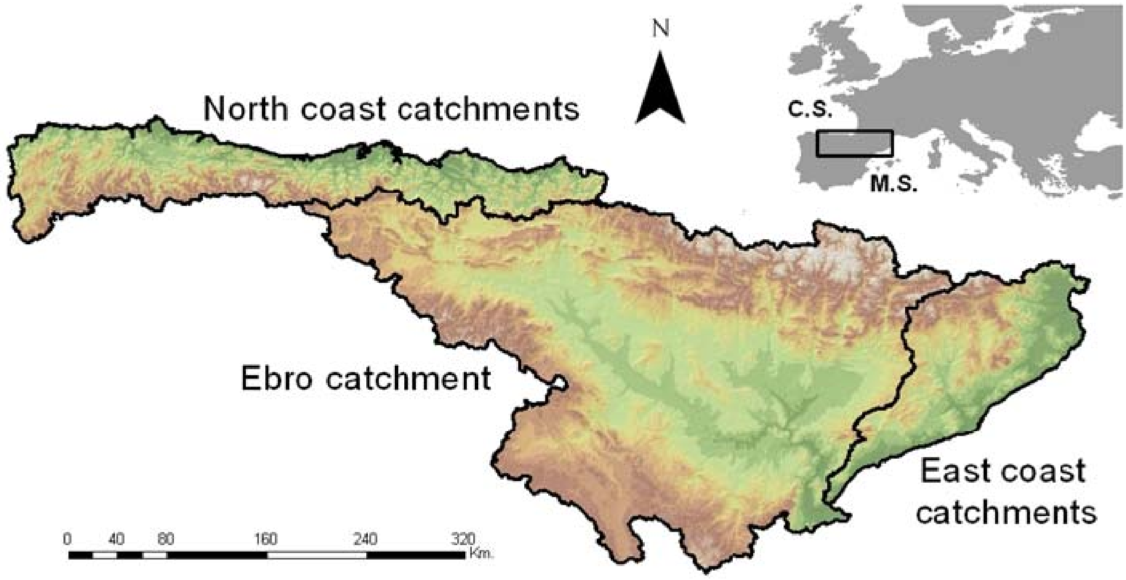

Figure 2.1 - Study area: Northern third of the Iberian Peninsula.

It presents heterogeneous environmental conditions and can be broadly segregated in three main zones. On one hand, the area draining into the Cantabric sea encompass several small basins with drainage areas ranging from 30 km^2 to 4.907 km^2 covering a total area of 22000 km^2. Rivers are confined by the Cantabrian Cordillera, a mountain range that runs parallel to the Atlantic Ocean coast and reaches up to 2600 m.a.s.l. Rivers are characterized by high slopes and short main stream length. This area has a humid oceanic temperate climate (Rivas-Martínez et al., 2004). Average annual temperature is 14 ºC and precipitation is abundant throughout the year with mean of 1300 mm year-1, presenting maximum rainfalls form December to February and minimum from July to September. However, the precipitation magnitude and distribution varies significantly according to local orography. Snow precipitation is frequent in winter above 1000 m.a.s.l.. More than 50% of the surface is occupied by deciduous forest, scrubs and grasslands, while 10% is occupied by agriculture. The population in this area amounts almost 3500000 inhabitants with a population density of 175 hab km^{-2} although it change a lot from region to region. On the other hand, the Mediterranean area is mainly occupied by the Ebro basin along with a set of medium size basins in the eastern zone. The Ebro basin covers a total extension of 85530 km^2. It is enclosed by the Cantabrian Mountains and the Pyrenees (3400 m.a.s.l.) in the North, by the Catalan Coastal Chain (1712 m.a.s.l.) in the East and from the North-West to the South-East by the Iberian massif (2300 m.a.s.l.) which creates a dense river network in the catchment boundaries and an extended flat surface in the interior. The Ebro Basin receives both temperate and Mediterranean climate influences. The Pyrenean area (northwest) and the northern part of the Iberian massif present oceanic temperate climate that change gradually to a typical Mediterranean climate in the central Ebro depression. Annual precipitation is 656 mm, however it varies significantly from 300 mm in the centre to the 1700 mm in the highest mountains (Bejarano et al., 2010) where snow is also common during the winter months. The precipitation regime in the Mediterranean region presents maxima in autumn and spring and minima in winter and summer. The temperature regime also presents an important oscillation throughout the year with temperatures over 30 ºC in summer and below 5 ºC during winter. Population density is below 35 hab km^{-2} which could be considered low, however more than 40% of the surface is occupied by agricultural land and, thus, the catchment is subjected to an intensive water resource control by means of more than 216 dams and other water engineering systems. The eastern zone of the study area comprises several medium catchments ranging from 72 to 5000 km^2, occupying a total extension of 16500 km^2 that drain directly from the Pyrenees or the Catalan costal chain to the sea. This area is dominated by the Mediterranean oceanic climate in the coast and by a temperate climate in the mountains. Precipitation declines from an annual mean of 1200 mm $year^{-1}$ in the northern river heads to less than 500 mm $year^{-1}$ in the Southern catchments. Coniferous and broadleaf forest, scrubs and grasslands occupies more than 60% of the surface in the northern catchments which are progressively replaced by agriculture lands in the south. There are a total of 6600000 inhabitants in this area, mostly concentrated in the city of Barcelona and its metropolitan area. Therefore, an important part of the water resources are also allocated to urban and industrial uses.

2.2 Development of a theoretical river network fluvial

Synthetic River Networks (SRNs) developed from Digital Elevation Models (DEM; Figure 2.2) provided the proper spatial framework and hierarchical organization to sort out hydrologic and environmental information.

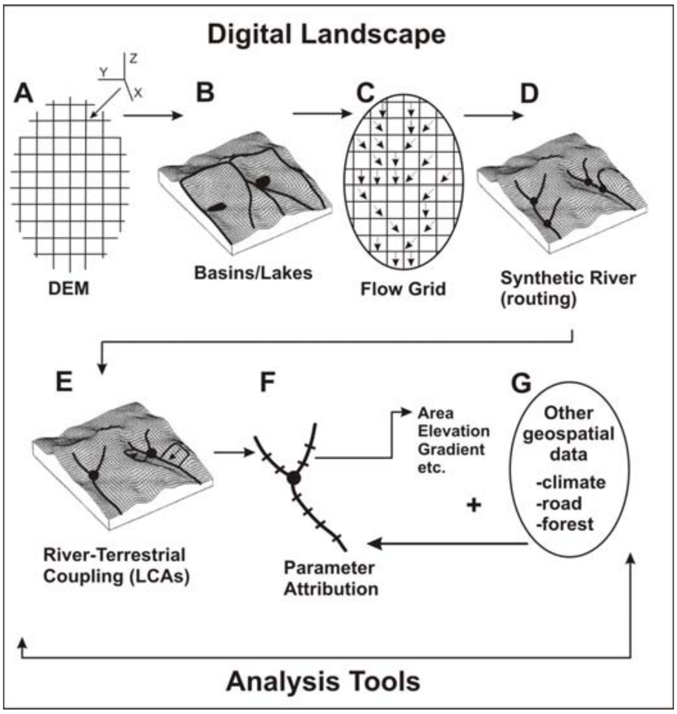

Figure 2.2 - Schematic representation of how Synthetic River Networks were extracted from Digital Elevation Models. Figure taken from Benda et al. (in prep.)

We used specific software packages (Buildgrids and Netrace) which are included in the 'NetMap' platform (Miller, 2002; www.terrainworks.com) to obtain the SRN for the study area. The SRN was delineated using flow directions inferred from a DEM with 30 m spatial resolution, using algorithms described by Clarke et al. (2008). We applied drainage enforcement in areas of lower relief (slope less than 30%) by reducing the elevation by two meters of the current cells in the DEM using GIS data with actual locations of river channels to avoid that these cells act as sinks. The actual locations of river channels were derived from the official river network. Then, the river network was divided into reaches ranging from 100 to 500 m length.

2.3 Hydrological data

2.3.1 Gauged flow series

The initial data set of hydrologic data consisted in series of mean daily flow recorded at 428 gauging stations operated by different Spanish water agencies and regional governments. Only gauges unaffected by impoundments (defined as large engineering structures) or large upstream abstractions were selected for analyses. In addition, we selected those gauges with available data for the period 1976-2010 and analyzed the quality of the series. First, an analysis of the flow series was carried out to eliminate those years without desirable data quality, which could be due to the presence of (1) periods of consecutive repeated values, (2) non-natural extreme low flows for short time periods, (3) periods of zero flow values in non- intermittent rivers, (4) non-natural flow magnitude rises and falls or (5) large differences between two periods, probably due to changes to flow recorder method. Years with more than 30 days of missing data were removed from the analysis. In the last step, we discarded the gauges that accounted with less than 8 years. After applying these restrictions, 156 gauges were selected with an average length of 17 years of data (Figure 2.3; Table 2.1).The 156 gauged flow series are both provided in daily and monthly time scale, within the supplementary material included in the DVD.

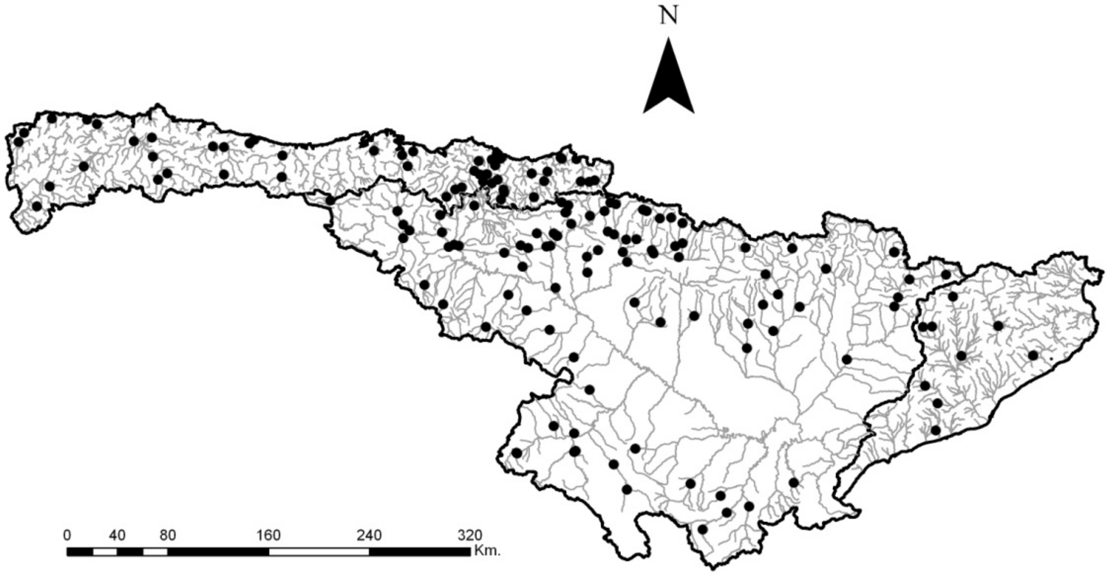

Figure 2.3 - Map of unregulated gauges (●; n=156) in the study area. Black lines divide the Cantabric, the Ebro and the Catalan catchments.

N. of years	N. of gauges	Frequency	Freq. acum.
>19	52	33.3	33.3
19	3	1.9	35.3
18	7	4.5	39.7
17	6	3.8	43.6
16	16	10.3	53.8
15	7	4.5	58.3
14	8	5.1	63.5
13	8	5.1	68.6
12	11	7.1	75.6
11	9	5.8	81.4
10	9	5.8	87.2
9	9	5.8	92.9
8	11	7.1	100.0

Table 2.1 - Number of retained years for flow time-series used in the analysis

2.3.2 Modelled flow series

We developed monthly flow time series in each gauge location using the results of the SIMPA model (the Spanish acronym meaning "Integrated System for Rainfall-Runoff modelling"). SIMPA is an implementation of a classic soil moisture balance model and it uses monthly precipitation and evapotranspiration from 1 km grid maps created from more than 5000 weather stations of the Spanish Network (Estrela and Quintas, 1996; Alvarez et al., 2005). The model has been calibrated and validated by means of comparison with reference and restored records in more than 100 control points. Based on the monthly specific runoff grid of 1 x 1 km and the directions map developed from the Digital Elevation Model, we generated the accumulated monthly flow data for the period 1980/81-2005/06 in each reach of the river network, which were also normalized. The 156 modelled flow series are provided within the supplementary material included in the DVD.

2.4 Environmental characteristics

Climate, topography, land cover and geology are hypothesised to be all important discriminators of the hydrologic regime regardless of geographic location. Thus, environmental variables were used to explain the hydrological character of the recorded flow series and predict this character onto the whole river network. Predictor variables describing several environmental attributes including climate, topography, land cover and geology were extracted from existing databases provided by several national and regional organizations. The variables for each segment represented the mean value of the variables in the upstream catchment An initial set of 50 environmental variables with potential influence on the different hydrological indices were selected. Pearson's correlation coefficient between each pair of variables was calculated previously to each model development and variables with correlation higher than 0.7 were discarded. A final set of 18 and 17 variables were selected to predict class membership (Chapter III and IV) or hydrological Indices (Chapter V), respectively (Table 2.2):

i) Climate: Variables related to precipitation, temperature and evapotranspiration were derived from monthly climate variables calculated in a 1 km grid map by means of interpolation procedure based on data recorded in more than 5000 weather stations of the Spanish network. These data were originally developed to be implemented into the Integrated System for Rainfall-Runoff modelling (in Spanish SIMPA model) by the Centre for Hydrographic Studies (CEDEX, Ministry of Public works and Ministry of Agriculture and Environment, Spain).

ii) Topography: Catchment area, slope, elevation, confluence density and drainage density were derived from the 30 m DEM.

iii) Land cover: The percentage surface occupied by broadleaf forest, coniferous forest, pasture, agricultural land, denuded areas and urban areas was derived from the Soil Occupancy Information System (in Spanish SIOSE) developed by the National Geographic Institute of the Spanish Government. SIOSE presents a scale of 1:25000 and integrates satellite and aerial images from several sources of information.

iv) Geology: The average rock hardness and the terrain permeability were derived from litostatigraphic and permeability maps at scale 1:200,000 developed by the Spanish Geologic and Miner Institute of the Spanish Government. These variables were calculated using procedures described elsewhere (Snelder *et al.*, 2008; Fernández *et al.*, 2012).

Environmental variables values for the 667406 segments are provided within the supplementary material included in the DVD.

Variable	Type	Units	Description	Source
[1,2]Annual Precipitation	CL	mm	Mean Annual precipitation	SIMPA
[2]April Precipitation	CL	Mm	Mean april precipitation	SIMPA
[2]Summer precipitation	CL	Mm	Mean quarterly precipitation (July-September)	SIMPA
[2]Maximum Precipitation	CL	Mm	Maximum monthly precipitation	SIMPA
[2]Minimum Precipitation	CL	Mm	Minimum monthly precipitation	SIMPA
[2]Minimum Month	CL	Month	Month of minimum precipitation	SIMPA
[1,2]Monthly Precipitation range	CL	-	Minimum monthly precipitation/ Maximum monthly precipitation	SIMPA
[1,2]Quarterly Precipitation range	CL	-	Minimum quarterly precipitation/ Maximum quarterly precipitation	SIMPA
[1,2]Temperature	CL	ºC	Mean annual temperature	SIMPA
[2]Summer temperature	CL	ºC	Mean quarterly temperature (July-September)	SIMPA
[1,2]Evapotranspiration	CL	mm	Annual catchment evapotranspiration	SIMPA
[2]Maximum Evapotranspiration	CL	mm	Maximum monthly evapotranspiration	SIMPA
[1, 2]Catchment area	TG	Km^2	Total catchment area	DEM
[1, 2]Gradient	TG	%	Average catchment gradient	DEM
[1, 2]Elevation	TG	m	Average catchment elevation	DEM
[1]Confluence density	TG	-	Number of rivers confluences by catchment area	DEM
[1]Drainage density	TG	-	Number of segments by the catchment area	DEM
[1]Permeability	GL	-	Terrain permeability	IGM
[1]Hardness	GL	-	Rock hardness	IGM

Table 2.2.-. Environmental variables used to predict hydrological classes (Chapter III and IV) and hydrological indices (Chapter V) into the ungauged segments of the river network (TG: Topography; CL: Climatic LC: Land Cover; GL: Geology). [1]Variables selected to predict class membership in Chapter III y IV. [2]Variables selected to predict 16 hydrological indices in Chapter V. Broadleaf forest and coniferous forest were unified in Chapter V within a unique variable (Forest) indicating surface occupied by forest.

Variable	Type	Units	Description	Source
[1, 2]Broadleaf forest	LC	%	Surface occupied by broadleaf forest	SIOSE
[1, 2]Coniferous forest	LC	%	Surface occupied by coniferous	SIOSE
[1]Pasture	LC	%	Surface occupied by pasture	SIOSE
[1, 2]Agriculture	LC	%	Surface occupied by agricultural land	SIOSE
[1,]Denuded	LC	%	Surface occupied by denuded areas	SIOSE
[1]Urban	LC	%	Surface occupied by urban areas	SIOSE

Table 2.2 - (*continued*)

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Chapter III

The influence of methodological procedures on hydrological classification performance

Chapter III. The influence of methodological procedures on hydrological classification performance

This chapter has led to the article entitled: "The influence of methodological procedures on hydrological classification performance" by Peñas, F.J., Barquín, J., Snelder, T.H, Booker, D.J. and Álvarez, C. It has been submitted for publication in the journal: Hydrology and Earth Systems Science.

Abstract

Hydrological classification has emerged as a suitable procedure to disentangle the inherent hydrological complexity of river networks. This practice has contributed to determine key biophysical relations in fluvial ecosystems and the effects of flow modification. Thus, a plethora of classification approaches, which agreed in general concepts and methods but differed largely in specific procedures, have emerged in the last decades. However, few studies have compared the implication of applying contrasting approaches over the same hydrological data. In this work, using cluster analysis and modelling approaches, we classify the entire river network covering the northern third of the Iberian Peninsula. Specifically, we developed classifications of increasing level of detail, ranging from 2 to 20-Class levels, either based on raw and normalized daily flow series and using two contrasting approaches to determine class membership: Classify-Then-Predict (ClasF) and Predict-Then-Classify (PredF). Classifications were compared in terms of their statistical strength, the hydrological interpretation, the ability to reduce the bias associated to the underrepresented parts of the hydrological space and the spatial correspondence. The results highlighted that both the data processing and the classification strategy largely influenced the classification outcomes and properties, although differences among procedures were not always statistically significant. The normalization of flow data removed the effect of flow size and generated more complex classifications in which a wider range of hydrologic characteristics were considered. The application of the PredF strategy produced, in most of the cases, classifications with higher discrimination ability, greater

ability to address the bias associated with the presence of distinctive gauges and classifications in which classes were more evenly distributed than using the ClasF strategy.

3.1 Introduction

Understanding hydrological natural variability has become crucial for river ecology and management because of three main reasons: (1) it is a primary factor influencing river geomorphology (Richter *et al.*, 1998; Benda *et al.*, 2004; Peñas *et al.*, 2012), water (Álvarez-Cabria et al., 2010; Chinnayakanahalli et al., 2011) and biological characteristics (Poff and Zimmerman, 2010), (2) its variability reflects climate (Morán-Tejeda et al., 2011) and catchment attributes (second order driver; Monk et al., 2007) and (3) freshwater resources are essential to maintain many human activities (Naiman and Dudgeon, 2011).

Much progress has been made over the last 20 years in understanding hydrologic variability and how it promotes self sustaining ecosystems (Gurnell *et al.*, 2000; Poff *et al.*, 2006). However, the inherently complexity of flow regimes hinders both the quantification of direct responses of hydrology to catchment characteristics, and the identification of key hydrology and ecology relationships. The identification and characterization of relevant ecological aspects of the flow regime and the organization of similar rivers into a geographical context (Poff, 1996), trough the definition of hydrological classifications, has emerged as a relevant procedure to structure analyses in hydroecological studies. Specifically, inductive hydrological classification approaches have been used to group river reaches into classes within which key flow regime (Snelder et al., 2009) and ecological attributes (McManamay et al., 2012) are assumed to be similar.

Many of the existing hydrological classifications following the inductive approach rely on the use of statistical procedures to reduce the redundancy of the hydrological information (Olden and Poff, 2003) and to minimize within group variability and maximize between group variability (Snelder and Booker, 2013). This tasks are usually accomplished using Principal Components Analysis (PCA) and Cluster Analysis (CA), respectively (Olden et al., 2012). Nevertheless, many steps within the hydrological classification process may be influenced by a series of subjective decisions depending on the rationale, objectives and available data. For example, many hydrological classifications are based on normalized flow data (Kennard *et al.*, 2010; McManamay *et al.*, 2012; Reidy Liermann *et al.*, 2012) while others used raw flow series (Alcázar and Palau, 2010; Belmar *et al.*, 2011; Zhang *et al.*, 2012). The main reason for normalization is to remove the scale dependence of flow magnitude indices to promote the classification of rivers according to the shape of the regimes. However, normalization can be viewed as a completely subjective choice in the classification process that depends on the objectives of the study (Olden et al., 2012). The shape of the hydrograph provides valuable information about the seasonality, the timing of specific flow events or the patterns of rise and fall of the flow. Undoubtedly these aspects influence river reach ecology (Richter *et al.*, 1998; Bunn and Arthington, 2002) and are key elements for understanding the relationship between climatic and streamflow patterns (Gámiz-Fortis et al., 2011). Nonetheless the size of a river reach and the absolute magnitude of flows also play a key role in ecological processes (Vannote *et al.*, 1980; Bunn and Arthington, 2002).

In addition, beyond the classification of specific sites for which hydrologic data are available (gauged or modelled sites), the scientific and management utility of hydrological classifications relies on the capacity to extrapolate the class membership to ungauged sites, providing a map of natural flow regimes (Snelder et al., 2009; Reidy Liermann et al., 2012). The Classify-then-Predict (ClasF) strategy has been the most common approach to fulfil this objective (e.g. Kennard et al., 2010; Reidy Liermann et al., 2012). ClasF predicts river reach class membership based on environmental data (climate, topography, geology or land-use) at observed locations. However, this method might pose some flaws when predicting onto an entire region, especially if the distribution of gauges is biased, i.e. specific kind of rivers are under or overrepresented (Snelder and Booker, 2013). If this is the case, the cluster step would fail in accounting for those hydrological features underrepresented in the data set. The presence of sites with exceptional hydrologic character might produce two effects. The first effect is that it may produce higher within-class heterogeneity, while the second is related to the loss of the “rare” hydrologic character when classes are predicted to the whole river network. Because of these reasons some researchers have attempted other approaches such as the Predict-then-Classify (PredF) strategy (Ferrier and Guisan, 2006; Snelder and Booker, 2013). Using this approach, hydrological indices obtained from the flow series are predicted onto the entire river network using climate and catchment characteristics, and classification of all river segments is performed as a final stage within the procedure.

The aim of this study was to investigate how the normalization of flow series data previous to the classification procedure and the use of ClasF and PredF influences (1) the classification performance, (2) the hydrological interpretation of the classifications and their ability to discriminate different hydrological characters, (3) their ability to reduce the bias associated to the underrepresented parts of the hydrological space and (4) the degree of spatial correspondence between classifications. To achieve this aim we will develop hydrological classifications of natural conditions over an entire river network in the northern third of the Iberian Peninsula, covering catchments of contrasting climate and spatial configuration. We hypothesised that normalization of river flow data will tend to classify rivers according to their annual regime and not only to the size of the river and also increase the contribution of other hydrological variables not related to flow magnitude. In addition, we hypothesised that the application of the PredF classification procedure will reduce within class heterogeneity, especially when gauges presenting distinctive regimes are included in the classification.

3.2 Methods

3.2.1 Hydrological and environmental data processing

Based in the gauged hydrological data introduced in Chapter II, in this study we developed two sorts of classifications, one obtained from normalized flow series and the other from non-normalized (raw) series. Normalization is used to minimize the influence of flow magnitude which allows setting the hydrological classes based on the "shape" of the regimes (Snelder et al., 2009). Flow series were normalized by dividing all daily flow values by the mean annual flow (Poff et al., 2006).

A set of 103 and 101 hydrologic indices (provided within the supplementary material included in the DVD.), which represent a wide range of ecologically meaningful attributes of the flow regime (Olden and Poff, 2003), were calculated for the raw and normalized flow series, respectively (Appendix, Table A1). These indices characterize the central tendency and dispersion of: (1) magnitude of annual and monthly flows conditions, (2) magnitude of severe high and low flow conditions, (3) timing of flows, (4) frequency and duration of high flow pulses and (5) rate of change of flow (Richter et al., 1996; Olden and Poff, 2003).

Given the strong correlation between several indices, the initial set of indices was reduced to a set of non-correlated synthetic indices using the procedure outlined in Olden and Poff (2003) and followed by many others (Belmar *et al.*, 2011; Chinnayakanahalli *et al.*, 2011; Zhang *et al.*, 2012). Principal Component Analysis (PCA) and the broken stick method (Jackson, 1993) were performed to obtain and define the optimal set of synthetic indices. Two PCAs were carried out independently, one for the hydrologic indices calculated from the raw flow series and another for hydrologic indices calculated from the normalized flow series. Each PC was standardized before conducting further analysis to give all the PCs equal weights. Snelder and Booker (2013) demonstrated that this additional step increased classification performance.

In addition, environmental variables introduced in Chapter II (Table 2.2) were used to develop empirical relationships and predict class membership or the synthetic hydrological indices to the river network.

3.2.2 Classification procedures

In this study, we derived classifications with increasing numbers of levels using the synthetic hydrologic indices derived from the PCAs performed on each flow series using two contrasting strategies (Figure 3.1; Snelder and Booker, 2013): (1) the classify-then-predict (rawClasF and norClasF) and the (2) predict-then-classify (rawPredF and norPredF). The prefix raw and nor indicates whether classification was based on the hydrological indices extracted from the raw or normalized flow series respectively. The final SRN classifications are provided within the supplementary material included in the DVD.

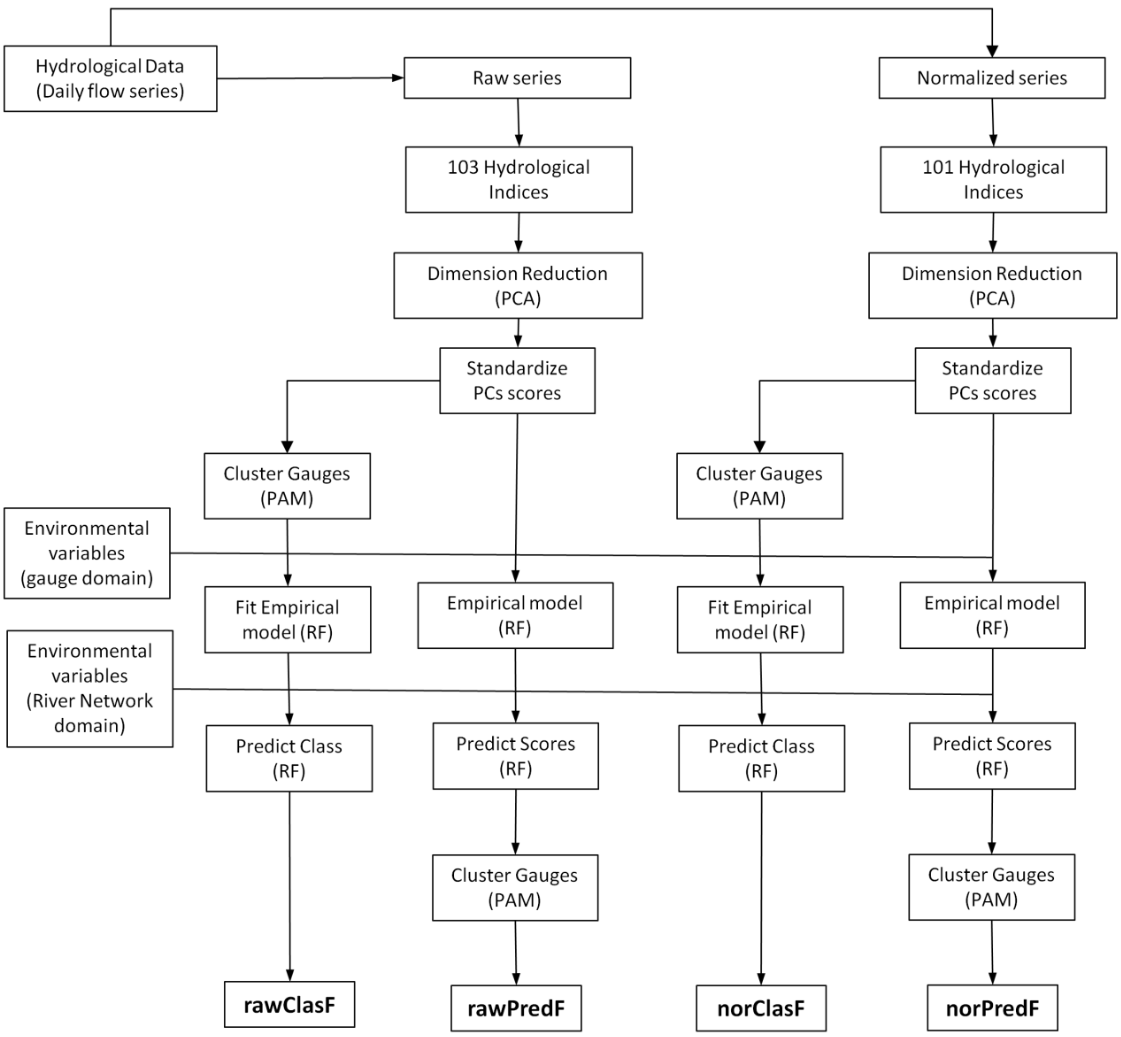

Figure. 3.1 - Schematic diagram summarising the strategies applied to define the 4 classifications.

3.2.2.1 Classify-then-predict (ClasF)

Partitioning Around Medoids (PAM; Kauffman and Rousseeuw, 1990) algorithm on the standardized synthetic indices was used to cluster gauges (Figure 3.1). PAM defines a set of k objects as medoids (data-points) of each cluster and minimizes the sum of dissimilarities between all objects and their assigned medoid (Kauffman and Rousseeuw, 1990). This technique allows the user to specify the number of clusters. We produced classifications with numbers of classes ranging from 2 to 20. We then used Random Forest (RF; Breiman, 2001) to developed empirical models that relate class memberships and catchment properties (Figure 3.1). We fitted one specific RF for each classification level (2 to 20-Class level) and then, these models were used to predict the most probable class of all the segments of the SRN for each classification, i.e. 19 sets of predictions.

3.2.2.2 Predict-then-Classify (PredF)

For the PredF strategy, empirical models were fitted to each of the standardized synthetic indices as a function of predictor catchment variables using RFs (Figure 3.1). Then predictions of the synthetic indices were made for the whole SRN, thereby generating predicted distributions for each synthetic index. Finally, classifications were produced by clustering all the modelled sites using the PAM algorithm varying again between 2 and 20 class levels.

Given the high number of gauges removed due to the presence of impoundments or abstraction upstream, the selected gauges represented “reasonably natural hydrological conditions” only, and probably do not represent the whole spectrum of natural hydrologic conditions in the study area. In addition, the SRN developed for this study presented many rivers of first and second order. Given that Mediterranean climate domains the study area, many of them are likely to be intermittent or perennial rivers, which is a character underrepresented in the hydrological data base. The prediction of the hydrological synthetic indices or class membership beyond the hydrological space represented in the selected gauges could lead to misleading results. Therefore, instead of using the whole SRN (667406 segments) in the prediction stage of each approach, those segments of the SRN that presented values of predictor variables out of the range (maximum/minimum) defined by these predictors in the selected the gauges were discarded. Thereby, 178297 segments were kept.

As stated before, both strategies are based in the use of RF (Breiman, 2001; Cutler et al., 2007). RF fits many classification and regression trees (CART; Breiman et al., 1984), each of them grown with a bootstrap sample of entry data and a randomized subset of predictors. Each CART is then used to predict the observations that were excluded from each bootstrap sample, named the out-of-bag (OOB) samples. These predictions are aggregated over all tress and the error (OOB-error), which provides an estimate of the predictive accuracy of the model, was expressed as a misclassification rate or a coefficient of determination if categorical response or continuous response variables were used, respectively. In addition, to assess the importance of a specific predictor variable, the values of the targeted variable are randomly permuted for the OOB observations, and then the modified OOB data are passed down the tree to get new predictions. The difference between the misclassification rate for the modified and original OOB data, divided by the standard error, is a measure of the importance of the variable (Snelder et al., 2011).

3.2.3 Comparison of classification performance

Both the performance of classifications with the same number of classes constructed by different strategies and the performance of classifications with different number of classes derived with the same strategy were compared. The performance of the classifications was measured using the classification strength (CS; Van Sickle, 1997) and ANOVA.

CS estimate the degree of dissimilarity of the hydrological character between gauges explained by the classifications (Snelder and Booker, 2013). Briefly, CS results from the difference between the mean hydrological dissimilarity between all pairs of replicate sites within classes (D_{within}) and the mean dissimilarity between all pairs of replicate sites in different classes ($D_{beetwen.}$). Higher values of CS indicate a greater uniformity within classes and greater differences between classes (Van Sickle, 1997). This analysis was performed on the hydrological indices with the highest loading on each of the PCs (test indices) using euclidean distances. In addition, test indices were standardized prior to calculating the dissimilarities so all indices, which have inherently different scales, had equal weight in defining hydrological dissimilarity. We calculated CS for each classification (rawClasF, rawPredF, norClasF and norPredF each with 2-20 classes). We applied the restriction that classes comprised a minimum of five gauges to reduce the influence in the analysis of classes represented by very few gauges.

In addition, we performed an ANOVA on all the hydrologic indices (103 and 101 for raw and normalized series, respectively) with the class membership as the explanatory variable to analyze the potential of classifications to discriminate each of the hydrological index. The coefficient of determination (R^2) was calculated for each level (2-20 classes) of the 4 classifications. The restriction of the five gauges per class was also applied.

Following the procedure outlined in Snelder and Booker (2013) and Snelder et al. (2012), both the CS and ANOVA analysis were performed on gauges not used in the fitted models by means of a five-fold cross validation procedure (Hastie et al., 2001). For this procedure, each of the gauges was randomly assigned to one of five subsets (folds). We then defined classifications by combining the other four subsets to train the inductive classifications and evaluated CS and R^2 statistics for the held-out subset at all hierarchical levels for each classification. This allowed us focusing on the “predictive performance” of the classifications. Each cross validation procedure was repeated 5 times in order to “smooth out” the variability inherent to each subset. Therefore, results of 25 estimates of predictive CS and R^2 statistics for each hierarchical level of classifications were obtained. Based on the “one standard error rule”, two classifications were assumed significantly different if standard errors of the statistics did not overlap.

3.2.4 Hydrological interpretation of classification

The original indices with the five highest values in each retained axis of the PCAs were used to interpret the hydrological meaning of the new synthetic indices. In addition, we used the ANOVA results to interpret each classification by looking at the different coefficients of determination for specific indices. We assumed that the higher the coefficient of determination the higher the importance of that index to discriminate classes.

3.2.5 Analysis of distinctive gauges

We also analyzed how each classification strategy resolved the problem of the bias associated with the presence of gauges that showed the most distinctive regimes (i.e. the most distant hydrological character). We quantified the effect that the most distinctive gauges produce on the specific classes where they were included. Independent analyses were made for classification based on raw and normalized flow series. First we calculated, based on the standardized synthetic indices scores, the dissimilarity between each pair of gauges and then, the corresponding mean dissimilarity for each gauge. We then selected the 4 most dissimilar gauges and recorded the classes they belonged to when the entire river network was classified. For each distinctive gauge two analyses were performed. Firstly, we calculate the distance between the distinctive gauge and the medoid of the classes in which it was were included. Larger distances indicated higher heterogeneity in the class. Secondly, we analyzed the proportion of the classification domain assigned to the classes where the distinctive gauges were included. Low frequency of these classes indicated the inability of the procedure to represent properly certain characteristics of the hydrological space in the entire SRN.

3.2.6 Correspondence between classifications

The correspondence between each pair of classifications, i.e. the extent to which two classifications define similar spatial patterns, was evaluated by means of the Adjusted Rand Index (ARI; Hubert and Arabie, 1985). ARI analyze the relationship of each pair of gauges and how they differ between two cluster solutions. It ranges between 0 (indicating that agreement between two clustering solutions is not better than chance) and 1 (indicating perfect agreement). Given the large number of segments in the SRN, we randomly selected a subset of 500 segments and computed ARI for all pairs of the four classifications.

Bespoke functions written in R were use to analyse flow series and calculate hydrological indices (Snelder and Booker 2013).

3.3 Results

3.3.1 PCA and Predictive mapping

The broken stick method selected the first five PCs of the PCA performed on the raw series. They explained 91% of the variance, accounting the PC1 alone for the 68% (Table 3.1).

Flow series	Axe	Variation Explained (%)	Hydrologic variables with the highest values in the PCs
Raw	PC1	68	-I1, -X25, -90HF, - 30HF, -M11
	PC2	10.6	-FRE7, -FRE3, -lcv, BFI, sdBFI
	PC3	5.9	-FRE1, -nPH, -FRE3, dPH, sdZFD
	PC4	3.6	sdnPos, sdnNeg, ikur, lca
	PC5	3.5	-sdnPHigh, sdJMax, -sdRev, -sdFRE3, -sdJmin
Normalized	PC1	38.6	- I2, X75, 90LF, 30LF, 7LF
	PC2	20.4	sd30HF, sd7HF, sd3HF, sd90HF, sdM5
	PC3	11.6	-M10, -sdM10, -MXM10, -FRE1, sdM9
	PC4	7.1	ikur, X25, MnM9, MnM2, MnM11
	PC5	6.1	-M1, M5, sdZFD, -sdM1, -MxM1,
	PC6	4.5	sdM8, MXM8, sdnPH, -MxM11, -sdM11

Table 3.1 - The 5 hydrologic indices with the highest loadings in each PC and the variation explained by the retained PCs using the raw (above) and the normalized flow series (below). A minus sign indicates negative relation with the PC.

The OBB misclassification rate of the RF models in the rawClassF ranged from 0.13 for the 2 classes level to 0.77 for the 20-Class level (Figure 3.2). The misclassification rate increased by 0.17 (from 0.35 to 0.52) when the classification level increment from 7 to 8 classes. The most important predictor variables of the RF were catchment area, precipitation, agriculture, pasture and elevation. For the rawPredF classification, the mean OBB R^2 for the RF models of the 5 synthetic indices was 0.4 decreasing from 0.65 for PC1 to 0.18 for the PC5. Predictors varied according to the modelled PC, but most of them included topography (catchment area, slope), climate (precipitation) and land cover (agriculture, coniferous and broadleaf forest) variables.

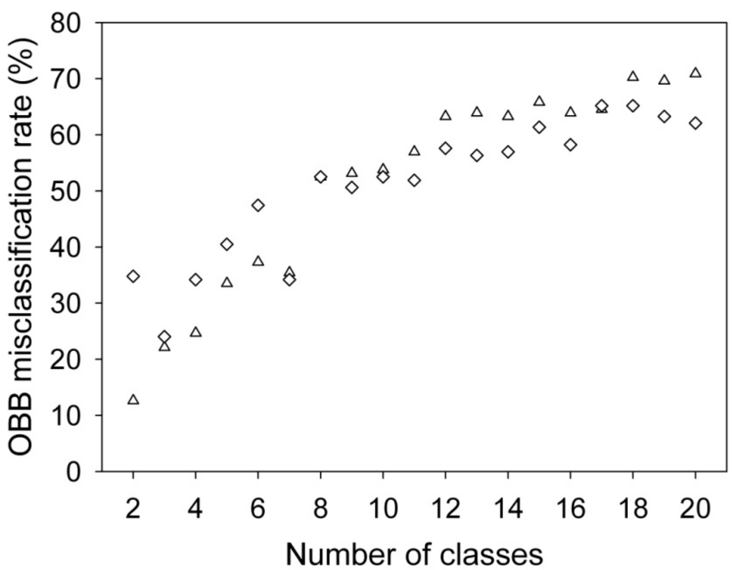

Figure 3.2 - Out-of-Bag misclassification rate of the random forest models developed for the 2 to 20-Class level classification using classify then predict strategy based on the synthetic indices derived from the raw (△: rawClasF) and the normalized flow series (◇: norClasF).

Parallel, the first six PCs of the PCA performed on the normalized flow series were retained. They explained 83.3% of the variance, with the PC1 and PC2 explaining 38.6% and 20.4%, respectively (Table 3.1). For the norClasF strategy the OOB misclassification rate for the RF models range from 0.22 to 0.66 for the 3 and the 18-Class levels, respectively (Figure 3.2). Abrupt changes in this rate were recorded between 6 to 7 (decrease) and 7 to 8 (increase) class levels. The most important variables differed between classifications comprising different class levels but in general precipitation, elevation, gradient and broadleaf forest were present in most models. For the norPredF strategy the mean OBB R^2s was 0.31 for the 6 PCs decreasing from 0.63 for PC2 to 0.08 for the PC6. The most important variables were not consistent between RF models although precipitation, elevation, and broadleaf forest were present in most of them.

3.3.2 Comparison of classification performance

CS statistics for the classifications based on the raw flow series (rawClasF and rawPredF) showed similar patterns. CS increased from 2 to 5-Class level, more pronounced in rawPredF, and decreased slightly beyond this number of level but, in general, the analysis did not reveal significant differences (i.e. overlapped among standard error bars) between levels of classification (Figure 3.3). RawPredF showed generally higher CS values than rawClasF, although in most cases differences were not significant.

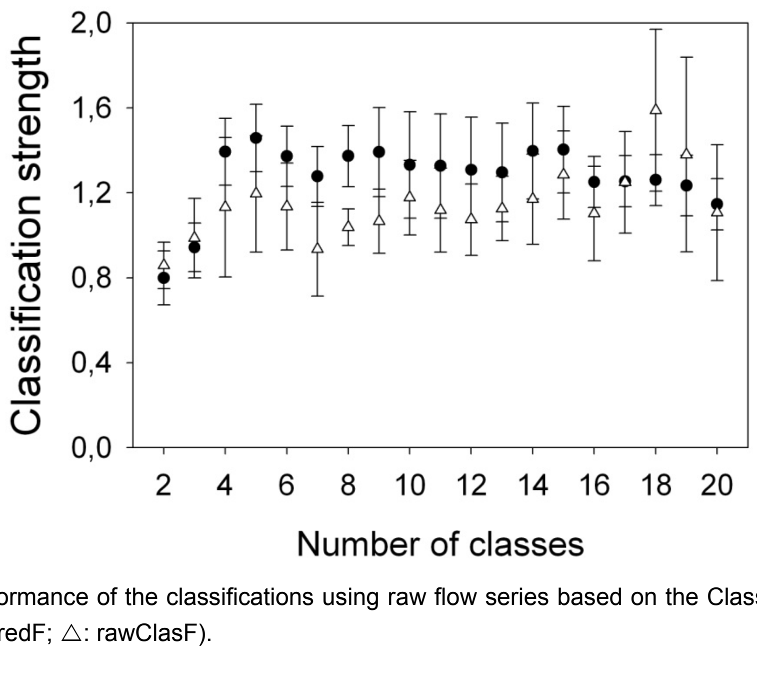

Figure 3.3 - Performance of the classifications using raw flow series based on the Classification Strength statistic (●: rawPredF; △: rawClasF).

The discrimination power of classifications for each of hydrological index based on the ANOVA analysis got higher with increasing number of classes (Figure 3.4 and Table S1.1 provided within the supplementary material). However, in most cases there were not significant differences from 6 or 7 to 20-Class levels. Moreover, rawPredF outperformed rawClasF, especially for those indices representing flow magnitude and duration (Figure 3.4).

NorPredF presented a progressive increment of CS from 2 to 10-Class level where it reached the maximum value, suffering then only slight variations (Figure 3.5). NorClasF presented a more unstable CS pattern than norPredF with constant rise and fall of the CS with the increase of class level. Except for specific class levels (2 and 4-Class levels), norPredF reached higher CS than norClasF presenting significant differences in the classifications with 6, 7 and 14-Class levels.

The discrimination ability of norClasF and norPredF based on the ANOVA analysis on individual indices showed similar patterns to those found for classifications using developed from raw series. An increase in R^2 with increasing number of classes and the presence of an inflexion located between 6 and 10-Class levels (Figure 3.6 and , Table S1.2 provided within the supplementary material) were observed. In addition, although norPredF performed better than norClasF, differences were not significant in several cases.

In general, classifications based on the raw flow series provided slightly higher CS (Figure 3.3 and 3.5) and R^2 values (Figures 3.4 and 3.6) than those based on normalized series.

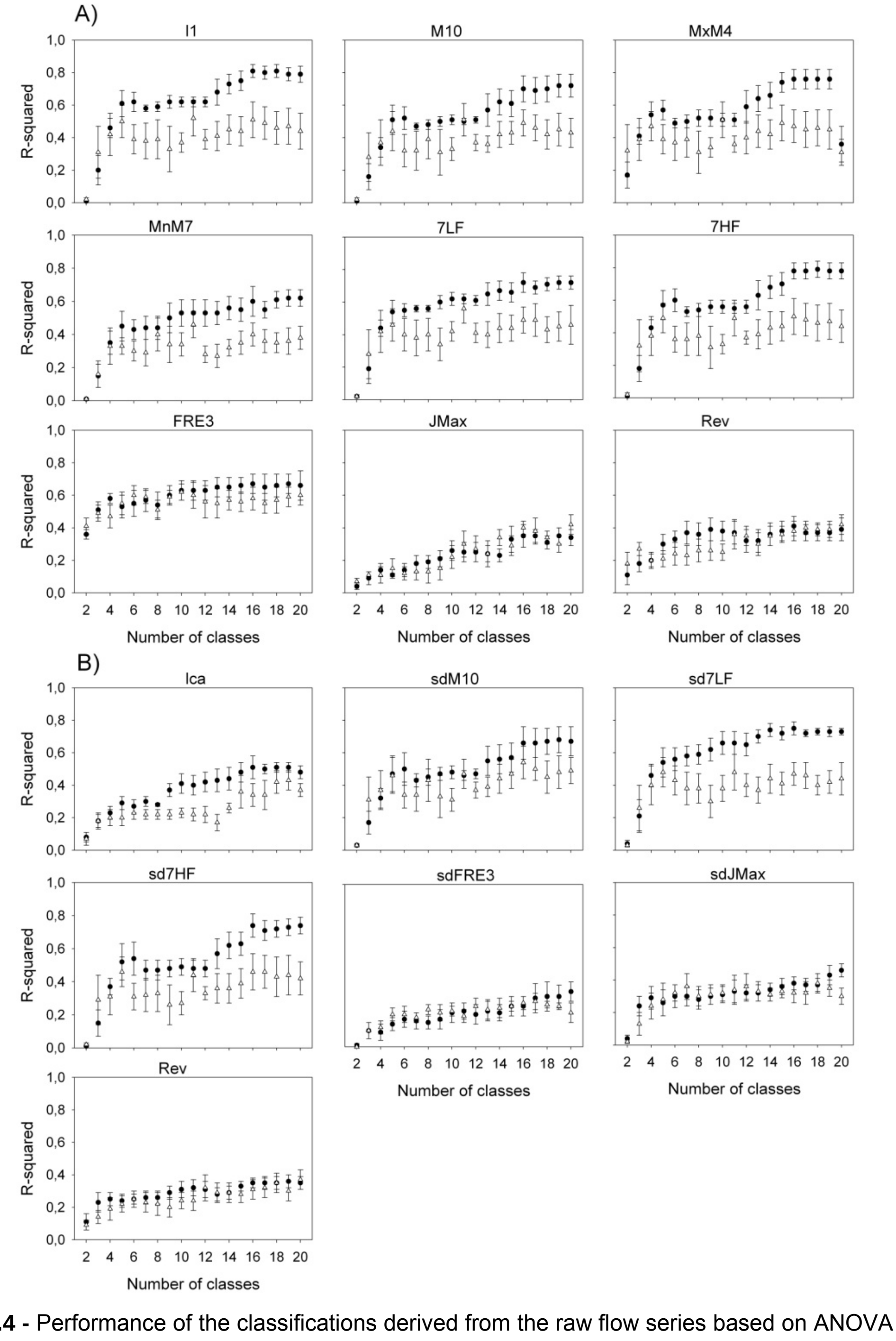

Figure 3.4 - Performance of the classifications derived from the raw flow series based on ANOVA analysis on individual index analysis. A) Indices representing mean values. B) Indices representing standard deviation. (●: rawPredF; △: rawClasF). We selected one index representing each aspect of the natural flow regime to illustrate the results (the values obtained for the 103 indices are included Table S.1.1 provided within the Supplementary material).

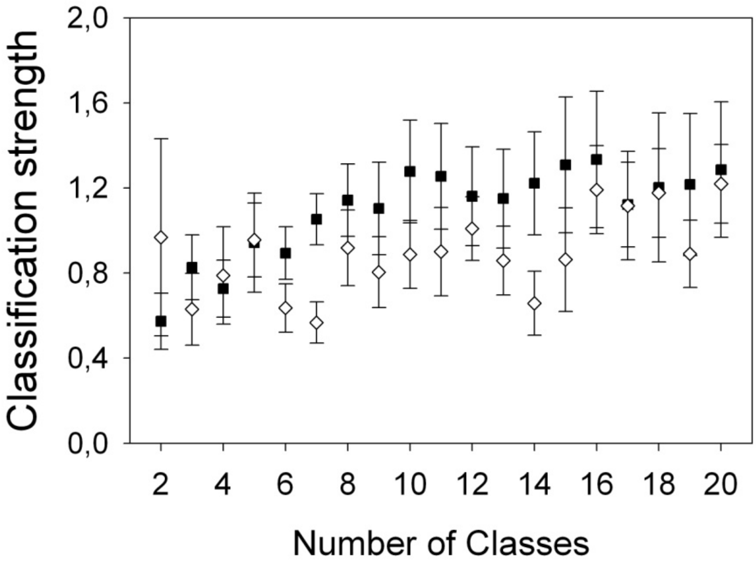

Figure 3.5 - Performance of the classifications using normalized flow series based on the Classification Strenght statistic (■: norPredF; ◇: norClasF).

3.3.3 Hydrological Interpretation of classification

According to the hydrological indices with the highest values on each axis in the PCA performed on the raw flow series, PC1 represented the magnitude of the mean annual flow and the magnitude and duration of high flows, while PC2 represented the frequency of high flow events and the magnitude of low flows. PC3 was also related to the frequency of high flow events while PC4 and PC5 represented the variability of rate of change, the asymmetry of flow series and the interannual variability of different hydrological characteristics, respectively (Table 3.1). However, it should be pointed out that interpreting axes becomes rather difficult when explained variability decreased. In addition, ANOVA analysis revealed higher R^2 values of indices related to flow magnitude and duration (I1, M10, MxM4, MnM7, 7LF, 7HF, sdM10, sd7LF, sd7HF) and frequency (FRE3) than those representing other aspects of the flow regime (JMax, Rev, sdFRE3, sdJMax and Rev; Figure 3.4 and Table S1.1 provided within the supplementary material).

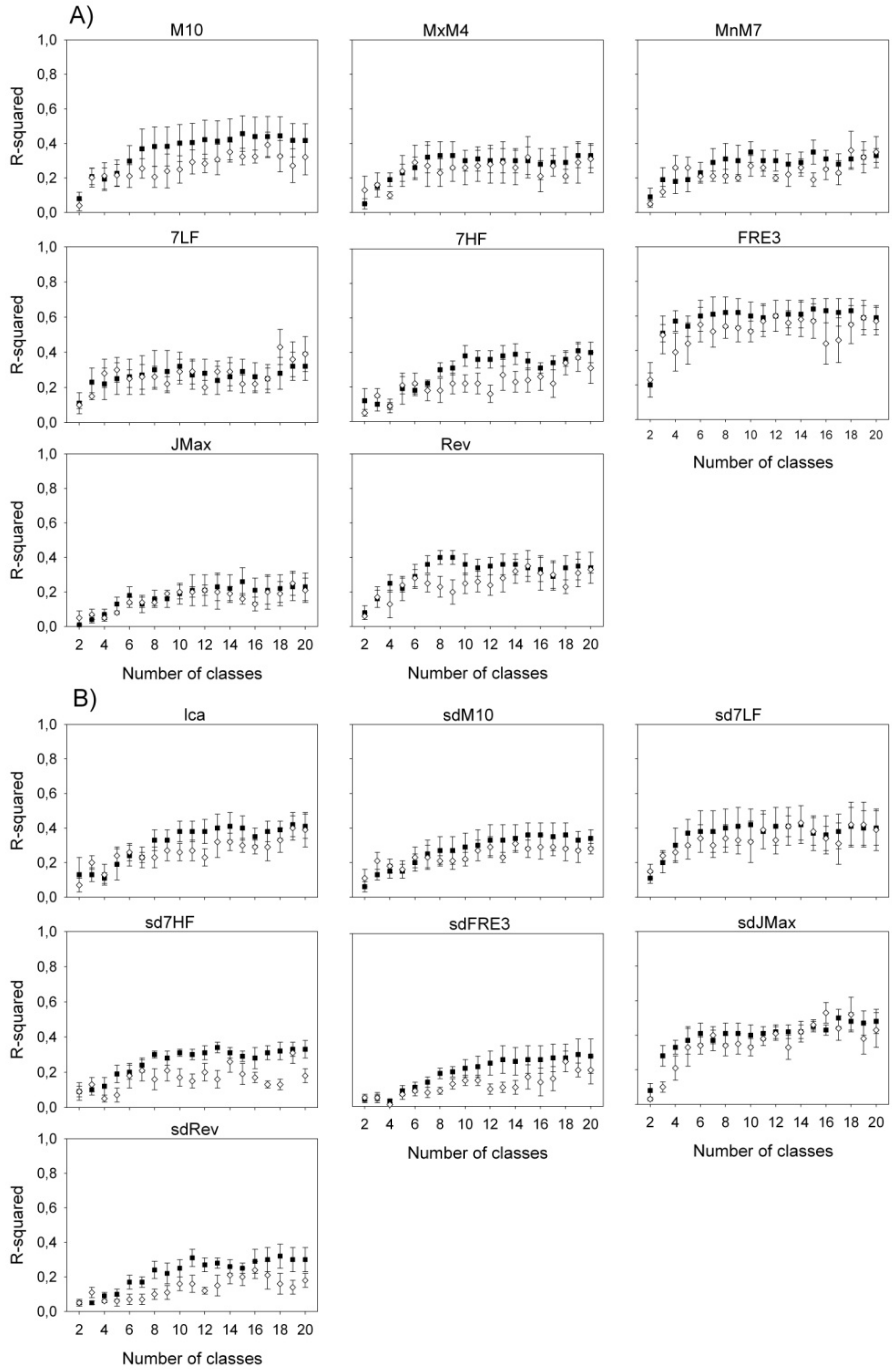

Figure 3.6 - Performance of the classifications derived from the normalized flow series based on individual index analysis. A) Indices representing mean values. B) Indices representing standard deviation. (■: norPredF; ◇: norClasF). We selected one index representing each aspect of the natural flow regime to illustrate results (the values obtained for the 101 indices are included in Table S1.2 provided within the supplementary material).

The PCA performed on the normalized flow series showed that PC1 represented the variability of the annual mean flow and the magnitude and duration of extreme low flows and PC2 represented the variability of the magnitude and duration of high flow events. PC3 was related to the mean and variability of the magnitude of monthly flows in the beginning of the humid season (October) while PC4 represented the variability of the magnitude of annual flows and the magnitude of the minimum flows. PC5 was related to mean winter (January) and spring (May) flows while PC6 represented the magnitude and variability of summer (August) flows (Table 3.1). Likewise, the physical interpretation of the PCs became more difficult as variance explained decreased. The highest R^2 values (maximum value around 0.5) were obtained for the indices representing mean monthly flows while the maxima for those indices representing mean and duration of extreme flows was 0.3 (Figure 3.6 and Table S1.2 provided within the supplementary material). In addition, both norClasF and norPredF showed high discrimination ability on indices representing the frequency of high flow events (FRE), despite these indices were not identified as important in the PCAs.

3.3.4 Analysis of distinctive gauges

Three of the four selected distinctive gauges within the classifications based on raw flow series were situated in the Ebro catchment and one in the Cantabric region. The distance between each distinctive gauge and its respective class medoid in the rawPredF classifications was lower than the distance in the rawClasF classification 63% of the times although only four times the relative differences were greater than 10% (Table 3.2).

In addition, for the rawClasF it was observed that the proportion of the classification domain assigned to the classes in which the distinctive gauges were included was very low compared to the most evenly distributed classification, i.e. if all the classes had the same proportion, and beyond the 6-Class level this proportion was below 1% for the four distinctive gauges (Figure 3.7A). Regarding the rawPredF the proportions of the classes containing the distinctive gauges were higher than for the rawClasF but in general these proportions were below the most even distributed classification (Figure 3.7B).

The classifications based on the normalized flow series presented two distinctive gauges situated in the Ebro catchment and the other two in two Catalan catchments. NorPredF showed smaller distances between the distinctive gauges and their respective class medoids than norClasF 89% of the times and the relative differences were many times over 40% (Table 3.3).

Raw flow series								
	DG 1		**DG 2**		**DG 3**		**DG 4**	
Level	rawClasF	rawPredF	rawClasF	rawPredF	rawClasF	rawPredF	rawClasF	rawPredF
4	15.92	**10.56**	13.57	**9.66**	7.01	**6.14**	**4.67**	5.17
6	18.19	**10.39**	9.55	**9.04**	**3.56**	3.88	**5.17**	5.50
8		10.49	9.55	**6.19**	**3.56**	3.79	5.17	**3.78**
10		10.23	9.55	**8.77**	**3.56**	3.62	4.69	**4.56**
12		2.61	9.55	**8.94**	3.56	**3.40**	4.40	**4.32**
16		9.63		6.19	3.56	**3.41**	3.10	**3.09**
20		8.17		6.41	3.56	**3.40**	**2.50**	3.09

Table 3.2 - Euclidean distance between the distinctive gauges (DG) and the medoid of the classes in which they were included for the 4, 6, 8, 10, 12, 16 and 20-Class level classification developed from the raw flow series. Empty cells indicated that the gauge is the unique gauge in the class. Bold letters indicate the procedure that showed the lowest distance.

The proportion of the classes containing the distinctive gauges in the norClasF was, in general, below the frequency showed by the most even distributed classification (Figure 3.7C) while the norPredF classifications presented the most similar proportions to the most evenly distributed classification (Figure 3.7D)

3.3.5 Correspondence between classifications

The ARIs for each pair of classifications were in the range 0.15-0.4 for the 6-Class level and in the range 0.15-0.3 for the 11, 16-Class level and the mean of all classification levels (Table 3.4). The highest ARI was obtained between rawPredF and norPredF

(≥ 0.4) and rawPredF and rawClasF (≥ 0.2). Contrary rawClasF and norClasF showed the lowest correspondence (≤ 0.15).

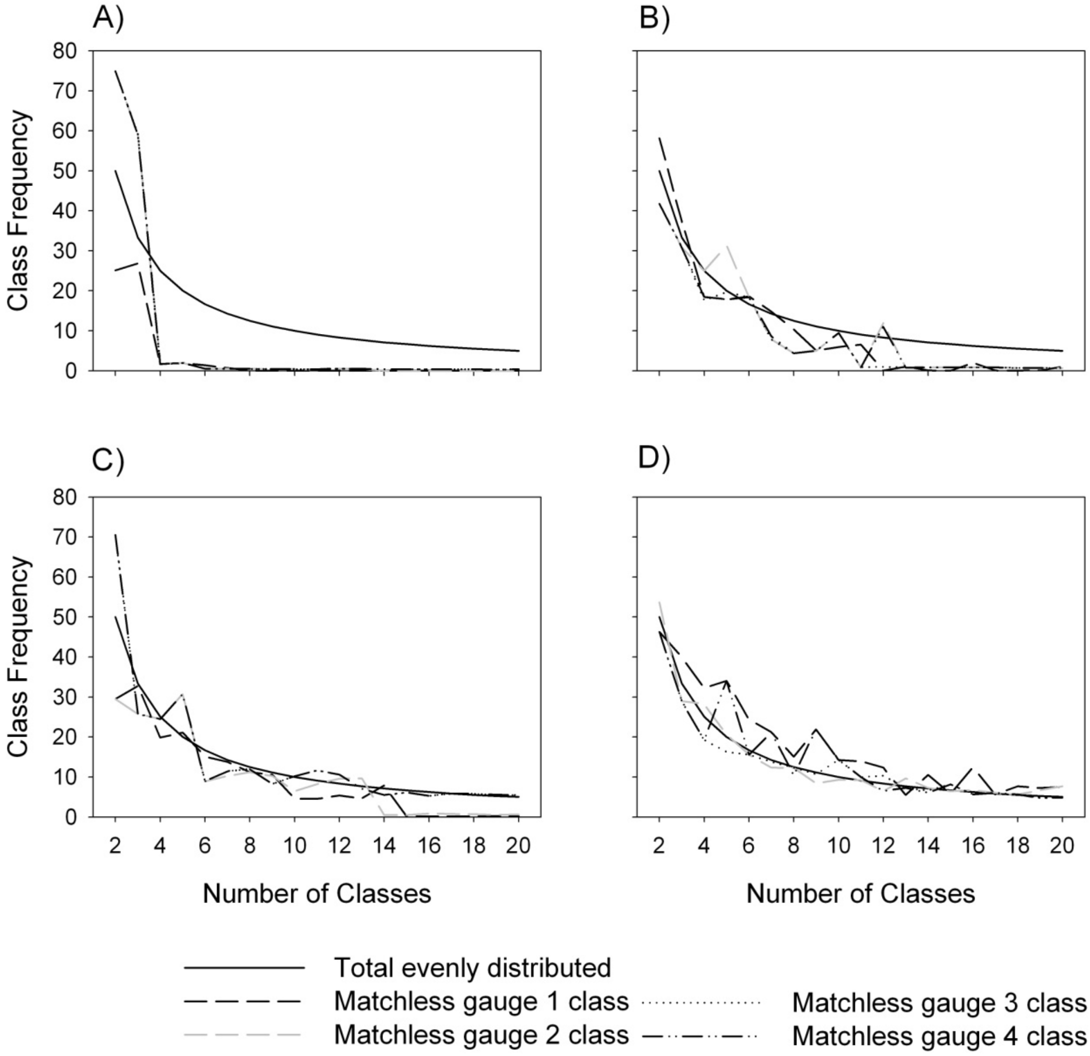

Figure 3.7 - Frequency (%) of the segments of the classification domain assigned to the classes where the distinctive gauges were included. (A: rawClasF ;B: rawPredF; C: norClasF;D: norPredF).

3.4 Discussion

As expected the normalization of flow data generated hydrological classifications in which a greater number of hydrological aspects not related with flow magnitude and the size of the river were considered than if data were not normalised. This made these classifications more difficult to interpret and predict. In addition, classifications based on the PredF procedure outperformed those obtained with ClasF procedure and in general, dealt better than ClasF with the bias associated to the underrepresented parts of the hydrological space in the original data set.

Normalized flow series								
	DG 1		DG 2		DG 3		DG 4	
Level	rawClasF	rawPredF	rawClasF	rawPredF	rawClasF	rawPredF	rawClasF	rawPredF
4	11.26	**6.12**	9.89	**5.66**	9.29	**4.85**	9.94	**5.13**
6	10.96	**5.36**	9.67	**5.25**	9.40	**5.08**	9.85	**5.05**
8	10.96	**6.11**	10.30	**5.31**	7.22	**5.72**	5.57	**4.45**
10	9.45	**6.04**	9.67	**5.31**	7.22	**5.17**	5.57	**4.42**
12	9.45	**4.93**	9.67	**4.93**	7.22	**4.85**	5.57	**4.41**
16		5.36	**5.45**	5.61	6.41	**3.55**	6.36	**3.51**
20		4.91	5.45	**5.11**	6.41	**5.19**	6.36	**3.51**

Table 3.3 - Euclidean distance between the distinctive gauges (DG) and the medoid of the classes in which they were included for the 4, 6, 8, 10, 12, 16 and 20-Class levels classification developed from the normalized flow series. Empty cells indicated that the gauge is the unique gauge in the class. Bold letters indicate the procedure that showed the lowest distance.

3.4.1 Comparison of classification performance

Similar classification performance measured through CS and ANOVA was observed in relation to the results obtained by Snelder and Booker (2013) in New Zealand rivers. This highlights the possibility of applying similar approaches to classify rivers and obtain equivalent results independently of their geographical location as is the case for hydrological regionalization where contiguous regions are delineated.

Our analysis demonstrated that in general, the PredF strategy performed better than ClasF and significant differences in the ability to discriminate hydrological characters were found for several class levels, especially when the classification approaches were applied over the raw flow series. The higher performance of PredF classifications is supported by the conceptual basis of this approach. ClasF imposes sharp barriers to the observed hydrological space and not over the whole hydrologic domain of the fluvial network. Then, the prediction step enforces congruence of all the river reaches with those previously stablished classes, whereas the real extent to which such discrete groupings exist is uncertain (Kennard et al., 2010).

		Classification		
Level	**Classification**	rawClasF	rawPredF	norClasF
6	rawPredF	0.20		
	norClasF	0.13	0.18	
	norPredF	0.19	0.41	0.19
11	rawPredF	0.24		
	norClasF	0.15	0.22	
	norPredF	0.18	0.31	0.22
16	rawPredF	0.23		
	norClasF	0.15	0.19	
	norPredF	0.17	0.30	0.19
Mean of all levels	rawPredF	0.22		
	norClasF	0.15	0.19	
	norPredF	0.17	0.31	0.20

Table 3.4 - Adjusted Rand Index (ARI) for the 6, 11 and 16-Class levels and the mean of all class levels classifications following the four approaches.

In contrast, the aim of PredF is to account for the whole hydrological variability in the SRN before conducting the classification. This process generates a more complete distribution of the hydrologic variables which is more likely to be in accordance with the hydrologic reality of the SRN, avoiding the bias associated to gauge location. Moreover, PredF does not assume any interactions between the various dependent variables for each RF, which is true as the PCA created orthogonal and independent variables. In addition, it must be pointed out that the PredF approach has not been commonly used in other hydrological classification studies and therefore, further analyses should be done to completely understand the strengths and weakness associated with this strategy.

In general, classifications based on raw flow series had higher discrimination ability for individual indices than those based on normalized flow series (Figures 3.4 and 3.6). As discussed below, classifications based on raw series discriminated rivers based almost exclusively on flow magnitude, which greatly depends on river size. In contrast, classifications based on normalized flow series considered a greater range of hydrological aspects. While the variability of river size shows in general a clear pattern across river networks and thus it is a straightforward approach to segregate river reaches, the consideration of a higher spectrum of hydrologic aspects hampered the creation of classes and thus classifications achieved lower discrimination ability.

3.4.2 Hydrological interpretation of classifications

Most of the published hydrological classifications are based on normalized flow series (Snelder *et al.*, 2009; Reidy Liermann *et al.*, 2012; Solans and Poff, 2013) or normalized hydrological indices (Kennard et al., 2010; McManamay et al., 2012) while few authors have used the untransformed (raw) data (Poff, 1996; Belmar *et al.*, 2011; Zhang *et al.*, 2012). The use of normalized data down weight the influence of flow magnitude on classifications and the application of this criterion significantly affects the final classification outcome. However, to our knowledge this is the first study that has assessed the concern of choosing one of the two approaches. The PCA performed on the raw series showed that the first PC, which was related to mean annual flows and magnitude and duration of high flows explained more than two thirds of the hydrological variation. Thereby, the classifications developed from these data segregated rivers according to their size, as expected. In addition, indices accounting with the frequency of high flow events obtained the highest loadings in the PC2 and PC3 and therefore, this flow regime attribute was relatively well represented in the classifications (Table 3.5). Moreover, the ANOVA analysis also showed that all the indices related to flow magnitude, even those not included as the most important ones in the PCA presented important differences between classes. This is not surprising given the high correlation between all the flow magnitude indices. Despite this segregation, they did not incorporate the severity of droughts as a critical aspect. Severity of droughts might be an essential attribute to be considered in the classifications given the Mediterranean character of the study zone. For instance, Belmar et al (2011) working in a Mediterranean catchment and Chinnayakanahalli et al (2011) covering the Western United States found that, besides the flow magnitude, other hydrologic characteristics related to drought events were contained in the synthetic hydrologic indices. We expected that the characteristic intermittency of many Mediterranean streams had been represented in the synthetic indices, although the lack of this attribute in our classifications may be due to the scarcity of gauges situated in intermittent streams. Moreover, the fact that the high differences in flow magnitude between large and small rives have accounted with the largest percentage of variability, have probably masked the effects of low flow attributes.

On the other hand, the interpretation of the classifications based on normalized flow series differed completely to those derived from raw flow series (Table 3.5). The main differences can be summarized in two essential aspects. First, despite both PCAs explained a similar portion of the total variance, the percentages explained by the different PCs were more evenly distributed in the normalized series. Therefore these classifications were not so obviously conditioned to just one hydrologic character as classifications based on raw series. Second, it was observed that the indices with the highest loading in each PC and hence, their interpretation, varied considerably depending on the data processing (Table 3.5). In the case of normalized flow series, PC1 represented the magnitude and duration of low flow conditions which means that this classification accounted, to some extent, for the Mediterranean character of the rivers. In addition, PC3 to PC6 were related to the magnitude of flows in different months and periods through the year, therefore classification accounted with the shape of the hydrograph as it has been observed in other works (Snelder *et al.*, 2009; Bejarano *et al.*, 2010; Solans and Poff, 2013). Contrary to expected, other indices not related to flow magnitude, such as the frequency of high flow events were not included as important indices in any PC. Nonetheless, the ANOVA analysis highlighted the ability of these classifications to discriminate the indices representing frequency and therefore it was assured that such an important hydrological aspect was incorporated into the classification.

Flow Attribute		Raw	Normalized
Magnitude of annual flows	Mean	***	
	Variability	*	***
Magnitude of monthly flows (shape of the hydrograph)	Mean	-	***
	Variability	-	**
Magnitude and duration of low flows	Mean	-	***
	Variability	-	-
Magnitude and duration of high flows	Mean	***	-
	Variability	-	***
Timing of extreme flow events	Mean	-	-
	Variability	*	-
Frequency and duration of high pulses	Mean	**	**
	Variability	-	-
Rate and frequency of flow change	Mean	-	-
	Variability	*	-

Table 3.5 - Relative representativeness of each flow regime attribute according to the data processing previous to classification procedure. (–None; *Limited; ** Moderate; *** High).

Finally, it must be pointed out that any of the classifications, whether they were based on raw or normalized data, failed to represent some other important hydrologic aspects such as timing of extreme flow events, predictability, duration of high flow events and rate of change (Table 3.5). Other studies based on daily flow series have also found low representativeness and a small contribution to the hydrologic classifications (Snelder *et al.*, 2009; Snelder and Booker, 2013). Analysis of the spatial distribution of the indices representing these flow attributes revealed low variability among rivers in the study area. Therefore, it is acknowledge that they do not represent critical attributes to segregate rivers.

3.4.3 Analysis of distinctive gauges

The analyses of the distinctive gauges demonstrated that the PredF approach presented greater capability than ClasF to deal with the underrepresented parts of the hydrological space in the data set. In contrast to Snelder and Booker (2013), we found an underrepresentation of unmodified gauges on large rivers, given the intense flow management that these type of rivers suffer in the study area. Nonetheless, the presence of gauges in small rivers of first and second order was also scarce. If data were not normalized, rawClasF approach generated classes that were comprised by the distinctive gauge plus a very limited number of gauges, in most of the cases less than four. Therefore classes were relatively homogeneous presenting dissimilarity values close to those found in the classifications based on the rawPredF strategy. However rawClasF produced classes with frequencies lower than 1% which probably were well below the actual frequencies of those river types. On the other hand, the normalization of the flow series smoothed the differences between gauges due to the reduction of the river size effect, which implied that distinctive gauges in the norClasF classifications were not isolated into independent classes. This greatly reduced the problem associated with the low frequency of these classes but in contrast, produced classes with high heterogeneity because distinctive gauges were grouped with other gauges with which they were not that similar. Contrary, the prediction of these rare hydrologic characteristics to a greater number of rivers reaches previous to the classification step through the PredF approach promoted that the proportion of reaches accounting with these rare characteristics increases. Therefore, in the subsequent step of classification, river reaches were grouped together generating classes with a greater degree of homogeneity and classes were more evenly distributed.

3.4.4 Correspondence between classification

The ARI analysis has shown that classifications performed over the same data (raw or normalized) with contrasting approaches (ClasF or PerdF) presented a similar correspondence. In general, many ARI values were around 0.2 which implies a certain degree of similarity but still important differences in the spatial distribution of classes.

Therefore, although the comparison of the classifications performance did not revealed significant differences for several classification levels, it did not imply that the classifications were equivalent regarding the spatial arrangement. This highlighted the importance of the classification procedure in the final outcome. In contrast to expected, ARI analyses also showed that classifications produced using the PredF approach, independently of the data being processing, presented a higher correspondence between them than any other pair. This result highlighted that the prediction of the hydrological characteristics to the entire SRN before classifying is probably generating classifications more adjusted to the actual spatial hydrology variability even if classifications presented different interpretation.

3.5 Conclusion

In conclusion, this study shows that the methodological procedures used throughout the classification process greatly influences classification outcomes and performance. Although the comparison between ClasF and PredF did not reveal significant differences for several classification levels, the classifications based on PredF produced, in general, higher classification performance, higher ability to discriminate individual indices between classes and greater ability to deal with the bias associated to the presence of gauges with distinctive regimes in the data set. Moreover, the application of the PredF strategy produced more evenly distributed classifications than the ClasF strategy and produced classifications more adjusted to the actual spatial arrangement of hydrologic variability. Therefore, we recommend the application of the PredF strategy although further analyses should be done to completely understand its strengths and weakness. Finally, the pre-processing of flow data influenced the meaning and interpretation of the hydrological classes. The normalization of flow data removed the effect of flow magnitude and generated classifications in which a wider spectrum of hydrologic characteristics was considered. However, the use of raw or normalized data is subject to the final objective and particular application of the classification.

3.6 References

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Chapter IV

Sources of variation in hydrological classifications: Time scale, flow series origin and classification procedure

Chapter IV. Sources of variation in hydrological classifications: Time scale, flow series origin and classification procedure

This chapter has led to the article entitled: "Sources of variation in hydrological classifications: Time scale, flow series origin and classification procedure" by Peñas, F.J., Barquín, J., and Álvarez, C. It has been submitted for publication in the journal Water Resources Research.

Abstract

The classification of flow regimes for different purposes in water management and hydroecological research has undergone a significant growth in recent years. However, depending on the available data and procedures applied, there may be several credible classifications for a specific catchment. In this study three inductive classifications from different initial flow data and one expert-driven classification have been defined and we have compared their hydrological interpretation, statistical performance and spatial correspondence. Specifically, Classification 1 was derived based on daily flow data series recorded in 156 unaltered gauges in the northern third of the Iberian Peninsula while Classification 2 and Classification 3 were derived based on monthly flow series, using gauged and modelled flow data, respectively. Classification 4 was based on a Spanish nationwide river hydrological classification, which has been used within the last River Basin Management Plans for different purposes such as the determination of environmental flows. Classification 2 accounted for much of the critical hydrological information of the study area and produced a similar spatial distribution of classes than Classification 1. However, it also presented limitations regarding the inability to represent several important hydroecological attributes. Classification 3 presented lower performance and a lower spatial correspondence to Classification 1 and 2 and thus, the use of modelled flow series should be limited to poor-gauged areas with a restricted number of final applications. Finally, the significantly reduced performance and the uneven distribution of classes found in Classification 4 questions its applications for different management objectives. This study shows that the selection of the most

suitable approach according to the available data have significant implications for the classification uses. Therefore caution is recommended, especially if classifications are to be use in a normative manner.

4.1 Introduction

Hydrological classifications (HCs) group river reaches according to their similarity relative to their natural flow regime (Snelder *et al.*, 2009) and is now regarded as one of the first steps in hydroecological research (Olden *et al.*, 2012). The ultimate aim of HCs is diverse. For instance, they have been employed to describe stream flow variability (Poff, 1996; Baeza and Garcia de Jalón, 2005; Solans and Poff, 2013), to indentify the spatial distribution of river classes across landscapes (Snelder *et al.*, 2009; Belmar *et al.*, 2011), to determine the extent to which climatic and catchment physical attributes influence the hydrologic character of streams (Snelder *et al.*, 2009; Bejarano *et al.*, 2010; Reidy Liermann *et al.*, 2012), to analyze the hydrological changes produced by water abstraction and impoundment infrastructures (Pegg and Pierce, 2002; Wang *et al.*, 2011) and to understand the influence of streamflow on river ecological processes (Jowett and Duncan, 1990; Chinnayakanahalli *et al.*, 2011; Monk *et al.*, 2011). Therefore, HCs play a key role in guiding water resource planning and management (Olden *et al.*, 2012) and are especially valuable for the determination of environmental flows (Kennard *et al.*, 2010; Poff *et al.*, 2010; Reidy Liermann *et al.*, 2012).

The classification of flow regimes has suffered an important development in the last decades, and HCs have been performed almost in every corner of the world using available data and a wide diversity of statistical procedures (Olden *et al.*, 2012). However, most published methods share a series of common steps (Olden *et al.*, 2012; Snelder and Booker, 2013): (1) computation of ecologically relevant indices using unaltered flow series (Olden and Poff, 2003), (2) reduction of the total number of indices to keep the most relevant and non-redundant information, (3) statistical clustering to group flow gauges according to their similarity and delineation of the most appropriate number of classes, (5) interpretation of hydrologic classes and (6) depending on the purpose of the classification, development of statistical models to predict class membership for ungauged locations. Each of these steps can be conducted following a collection of different scientifically defensible methods depending on the rationale, objectives and available data, and many of the classifications have been demonstrated to be defensible and statistically robust.

Regarding the type of data used on HCs, it is generally accepted that daily hydrologic data provide the appropriate temporal resolution for understanding stream ecology and guiding hydroecological research. Poff (1996) demonstrated that monthly data produced a high error rate in capturing the magnitude and temporal distribution of short duration high flow events. Many of the hydrologic attributes related to daily information (frequency, magnitude and duration of short-term high flow events, the timing of annual extremes, or the rate and frequency of hydrograph changes) influence a wide range of ecosystem functions and processes (Richter *et al.*, 1998; Bunn and Arthington, 2002). Hence, their omission may lead to inaccurate or incomplete vision of the ecologically relevant hydrology. However, in cases where daily series are unavailable, monthly data may adequately gather much of the ecological relevant information dealing with the magnitude and timing of mean discharge conditions, the shape of the hydrograph and the magnitude, duration and frequency of long-duration high flow events (Harris *et al.*, 2000; Solans and Poff, 2013). Moreover, Poff (1996) postulated that coarse grain data would be useful for the analysis of low flow events as they generally present higher duration.

There exist basins and regions where gauging stations representing unaltered hydrological regimes are very rare (Wang *et al.*, 2011). This situation is very common in developed areas of the world where water resources are unevenly distributed over the year and there is an intense hydrologic regulation. This is the case of the Mediterranean area of Spain (Bejarano *et al.*, 2010; Belmar *et al.*, 2011). The classification of rivers in these situations, can follow two approaches: (1) apply a deductive, or *a priori* classification which postulate the organization of patterns in flow regimes in terms of environmental factors such as climate, topography and geology

(Snelder and Biggs, 2002), or (2) generate flow time-series provided by hydrologic rainfall–runoff simulation models to develop an inductive classification. The classifications of rivers through deductive procedures is widely accepted and it has been applied in many regions (Snelder and Biggs, 2002; Wolock *et al.*, 2004). Nonetheless, Belmar et al (2012) and Snelder and Booker (2013) demonstrated that inductive classifications based on simulated or gauged flow series, respectively, outperformed deductive classifications. By contrast, the comparison of inductive hydrologic classifications based on gauged and modelled flow series has not been addressed to date.

A third type of classification is the named expert-driven classifications. This classification can be based on gauged or modelled flow series, however, they do not relay on the multivariate statistical analysis most commonly used in HC to define class boundaries but in experts' rules. There are not many examples of this method (but see Krasovskaia *et al.*, 1994; Kachroo *et al.*, 2000; Hughes and Hannart, 2003; CEDEX, 2009). Expert-driven classifications, lack, in general, the desirable qualities of objectivity, transparency, interpretability and repeatability. Indeed, depending on the expert, results may differ greatly from one classification to another. Therefore, although they have not been compared to date, expert-driven classifications may have a lower performance than inductive classification, and hence, their implementation might have critical consequences for water management and environmental conservation.

In the present study we are interested on looking at how time scale (daily versus monthly), flow series origin (gauged versus modelled) and classification procedure (inductive versus expert) influence HC performance and interpretability. This will allow identifying which are the main drawbacks of using a simplified dataset for developing HCs, and, thus, will allow framing the use of HCs in those areas where daily gauged data are not available.

To achieve that, we will develop three inductive classifications and one expert-driven classification covering the northern third of the Iberian Peninsula. One of the inductive classifications was based on daily gauged series and it was used as the best possible classification approach, while the other two used monthly flow series. These two monthly flow series were derived from the daily flow series and simulated from a nationwide rainfall-runoff model, respectively. The four classifications will be compared in terms of their performance (classification strength and discrimination ability), interpretability (most influential hydrological indices) and spatial arrangement (spatial configuration of classes). We hypothesized that expert-driven classifications would present the lowest performance and will be the most difficult to interpret. It would also present the greatest differences regarding the comparison of classification spatial arrangement. On the other hand, daily flow series would outperform the classification based on monthly flow series. Moreover, we expect that the classification based on monthly gauged series would perform better than the classification based on simulated flow series and would produce a more similar spatial pattern to the classification based on daily flow series. Regarding the interpretation of the classifications based on monthly flow series (gauged or natural) we do not know a priori whether they will differ much or not from daily flow classifications. Finally, implications for river management will be drawn on the basis of these differences.

4.2 Methods

4.2.1 Hydrological data processing

We used the daily gauged and monthly modelled flow series introduced in Chapter II to develop three inductive classifications in this study. Daily time series were aggregated and transformed into monthly flow series in order to analyze the effect of reducing the detail of the time scale of the flow series (i.e. use of monthly flow series instead of daily). Both gauged and modelled and daily and monthly series were normalized in order to eliminate the influence of flow magnitude (Snelder *et al.*, 2009). Normalization was obtained by dividing all daily or monthly flow values by the mean annual flow (Poff *et al.*, 2006). In addition, we used modelled hydrologic information to develop a third classification.

4.2.1.1 Hydrologic Indices Calculated form daily flow series.

A set of 101 ecologically meaningful hydrologic indices introduced by Olden and Poff (2003) were calculated for the daily flow series (Appendix: Table A1). These indices characterized the central tendency and dispersion of: (1) magnitude of annual and monthly flow conditions, (2) magnitude and duration of annual extreme flows, (3) timing and predictability of flows, (4) frequency and duration of high flow pulses and (5) frequency of change of flow (Richter *et al.*, 1996; Olden and Poff, 2003).

4.2.1.2 Hydrologic Indices Calculated form monthly flow series

The use of monthly series involved a decrease in the number of hydrological indices that can be calculated in comparison with the daily flow series. We calculated a set of 72 hydrologic indices introduced by Olen and Poff (2003) and used when developing HCs in different Iberian catchments (Appendix A: Table A2; Belmar *et al.*, 2011; Solans and Poff, 2013). These indices characterized the central tendency and dispersion of (1) magnitude of annual and monthly flow conditions, (2) magnitude and duration of annual extreme flows, (3) frequency of high flows. Other important hydrological aspects such as timing and rate of change could not be calculated.

4.2.2 Classification procedures

4.2.2.1 Data driven: Classification 1, Classification 2 and Classification 3

Given the strong correlation between several indices at both scales (daily and monthly), the initial set of indices was reduced to a set of non-correlated synthetic indices using Principal Component Analysis (PCA) (Olden and Poff, 2003). The broken stick method was used to define the optimal number of PCs (Jackson, 1993). Three independent PCAs were carried out using the hydrologic indices derived from the daily flow series, the monthly gauged series and the monthly modelled series (Figure 4.1). Scores for the selected number of PCs were used as new synthetic indices for cluster analysis. Each PC was standardized before conducting further analysis to give them equal weights.

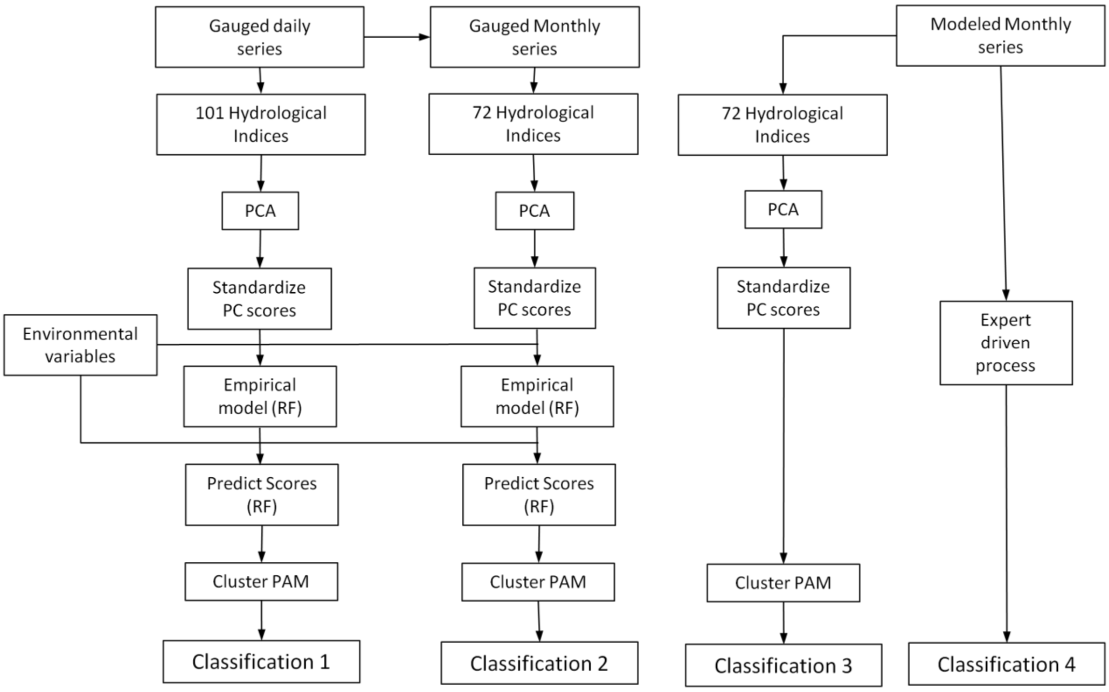

Figure 4.1 - Schematic diagram summarizing the strategies applied to define the 4 classifications.

For the gauged daily and monthly flow series the Predict-first-Classify-later (Chapter III) approach was applied to classify the gauges (Classification 1 and Classification 2; Figure 4.1). In this approach empirical models of the standardized synthetic indices were initially fitted one at a time as a function of predictor catchment variables (Chapter II, Table 2.2) by means of Random Forest (Breiman, 2001; Cutler *et al.*, 2007). Then the synthetic indices were predicted for the gauge domain, generating a separated predicted distribution for each synthetic index. Classifications were produced by clustering all the modelled sites using the Partitioning Around Medoids (PAM) algorithm. Classifications of increasing number of classes from 2 to 26-Class levels were produced. Classification 1 was considered as the best possible given that it provided the highest amount of hydrologic information.

For the classifications based on modelled monthly flow series (Classification 3), gauges were clustered using the previously developed synthetic indices and the PAM algorithm

(Figure 4.1). We produced a classification with a number of classes ranging from 2 to 26-Class levels.

4.2.2.2 Expert Driven: Classification 4

The expert driven classification (Classification 4) used in this work is based on the hydroregions map at the national scale developed by the Spanish Ministry of Agriculture, Food and Environment and the Ministry of Public Works (CEDEX, 2009). This map has been used for the assessment of environmental flows in the new River Basin Management Plans (RBMPs) carried out to fulfil the EU Water Framework Directive (WFD) in Spain. This classification used the hydrological information provided by the monthly specific runoff obtained from the SIMPA model for the period 1946-2006. This monthly flow series were aggregated for catchments defined according to the WFD requirements. Based on this aggregated monthly series a set of hydrological indices were calculated (Figure 4.2). First a series of annual values was derived for each catchment. This included, annual minima and maxima divided by the annual mean (MI1 and MA1, respectively), and the mean of the 3 minimum and maximum monthly flows divided by the annual mean (MI2 and MA2, respectively). Finally, a set of eight indicators were obtained by calculating the mean (intrannual indicators) and coefficient of variation (interannual indicators) for the four series obtained above ($MI1_{Inter}$, $MI1_{Intra}$, $MI2_{Inter}$, $MI2_{Intra}$, $MA1_{Inter}$, $MA1_{Intra}$,$MA2_{Inter}$ and $MA2_{Intra}$, respectively; Appendix: Table A3) Then, based on the frequency distribution of each indicator a set of three intervals were defined. For the intrannual indicators three intervals were defined according to the ± 1 standard deviation of the series, while for the interannual indicators the intervals were defined according to the ± standard deviation divided by two. Finally, each catchment was assigned to its corresponding interval and pairs of indicators concerning the same hydrologic aspect (Minimum/maximum, inter/intra) were combined and assigned to a group ranging from A to D (see example on Figure 4.2). Following, these groups were again grouped by pairs in relation to the assignment of interannual indicators in one hand and interannual indicators in the other. Next, interannual indicator classes were joined with intrannual indicator classes. This yielded a classification comprised by 41 different classes (note that not all possible combinations were present), Out of these, only 16 classes were present within the study area (Level 4).

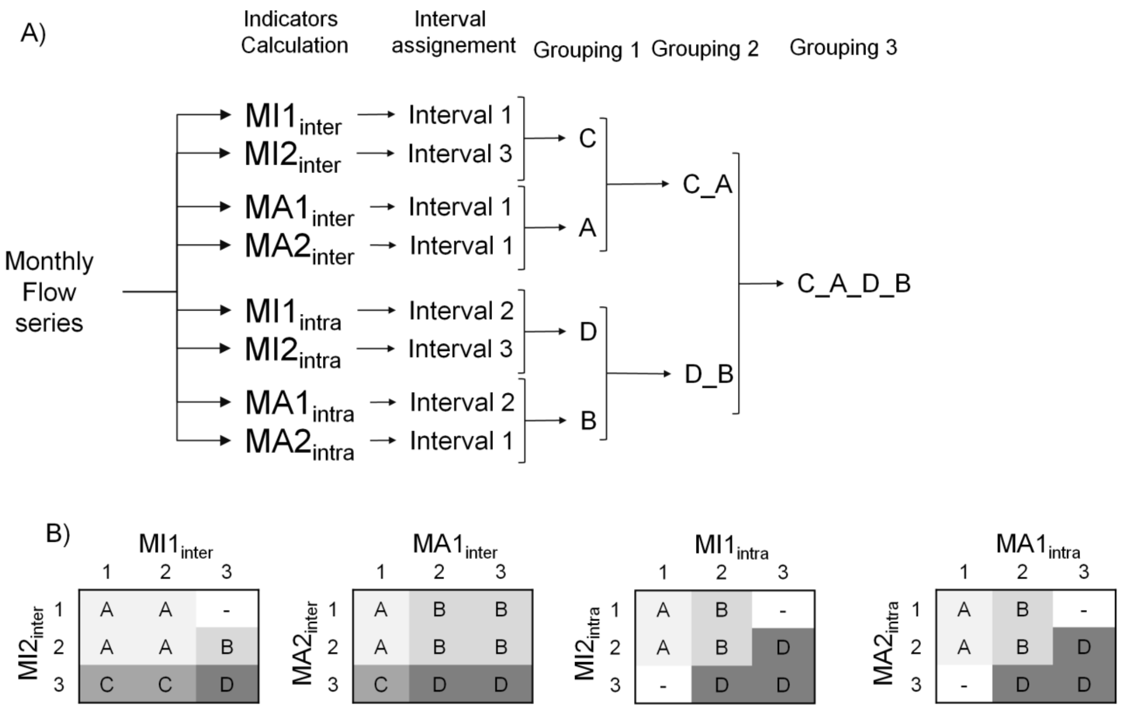

Figure 4.2 - A) Schematic diagram summarizing the hydrologic indices and main steps of the aggregation process used in the definition of level 4 of Classification 4. B) Procedures followed to combine each pair of indicators to define grouping 1. Note that in the original classification, the procedure to group each pair of indicators (Grouping 1) presented a different mixing table.

Finally, to obtain the last level of the classification (Level 5) four extra indicators related to the timing of the minimum and maximum discharge and the recurrence of the months that presented the minimum and maximum discharges throughout the complete series were also considered (for brevity we do not explain how this has been calculated, for more information see: CEDEX, 2009). Once considering these aspects and having weighted the indicators according to their importance in the classification a final map of 90 supra-regions was defined, from which 26 classes were present in the study area (Figure 4.3). Within this study we compared the different levels of this expert-driven classification with the levels of the data driven classification. To achieve that, we needed to derive Level 1, 2 and 3 of this classification by splitting the codes obtained at each step of the procedure. For example, for a gauge classified at level 5 as A_B_A_C_VII, level 1 was considered as class A, level 2 as A_B and so on (Table 4.1). It should be noted that only the last level of the expert driven classification (Level 5) should be considered when evaluating its performance.

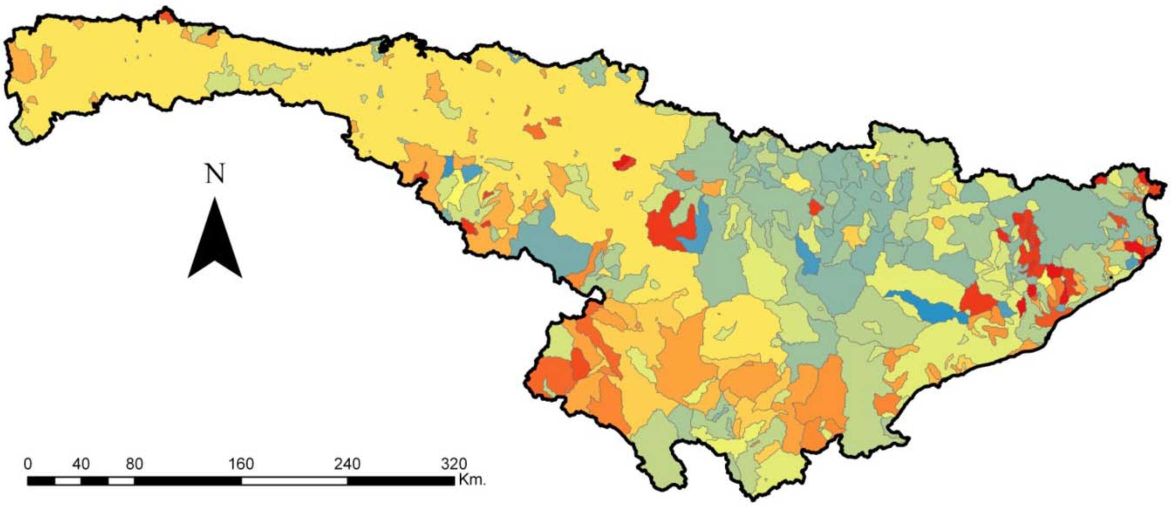

Figure 4.3 - Map of supraregions in the study area derived from the expert driven classification (Source CEDEX, 2009).

4.2.3 Comparison of classification performance

The performance of the classifications was measured using the classification strength (CS; Van Sickle, 1997) and ANOVA. For the CS the hydrological indices with the highest loading on each of the retained PC of the three data driven classifications were selected. These hydrological indices were used as test indices.

CS estimate the degree of dissimilarity of the hydrological character between gauges explained by the classifications (Snelder and Booker, 2013). Briefly, CS results from the difference between the mean hydrological dissimilarity between all pairs of replicate sites within classes (D_{within}) and the mean dissimilarity of all dissimilarities between classes ($D_{beetwen}$). Higher values of CS indicate a greater uniformity within classes and greater differences between classes (Van Sickle, 1997). We calculated CS for each class level of the 4 classifications. We applied the restriction that classes at each hierarchical level were comprised by at least 3 gauges. This reduces the weight given to individual classes. We also accompanied this analysis with box plots of the most important hydrological indices within the PCAs at the level 5 of the expert rule classification (26 classes). For brevity we selected for graphical representation only those classes with minimum, median and maximum values.

In addition, we performed an ANOVA to analyze the potential of classifications to discriminate each of the 101 hydrological indices. For the four classifications independent ANOVAs were performed on each index using the class membership as the explanatory factor. The coefficient of determination (R^2) was calculated for each class level of the 4 classifications. The restriction of the 3 gauges per class was also applied.

With the objective of "smoothing out" the variability inherent in the sub-setting of the selected gauges and to be able to calculate the confidence intervals for the CS and R^2 statistics a bootstrap procedure was applied. Bootstrap samples were constructed by selecting the 90% of the gauges each time and repeat the process 20 times. The mean and the 95th upper and lower confidence intervals were calculated from the distribution of values. Two classifications were assumed significantly different if confidence intervals for CS and R^2 statistics did not overlap.

4.2.4 Hydrological interpretation

The original indices with the highest values in each retained axe of the PCAs were used to interpret the hydrological meaning of the new synthetic indices and the classifications (Snelder *et al.*, 2009). In addition, we used the ANOVA results to interpret each classification by looking at the different coefficient of determination for specific indices. We assumed that the higher the coefficient of determination the higher the importance of that index to discriminate among classes.

	Level 1		Level 2		Level 3		Level 4		Level 5	
Class	**total**	**percent**	**total**	**percent**	**total**	**percent**	**total**	**percent**	**total**	**percent**
1	149	95.5	114	73.1	3	1.9	3	1.9	3	1.9
2	2	1.3	22	14.1	105	67.3	1	0.6	1	0.6
3	1	6.6	13	8.3	6	3.8	104	66.7	3	1.9
4	4	2.6	2	1.3	1	0.6	4	2.6	13	8.3
5			1	0.6	14	9	2	1.3	2	1.3
6			4	2.6	7	4.5	1	0.6	86	55.1
7					6	3.8	14	9	4	2.6
8					7	4.5	2	1.3	1	0.6
9					2	1.3	5	3.2	1	0.6
10					1	6.6	5	3.2	1	0.6
11					4	2.6	1	0.7	4	2.6
12							4	2.6	7	4.5
13							3	1.9	4	2.6
14							2	1.3	1	0.6
15							1	6.6	1	0.6
16							4	2.6	3	1.9
17									2	1.3
18									2	1.3
19									3	1.9
20									1	0.6
21									2	1.3
22									2	1.3
23									3	1.9
24									2	1.3
25									1	0.6
26									4	2.6

Table 4.1 - Number and percentage of gauges in each class at the five levels defined for Classification 4**.**

4.2.5 Correspondence between classifications

The spatial agreement between each pair of classifications was evaluated by means of the Adjusted Rand Index (ARI; Hubert and Arabie, 1985). ARI analyze the relationship of each pair of gauges and how they differ between two cluster solutions. It ranges between 0 (indicating that agreement between two clustering solutions is not better than chance) and 1 (indicating perfect agreement). Kennard et al (2010) analyzed the correspondence between 14 classification and demonstrated that ARIs above 0.45 were indicative of little differences between classification group structure. This suggests that classifications with ARI higher than 0.2 still exhibited certain level of spatial correspondence while values below indicated low spatial correspondence.

4.3 Results

4.3.1 Classification performance

Classification 1 and 2 presented higher CS than Classification 3 and 4 for all levels of classification (Figure 4.3). In addition, generally Classification 1 performed better than Classification 2. Nonetheless, for the low (2 to 6-Class level) and high (23 to 26-Class level) levels of classifications the differences were not significant. Moreover, Classification 2 outperformed Classification 1 several times. The differences between Classification 1 and 2 and Classification 3 and 4 were more evident for the mid and high detailed classifications. In this regard, Classification 1 and 2 showed a gradual increment of CS from 6-Class level up to 17-Class level, while CS for Classification 3 and 4 did not increase significantly beyond the 6-Class level (Figure 4.4). Classification 3 performed better than Classification 4; however for 11 and 26-Class level the differences were not significant.

Box-Plots revealed that the 26-Class level of Classification 1 and Classification 2 presented a similar ability to segregate classes. However for certain test indices such as lkur, sd30HF and X5, Classification 1 presented higher discrimination ability (Figure 4.5). Classification 3 presented more heterogeneous classes and therefore a greater degree of overlap between classes. Finally, Classification 4 was composed by classes that presented, for most of the hydrologic indices, similar median values and high heterogeneity. This implied that, in general, the classes with the minimum, median and maximum values do not present almost any difference in regard to the distribution of indices values.

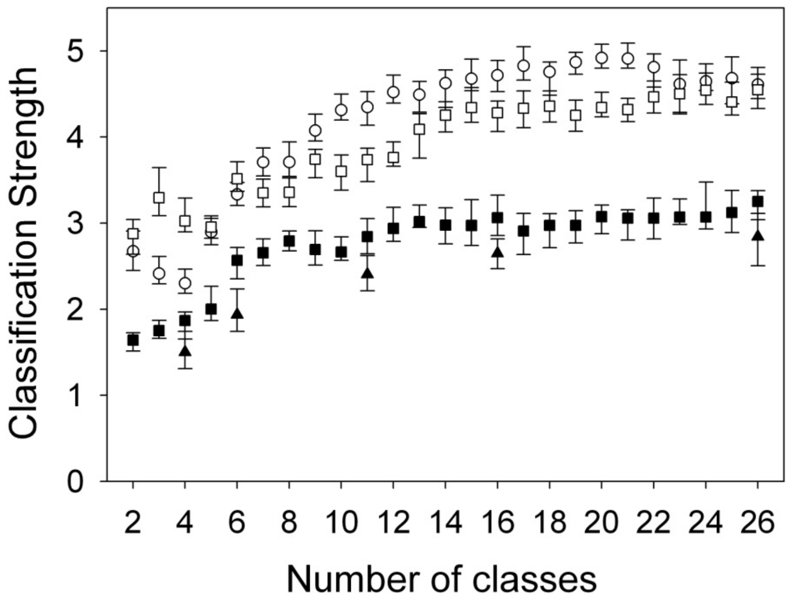

Figure 4.4 - Performance of the classifications based on the Classification Strength statistic. Symbols represent the mean and whiskers the lower and upper 95% confidence interval for the CS values at 2 to 26-Class levels (○: Classification 1; □: Classification 2; ■ : Classification 3; ▲: Classification 4).

The ANOVA analysis revealed that Classification 2 performed better than Classification 1 over 35% of the times for the 4-Class level while at 11, 16 and 26-Class levels Classification 1 outperformed Classification 2 over 20% of the times (Table 4.2; Auxiliary material provided in digital format). Nonetheless, for most of the indices these two classifications did not present significant differences.

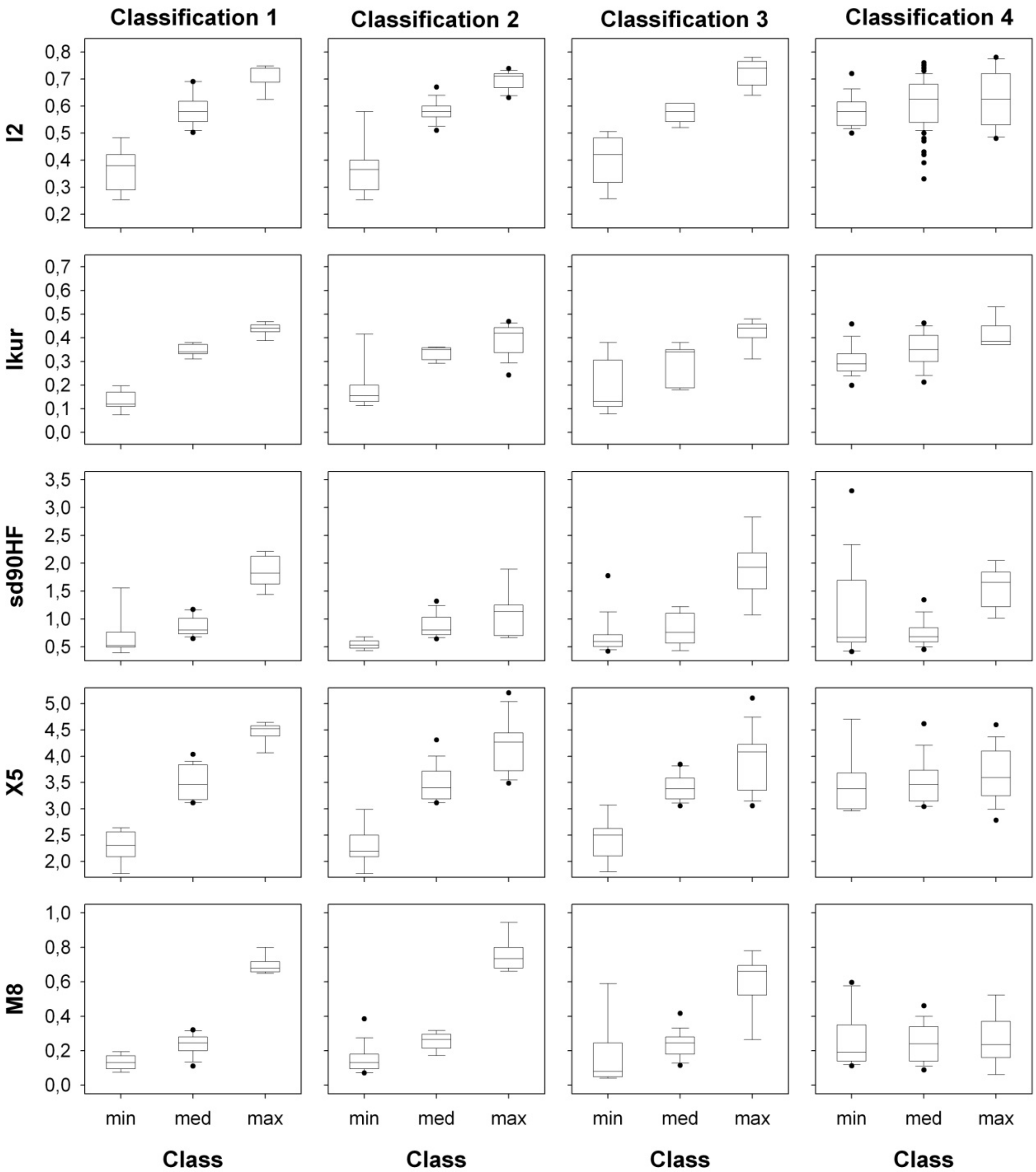

Figure 4.5 - Box plot for the comparison of selected hydrologic metrics variation between classifications at the 26-Class level. Metrics with the highest loadings in the PCAs were selected. The lines at the top, middle and bottom of each box represent the 75th, median and 25th percentile of the metric, respectively. Whiskers represent 90^{th} and 10^{th} percentiles and outliers are represented by ●.

	Classifications								
Level	**1>2**	**2>1**	**2=1**	**1>3**	**3>1**	**3=1**	**1>4**	**4>1**	**4=1**
4-Class	23.8	37.6	38.6	31.7	15.8	52.5	84.2	7.9	7.9
6-Class	20.8	17.8	61.4	45.5	5.0	49.5	79.2	2.0	18.8
11-Class	28.7	6.9	64.4	71.3	0.0	28.7	93.1	0.0	6.9
16-Class	26.7	7.9	65.3	72.3	1.0	26.7	91.1	0.0	8.9
26-Class	22.8	10.9	66.3	63.4	0.0	36.6	69.3	0.0	30.7
	2>3	**3>2**	**3=2**	**2>4**	**4>2**	**4=2**			
4-Class	30.7	8.9	60.4	79.2	5.0	15.8			
6-Class	45.5	4.0	50.5	89.1	1.0	9.9			
11-Class	43.6	1.0	55.4	93.1	0.0	6.9			
16-Class	50.5	0.0	49.5	89.1	0.0	10.9			
26-Class	57.4	2.0	40.6	71.3	2.0	26.7			
	3>4	**4>3**	**4=3**						
4-Class	73.3	6.9	19.8						
6-Class	70.3	5.0	24.8						
11-Class	67.3	0.0	32.7						
16-Class	64.4	0.0	35.6						
26-Class	26.7	1.0	72.3						

Table 4.2 - Percentage of times that one classification presented higher, lower or equal R^2 than other classification at 4, 6, 11 and 16 and 26-Class level. Equal R^2 values were supposed when there was no overlap among confidence intervals.

In contrast, Classification 1 and Classification 3 performed similarly for the low detailed classifications (4 and 6-Class levels) and the differences increased for higher detailed classifications. Hence, for 11, 16 and 26-Class levels Classification 1 outperformed Classification 3 more than two thirds of the times (Table 4.2). On the other hand, Classifications 2 and 3 did not show significant differences half of the times. However, for the 11, 16 and 26-Class levels the percentage of times that Classification 2 outperformed Classification 3 increased from 43 to 57%. Finally, it was observed that, in general, classifications 1, 2 and 3 performed better than Classification 4. In this regard, Classification 1 and 2 outperformed Classification 4 more than 80% of the times. However for the 26-Class level more than 25% of the times Classification 1 and 2 and Classification 4 did not showed significant differences. Finally, Classification 3 presented lower differences relative to Classification 4. Indeed, for the 26-Class level they did not presented significant differences 72% of the times. In general, those indices that presented the lowest classification performance (Jmax, Rev, sdFRE3, sdRev) also showed the smallest differences between classifications.

4.3.2 Principal components analysis results and hydrological interpretation of classifications

The first six PCs of the PCA based on the daily flow series explained 87.4% of the total variance (Table 4.3). According to the indices with the highest loading, PC1 represented the variability of the annual mean flow and the magnitude and duration of extreme low flows and PC2 represented the variability of the magnitude and duration of high flow events. PC3 was related to the magnitude and variability of October flows, while PC4 represented the variability of annual flows and the magnitude of high flows. PC5 was related to mean January and May flow magnitude while PC6 represented the magnitude and variability of August flows (Table 4.3).

Regarding the PCA performed on indices calculated from the gauged monthly flow series, the first five PC explained 84.6% of the total variance. PC1 represented the variability of the annual mean flow and the magnitude and duration of seasonal high flows, while PC2 represented the variability of the series distribution and the variability of May flows. PC3 was related to mean and maximum magnitude of October flows, PC4 to the mean magnitude of May and April flows and PC5 to the mean magnitude and variability of September flows (Table 4.3).

Finally, the four first PCs of the PCA performed on indices calculated from the monthly modelled series explained 86.4% of the total variance. The first PC was related to the magnitude of extreme high flows and the variability of annual flows. PC2 represented the mean magnitude of August and June flows while PC3 and PC4 were related with the mean magnitude and variability of November and October flows, respectively (Table 4.3).

	Daily series		Monthly Series		Monthly Modeled Series	
Axe	Indices	Var. Exp	Indices	Var. Exp	Indices	Var. Exp.
PC1	**-I2**; 90LF	38.5	**-I2**; -M3HF	38.5	**X5**; **I2**	41
PC2	**Sd30HF**; sd7HF	20.1	**Ikur**; sdM5	22.5	**-M8**; -M6	30.3
PC3	**-M10**; -sdM10	11.6	**-M10**; -**MxM10**	11.5	**-M11**; -sdM11	8.4
PC4	**Ikur**; -X25	7.5	**M5**; M4	6.8	**MxM10**; sdM10	6.7
PC5	**-M1**; **M5**	6.2	**sdM9**; MxM9	5.3		
PC6	sdM8; MxM8	4.5				

Table 4.3 - The two hydrologic indices with the highest loadings in each retained PC and the variation explained by the retained PCs are shown. A minus sign indicates negative relation with the PC. The indices in bold letters were used to calculate the Classification Strength.

In addition, the ANOVA analysis showed that the ability of classifications to discriminate each of the hydrological indices presented analogous patterns for all considered indices (Figure 4.6; Tables S2.1 to S.2.5 provided within the supplementary material included in the DVD). In general, R^2 increased with the increasing classification detail although for many indices R^2 did not present significant increments beyond the 7 or 10-Class level (Figure 4.5). Hydrologic indices representing the mean and variability of flow magnitude (e.g. M10, MxM4, MnM7, 7LF, 7HF, Ica, sdM10, sd7LF, sd7HF) and frequency (FRE3) presented higher R^2s than indices representing timing (Jmax) and rate of change (rev). It must be pointed out that Classification 1 showed the highest R^2 100% of the times for the indices dealing with mean frequency and duration of high pulses (Table 4.2; Figure 4.6).

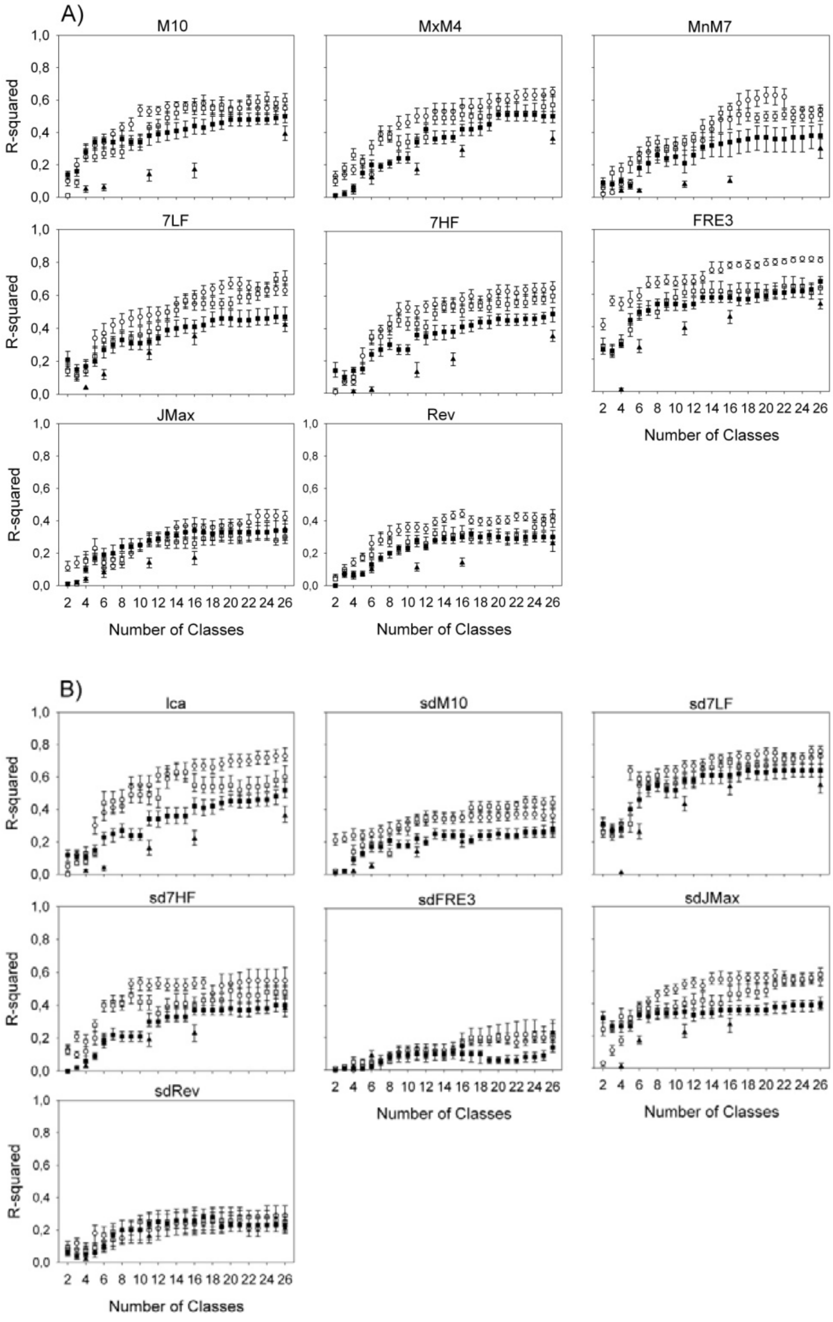

Figure 4.6 - Performance of the 4 classifications based on individual index analysis. Symbols represent the mean and whiskers the lower and upper 95% interval confidence interval for the R^2 values at 2 to 26-Class levels (○: Classification 1; □: Classification 2; ■: Classification 3; ▲: Classification 4). We selected one index representing each aspect of the natural flow regime to illustrate the results A) Indices representing mean values. B) Indices representing standard deviation (the values obtained for the 101 indices for the 4, 6, 11, 16 and 26-Class levels are included in Tables S2.1-S2.5 provided within the supplementary material).

4.3.3 Analysis of correspondence

Classification 1 and Classification 2 presented ARI values over 0.25 for the low detailed classification (4 and 6-Class Levels) which increased over 0.4 for the 11, 16 and 26-Class level (Table 4.4). Classification 3 and Classification 1 and 2 had fairly constant ARI values for the different levels of classification close to 0.2 in most of the cases (Table 4.4). Finally, Classification 4 presented the lowest spatial correspondence values with the three inductive classifications. In most of the cases the comparisons between Classification 4 and classifications 1 and 2 revealed that ARI values were not above 0.1 while these values were close to 0.15 when it was compared with Classification 3 (Table 4.4).

Level	**Classification**	**Classification**		
		Class 1	Class 2	Class 3
4	Class 2	**0.25**		
	Class 3	**0.20**	0.14	
	Class 4	0.01	0.00	0.01
6	Class 2	**0.32**		
	Class 3	**0.25**	**0.24**	
	Class 4	0.16	0.18	0.17
11	Class 2	**0.44**		
	Class 3	**0.23**	**0.21**	
	Class 4	0.13	0.09	0.16
16	Class 2	**0.40**		
	Class 3	**0.26**	**0.22**	
	Class 4	0.10	0.07	0.15
26	Class 2	**0.40**		
	Class 3	**0.20**	**0.25**	
	Class 4	0.09	0.09	0.16
Mean of all levels	Class 2	**0.38**		
	Class 3	**0.22**	0.19	
	Class 4	0.10	0.10	0.13

Table 4.4 - Adjusted Rand Index (ARI) for the 4, 6, 11, 16 and 26-Class level between each pair of classification. Bold ARI values indicate at least moderate spatial agreement (ARI > 0,2).

4.4 Discussion

Our results support the initial hypothesis that expert driven classifications performed worse than inductive classifications. Moreover, expert driven process created a completely different and unevenly spatial distribution of classes. However, the differences in the discrimination ability of hydrologic indices between Classification 4 and 3 were not so evident. This study also shows that the time scale of the flow series is not as important as expected. In this regard, Classification 2 presented similar performance, interpretation and spatial distribution than Classification 1. Nonetheless, Classification 1 outperformed Classification 2 in most of the cases and some important flow regime attributes, mainly those related to the frequency of high flow events were not well captured by the monthly series and thus they were neglected in the classification.

4.4.1 Classification performance

Given that monthly series account for the most relevant information dealing with the annual flow variability (e.g. I2) and the shape of the hydrograph, significant differences is CS and R^2 between Classifications 1 and 2 were not observed for several classification levels. Nonetheless, the aggregation of flow series form daily to monthly produced a loss of information. For instance, the box plots showed that for several important hydrologic indices (e.g. Ikur, sd90HF or X5) Classification 2 produced classes in which these indices were not as well segregated as in Classification 1 and thus, for some class level, Classification 1 outperformed Classification 2. Our results matched in part with those obtained by Poff (1996) who found that classifications developed from daily, weekly, monthly, seasonal and annual flow series were equally able to segregate classes according to their predictability and coefficient of variation. In contrast, other indices dealing with high flow events of short-duration were not adequately segregated when using coarse-grained hydrological data, especially in low variable streams.

On the other hand, the analyses also highlighted a significant lower ability of classification derived from modelled flow series to segregate rivers according to the actual (i.e. measured) flow regime. Even for those indices identified in the PCA as the most important in explaining the hydrologic variability of the modelled flow series (e.g. X5, M8), Classification 3 produced high heterogeneous classes with greater overlap between them (Figure 4.5) and a lower discrimination ability (Figures 4.4 and 4.6) than Classifications 1 and 2. The lower segregation ability of Classification 3 was probably due to the complexity of simulate flow series through numerical tools. The inaccurate parameterization of numerical models (Littlewood and Croke, 2013) is many times related with the difficulty of conceptualize river basins (Wagener and Gupta, 2005) and the need of high quality information of numerous factors (Wagener and Montanari, 2011). For instance, climate, land use, geology, soil information and morphology of the basin many times do not have the proper quality to reproduce reliable flow series (García et al., 2008). These limitations are multiplied when models must be developed at coarser time scales (Wang et al., 2009) and for large areas with contrasting climatic and environment characteristics, as is the case of the SIMPA model developed for Spain. The ability of the model to simulate the actual hydrology is an essential task since the use of initial flow time series with poor quality compromises the final classification outcomes which, at the end, introduces an important level of uncertainty for further uses of this classification.

As expected, Classification 4 produced the lowest CS and R^2s for most of the indices. Nonetheless, the differences between Classification 4 and 3 were not so evident, especially for the 26-Class level. Attending to this result it may be concluded that the type of data is more important than the classification procedure in determining classification performance. Nonetheless the box plot analyses demonstrated that classes in Classification 4 are less different than classes in Classification 3 which highlighted that the procedure is also a critical aspect that should be taken into account. Attending to these results we can conclude that, the utilisation of Classification 4 is very limited independently of the scope of the future application.

4.4.2 Hydrological interpretation

The reduction of the initial sets of hydrological indices through the PCAs in the 3 data driven classifications produced synthetic indices that in general displayed consistent hydrological interpretations independently of the time scale or the origin of the flow series. For instance, the three PCAs included I2, a measure of the interannual flow variability, as one of the index explaining a great part of the hydrologic variability in the study area. The consideration of this index involved that during the classification process, rivers with fairly constant annual flows were split from those with high interannual variability. In addition, many of the significant PCs of the three classifications were related to the mean and variability of the magnitude of monthly flows. The ANOVA analysis did not highlighted significant differences between Classifications 1, 2 and 3 in the ability to segregate rivers according to the mean monthly flows for several classification levels, although in general, Classification 1 outperformed Classification 2 and this outperformed Classification 3. Therefore, considering the importance of these indices, the shape of the annual hydrograph, i.e. the intrannual flow variability, may play an essential role in the three classifications, as it was found by several authors using daily (Snelder *et al.*, 2009; Kennard *et al.*, 2010; Reidy Liermann *et al.*, 2012) and monthly flow series (Belmar *et al.*, 2011; Solans and Poff, 2013). In this regard, other hydrological classification carried out in the Ebro Basin found that 10 indices representing the mean and variability of the magnitude of monthly flow out of 19 indices maximized differences among hydrological classes (Solans and Poff, 2013). The inclusion of these indices enabled to differentiate rivers presenting pluvial, nival or pluvio-nival streamflow regimes and also rivers influenced by Oceanic climate from those subjected to the Mediterranean climate (Solans and Poff, 2013). Bejarano et al (2010) found a similar classification pattern to Solans and Poff (2013) but using uniquely the 12 indices representing mean monthly flows. The correspondence between the different Ebro basin classifications interpretation highlight the significant influence that mean monthly flows have within the flow regime variability.

However, the exclusive use of these indices could limit the application of those classifications due to the loss of other highly relevant hydrological information.

Results from PCAs also revealed some differences between the daily and the monthly flow series. For example, the PC1 of the Classification 1 was related to the magnitude and duration of low flow conditions. The ANOVA analysis demonstrated that Classification 1, for most classification levels, presented the highest ability to segregate classes according to the severity and duration of droughts (Figure 4.6), while Classification 2 and 3 missed partially this attribute. Many rivers in the study area present a strong Mediterranean character and, thus, the consideration of this hydrological feature should be of principal concern in the hydrological classification. However, it depends on the final application and scope of the classification. For instance, classifications based on both daily and monthly flow series, especially those derived from gauge measurements, result useful to explore and identify the stream flow variability and the spatial distribution of river classes across landscapes and even, to aid in general water resources planning and management actions. Nonetheless, the lack of information related with the severity and duration of droughts would limit their use in other management issues like the assessment of minimum environmental flows which is one of the most extended applications of hydrological classifications (Kennard *et al.*, 2010; Poff *et al.*, 2010).

On the other hand, PCAs of Classification 2 and 3 found that magnitude and duration of high flow conditions (M3HF, X5) explained a significant portion of the total hydrological variability. This hydrological attribute was not included as one of the most relevant variables in Classification 1. Nonetheless, the ANOVA analysis demonstrated that Classification 1 presented equal or higher ability to discriminate classes according to high flow indices than Classification 2 (Figure 4.6). These results showed that monthly flow series extracted from gauged data were still capable of accounting for the magnitude of the high flow events signature present in the daily flow series. Nevertheless, this ability was reduced as the duration of high flow events duration got shorter, i.e. 1 day, 3 days and 7 days. Finally, Classification 1 presented always a higher ability than Classification 2 and 3 to discriminate indices representing frequency of high flow events (FRE1, FRE3, FRE 7, nPHigh, dPHigh). Thus, classifications based on monthly flow series will be limited to understand some key biophysical relations in fluvial ecosystems and also to evaluate impairment of hydro-morphological pressures that alter these flow regime components.

Finally, the PCAs and ANOVA analysis evidenced that the twelve indices used in Classification 4 could only account for a limited proportion of the hydrological variability in the study zone. The indices related to the mean and variability of high and low flow conditions in which Classification 4 was based were represented in PC1 and PC2 of the Classification 1 and the PC1 of the Classifications 2 and 3. In contrast, none of these PCAs recognized timing of minimum and maximum discharge as important aspects in the classification due to the low spatial variability in the study domain. The ANOVA analysis demonstrated that for all the hydrologic indices, including those related with timing, Classification 4 presented the lowest ability to discriminate between classes. The lack of information of Classification 4 in relation to the variability of the annual mean flow conditions, the shape of the annual hygrograph or the magnitude and duration of high and low flow attributes of the flow regime questions its implementation for the assessment of environmental flow regimes, which, in fact, was the last objective of this classification (CEDEX, 2009).

4.4.3 Correspondence between classifications

The high spatial correspondence between Classification 1 and 2, especially for the most detailed classification, highlighted that monthly time series presented a great potential to identify the spatial distribution of river types and also to determine the main climatic and catchment attributes that influence this distribution. These applications have been some of the principal scopes of HCs (Snelder et al., 2009; Belmar et al., 2011). In this regard, for the 6-class level, Classification 1 and Classification 2 coincided in part with the spatial arrangement of the hydrologic classification presented by Solans and Poff (2013) for the Ebro basin. These authors (Solans and Poff, 2013) applied a different classification procedure to the one used in this study, especially in relation to the selection of the critical hydrological indices and the cluster algorithm. However the spatial coincidence between the 3 classifications evidences that the data used in the analysis may be more important than the classification procedure. In this sense, we observed that Classification 3 which was developed using the same hydrological indices and cluster algorithm but modelled flow series presented a lower correspondence with Classification 1 than Classification 2. Nonetheless, it must be pointed out that ARI values between Classification 1 and 3 were in general greater than 0.20, which, to some extent, indicated certain degree of similarity between class spatial distributions. This result implies that in the absence of other flow data, the modelled flow series can still be useful to understand the actual distribution of river types (e.g. Belmar *et al.*, 2011).

On the other hand, the low correspondence between Classification 4 and the inductive classifications was corroborated in the analysis of the spatial arrangement of classes. Independently of the classification level, Classification 4 always presented a class that gather more than two thirds of the total number of gauges. This class covered much of the study area and grouped gauges situated in the north catchments, the Pyrenees' headwaters and the southern Iberian Massif. The hydrologic differences between rivers situated in these areas has been evidenced by the classifications developed in this and other works (Bejarano *et al.*, 2010; Gámiz-Fortis *et al.*, 2011; Solans and Poff, 2013). Therefore, this study shows that Classification 4 was not able to properly account with the actual distribution of hydrological types. This could be attributed to different sources of uncertainty including the origin of flow series, the selection of specific hydrological indices or the subjective steps implemented in the classification procedure.

4.5 Conclusion

In conclusion, the aggregation of daily data into monthly flow series produced classifications that still account with much of the critical hydrological information, presented high ability to segregate classes and produced classes with a spatial arrangement similar to daily flow classifications. Therefore, in the absence of daily series, classifications based on monthly flows represent an adequate alternative. Nonetheless, there exists certain limitation for monthly series to represent several hydrological attributes, especially relevant to understand key biophysical relationships. On the other hand, the use of simulated flow series generated classifications with lower performance and different spatial arrangement of classes. Therefore, the use of modelled flow series is not recommended if possible. However, since they still presented some ability to discriminate essential hydrological characters and a certain degree of spatial homology with classifications based on gauged series, the use of modelled flow series should be considered to outline the spatial distribution of river types and aid in general water resources management in the absence of suitable gauged data. The greatest impediment in the classification process was not related to the scale or origin of the data but to the procedure. The significantly reduced performance and the uneven distribution of classes found in the expert driven classification, highlighted the importance of selecting adequate hydrologic indices able to represent the hydrological reality of the study area and the necessity of applying objective and scientifically reliable criteria all throughout the process. The use of one or another approach may have significant implications depending on the applications of the classifications as they could lead to significantly different conclusions. Therefore caution is recommended in the selection of the hydrological data and the classification procedure, especially if classifications are to be use with a normative scope, such as the determination of environmental flows within the RBMPs.

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Chapter V

A comparison of statistical techniques and strategies to model hydrological indices to ungauged rivers

Chapter V. A comparison of statistical techniques and strategies to model hydrological indices to ungauged rivers

This chapter has led to the article entitled: "A comparison of statistical techniques and strategies to model hydrological indices to ungauged rivers" by Peñas, F.J., Barquín, J. and Álvarez, C. It has been submitted for publication in the journal Water Resources Research.

Abstract

The prediction of the natural flow regime to ungauged rivers represents a critical issue to afford new challenges in water resource management and freshwater ecology. We developed models to predict 16 ecologically meaningful hydrological indices to a complete river network covering the northern third of the Iberian Peninsula. The statistical techniques used were Multiple Linear Regression (MLR), Generalized Additive Models (GAM), Random Forest (RF), Artificial Neural Network (ANN) and Adaptative Neuro Fuzzy Inference Systems (ANFIS). Results were compared in terms of model predictive performance. In addition, the benefits of the Regional Regression Approach (RRA) were analyzed after segregating gauges into different levels of a regional hydrological classification. Our results showed that predictive performance varied greatly depending on the natural flow attribute been modelled. Indices representing magnitude and frequency were predicted with adjusted R^2s over 0.7. In contrast, other indices such as timing, duration and rate of change were poorly predicted by all techniques, which highlighted the necessity of developing new preditor variables that might exert a greater control of these hydrologic characteristics. In addition, our results showed that complex statistical techniques do not always outperform linear models and no single approach was optimal for all indices. Hence, beyond the prediction performance, other features such as the computing resources, the interpretability of the models regarding the causal links and the potential to account with non-linear relationships must be assessed before selecting the most appropriate

technique. Finally, the RRA just enhanced model accuracy in those classes dominated by fairly predictable climate patterns, where precipitation is the major source of flow. In contrast, the reduction of sites in several classes significantly reduced the prediction ability of MLR. This is a major drawback of the RRA when available hydrologic and environmental information is limited.

5.1 Introduction

River flow regime is a key element that structures freshwater ecosystems (Richter *et al.*, 1996; Poff *et al.*, 1997). Indeed, hydrologic changes have consistently been linked to changes in ecosystem processes and functions (Bunn and Arthington, 2002; Kennen *et al.*, 2008). Accordingly, the understanding of the bio-physical associations between hydrologic variability and stream biological communities is a critical scientific and management challenge. This would allow predicting how human perturbations affect river ecosystem (Poff *et al.*, 1996; Poff *et al.*, 2010) and the alteration thresholds that should not be exceed to maintain and restore these ecosystems and the associated services they provide (Naiman et al., 2008).

However, it frequently happens that little or no streamflow data are available at a site of interest, e.g. where biomonitoring is carried out (Sanborn and Bledsoe, 2006; Zhang et al., 2008; Poff and Zimmerman, 2010). This hinders the exploration of the flow regime influence over stream ecology. Natural flow regime can be disentangle and simplified in a collection of ecological relevant hydrological indices (Olden and Poff, 2003). Hence, the interest in the prediction of these hydrological indices at ungauged streams has rapidly grown in last years (Kennen et al., 2008; Carlisle et al., 2010). Flow regime has been usually predicted through the development of numerical rainfall-runoff models which allows the simulation of continuous hydrographs across periods of several decades (Yadav *et al.*, 2007; Murphy *et al.*, 2013). The extensive application of these models is associated with their flexibility to calculate any number of hydrological indices. However, the reliability of the modelled series may be constrained given the complexity to estimate model parameters (Duan et al., 2006), the large set of gauged basins and spatial coverage of rainfall needed to calibrate models (Sauquet, 2006), the conceptual errors in the models (Kirchner, 2006) and the inadequate quantification of uncertainty (Beven, 2006; Wagener and Montanari, 2011). Other approaches have been designed to increase the spatial extend of forecasting river flow regimes. For instance, statistical downscaling models have been developed to simulate flows directly from atmospheric variables (Tisseuil et al., 2010). However, the oversimplification of the hydrological cycle and the catchment functioning are major criticisms to this approach.

On the other hand, empirical relationships and models for predicting specific hydrological indices based on climate, catchment spatial configuration, geology and land uses have also received wide attention for several decades (Rice, 1972; Stedinger and Tasker, 1985; Burn and Boorman, 1993; Yu et al., 2002). Most of the work has been accomplished from an engineering perspective to deal with water resource and flooding issues. Hence, models to predict average flows, flood quantiles, durations and volumes, flow duration curve parameters or low flow parameters dominate the literature (Sanborn and Bledsoe, 2006). In contrast, prediction of ecologically relevant hydrological indices have received limited attention (Knight et al., 2011). Most often they have not gone beyond the prediction of minimum environmental flows (O'Shea, 1995; Alcázar and Palau, 2010) while few studies have focused on ensembles of hydrological indices embracing different aspects of the flow regime (Sanborn and Bledsoe, 2006; Carlisle et al., 2010; Knight et al., 2011).

Despite the non-linearity and complexity of hydrological processes emphasized by several authors (Dawson *et al.*, 2006; Shu and Ouarda, 2008; Snelder *et al.*, 2009), multiple linear regression has been the most common statistical technique in the prediction of hydrological indices (Sanborn and Bledsoe, 2006; Yadav *et al.*, 2007; Knight *et al.*, 2011). Several authors have pointed out the potential improvement on model performance when using other statistical procedures that do not assume specific distribution fittings (Sanborn and Bledsoe, 2006; Shu and Ouarda, 2008). In this regard, there are a number of machine learning techniques that vary in how they fit functions, model the distribution of the response variable, manage variable interactions and weight the contribution of predictor variables (Elith et al., 2006; Olden et al., 2008). Many examples exist on the use of these statistical techniques to model species distribution (Manel *et al.*, 1999; Olden and Jackson, 2002; Elith *et al.*, 2006), geomorphology and landforms (Luoto and Hjort, 2005; Marmion et al., 2008), forest characteristics (Moisen and Frescino, 2002), nutrient load dynamics (Marce et al., 2004) or water quality (Zhang et al., 2012). However, the application of machine learning techniques to predict hydrological indices has been still vague (Muttiah *et al.*, 1997; Dawson *et al.*, 2006; Alcázar *et al.*, 2008; Shu and Ouarda, 2008). In addition, to our knowledge there are no studies which have analyzed the actual benefits of machine learning techniques over multiple linear regressions in the field of hydrology (but see Dawson et al., 2006; Snelder et al., 2009).

On the other hand, several authors (Laaha and Bloschl, 2006; Sanborn and Bledsoe, 2006; Alcázar and Palau, 2010) have pointed out the importance of segregating streams in hydrologically similar classes before conducting the statistical modelling. This named “Regional Regression Approach” (RRA) has been widely applied for the prediction of both low (Santhi *et al.*, 2008; Alcázar and Palau, 2010) and high flow hydrological indices (Burn and Boorman, 1993; Shu and Ouarda, 2008). By dividing a study area into classes the intra-class homogeneity generally increases and regression equations may be used with a greater confidence (Yu et al., 2002). However, the improvement in the prediction accuracy does not depend only in the reduction of the intra-class heterogeneity but in the linearization of the relationship between response and predictor variables, which is not always achieved when using the RRA. In contrast, Booker and Snelder (2012) and Dawson et al. (2006) pointed out the inconvenience of reducing the number of sites (i.e. data) when running regressions. Hence, a trade-off between homogeneity and the size of the group must be considered (Ouarda et al., 2001).

In this study we concentrated on developing statistical models for 16 hydrological indices covering the full range of ecologically relevant hydrological attributes (i.e.

magnitude, timing, frequency, duration and rate of change; Poff et al., 1997). We used one traditional technique (Multiple Linear Regression: MLR) and four more complex techniques which apply contrasting rationale to model the distribution of the response variable: Generalized Additive models (GAM), Random Forest (RF), Artificial Neural Network (ANN) and Adaptative Neuro-Fuzzy Inference System (ANFIS). In addition, we looked at whether the RRA has any advantages on model performance in comparison to the global MLR model. To achieve this, individual MLR models were obtained for specific hydrological classes and their performance was compared to a MLR developed on the overall data set. Therefore, the objectives of this study were to (1) explore the ability of models to predict different types of hydrological indices, (2) evaluate and compare the performance of 5 statistical techniques to predict 16 hydrological indices to ungauged sites and (3) examine the benefits associated to model hydrological indices when using a "Regional Regression Approach". We hypothesize that the four complex techniques would deal better with the non-linear relationship between environmental variables and hydrological indices and thus, outperform MLR. Moreover, we expect that the classification process would homogenize the relationship between hydrological indices and catchment characteristics and, thus, MLR class models would outperform the global model.

5.2 Methods

5.2.1 Hydrological indices and environmental variables selection and processing

Many studies support the use of hydrological indices to analyze processes in freshwater ecosystems (Olden and Poff, 2003), including the effects over invertebrates (Larned et al., 2010; Chinnayakanahalli et al., 2011), fishes (Fausch *et al.*, 2001; Snelder and Lamouroux, 2010), riparian vegetation (Pettit et al., 2001; Bejarano et al., 2011) and geomorphology (Flores et al., 2006; Peñas et al., 2011; Belmar et al., 2013). However, it was beyond the scope of this study to predict and evaluate all the hydrological indices currently in use (see Olden and Poff, 2003) and therefore, we selected one or several indices representing each of the five ecological relevant aspects of the flow regime, i.e. magnitude, timing, frequency, duration and rate of change (Table 5.1).

Index	Type	Units	Description	MLR transformation
L1	MA	m^3/s	Linear moment that represents the mean daily annual flow	$x^{1/5}$
L2	MA	m^3/s	Linear moment that represents the variance of the daily annual flow.	$x^{1/5}$
M4	MA	m^3/s	Mean daily april flow	$x^{1/5}$
M9	MA	m^3/s	Mean daily september flow	$x^{1/5}$
30LF	ML	m^3/s	Magnitude of minimum annual flow of 30 day duration.	$x^{1/6}$
X95	ML	m^3/s	Mean magnitude of flow exceeded 95% of the time	$x^{1/4}$
30HF	MH	m^3/s	Magnitude of maxima annual flow of 30 day duration	$x^{1/5}$
X5	MH	m^3/s	Mean magnitude of flow exceeded 5% of the time	$x^{1/6}$
Jmax	T	Day of year	Julian day of annual maximum	none
Jmin	T	Day of year	Julian day of annual minimum	none
Pred	T		Predictability	log(x+1)
FRE3	F	Events/year	Number of high flow events per year using an upper threshold of 3 time median flow over all years	none
dPHigh	DH	Days	Duration of high flow pulses	log(x+1)
dPLow	DL	Days	Duration of low flow pulses	$x^{1/6}$
nPos	RC	Days	Number of days with increasing flow	log(x+1)
nNeg	RC	Days	Number of days with decreasing flow	none

Table 5.1 - Hydrological Indices for which models were developed and their type of hydrological attribute (MA: Magnitude Average; MH: Magnitude High; ML: Magnitude Low; T: Timing; F: Frequency; DH: Duration of high flow events; DL: Duration of low flow events; RC: Rate of change).

In addition, a final set of 17 variables describing several environmental attributes including climate, topography, land cover and geology were selected (Chapter II; Table

2.2.). It must be pointed out that variables related to catchment geology and soil permeability were initially included to fit the models. However, given that these variables were not selected by any model they were excluded from posterior analyses. In addition, the limitations associated with the maximum number of degrees of freedom allowed by the different techniques were considered and hence, a maximum of 6 variables was established for the initial models (before conducting a stepwise regression). The selection of these 6 variables was based on the combination of scatter plots (hydrological indices versus environmental variables) and parametric correlations to identify those environmental variables that were most meaningful for prediction of each dependent variable (Knight *et al.*, 2011).

Both hydrological indices and environmental variables were transformed according to the requirements of MLR, GAM, ANN and ANFIS, while the raw data were used in the RF models. Specific transformations (Tables 1 and 2) were applied to meet assumptions of normality, homoscedasticity and linearity for the MLR. If data did not meet the assumptions by any transformation the one that was closer to meet the requirements was used. Regarding ANN and ANFIS, the dependent and independent variables must exhibit particular distributional characteristics (Olden and Jackson, 2002).Thus, the hydrological indices were converted to the range [0 1] while the environmental variables were converted to z-scores (i.e. mean=0, standard deviation=1).

5.2.2 Modelling Techniques

5.2.2.1 Multiple Linear Regression (MLR)

Multiple Linear regressions (MLR) assume a linear relationship between the predictor and the response variables. MLR provides an equation that takes the form:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n + \varepsilon$$

Where Y is the hydrological index of interest, βo is the intercept, Xi are the selected environmental variables, βi are the model parameters and ε are the normally distributed model errors. The relative importance of each variable was established based in the comparison of the regression test statistic T value and its associated p-value.

Variable	Acronym	MLR Transformation
Annual Precipitation	Pre	none
April Precipitation	Pre4	none
Summer precipitation	PreQ7	$x^{1/3}$
Maximum Precipitation	PreMx	none
Minimum Precipitation	PreMn	$x^{1/2}$
Minimum Month	MPrMn	None
Monthly Precipitation range	MPrRn	$x^{1/6}$
Quarterly Precipitation range	QPrRn	$x^{1/3}$
Temperature	Tem	none
Summer temperature	TemQ7	none
Annual Precipitation	Pre	none
April Precipitation	Pre4	none
Summer precipitation	PreQ7	$x^{1/3}$
Catchment area	Are	$x^{1/5}$
Gradient	Gra	$x^{1/2}$
Elevation	Ele	$x^{1/2}$
Agriculture	Agr	arcsin(x)
Forest	For	arcsin(x)

Table 5.2 - Environmental variables and transformations used in the models of the 16 hydrological indices.

As exposed above, several authors (Sanborn and Bledsoe, 2006; Alcázar and Palau, 2010), considered the classification of the study area into distinct streamflow regime types as a critical step for developing robust predictive models (the RRA approach). The classification of the study zone may reduce the intra-group heterogeneity and thus, it would improve the models that are based on the overall data set. Based on this hypothesis we tested the predictive performance of MLRs developed for the 16 hydrological indices using the entire dataset (all sites included: the global MLR model) with MLR models developed for each hydrological class. We used 2 hydrological classifications with 2 and 6-Class levels (Figure 5.1), thus, 2 and 6 MLR models were developed for each of the 16 hydrological indices. Both classifications were developed using the Predict-Then-Classify strategy (Chapter III). The 2-Class levels classification segregates the streams situated in the aridest zones of the study area from all the others. In the 6-Class level classification classes 1 and 2 are distributed throughout the northern coastal catchments and the north-western section of the Ebro basin. Class 3 extends throughout the headwaters and mid reaches draining from the Pyrenean range, while Class 4 is represented by rivers situated in the western most section of the Ebro depression. Class 5 includes rivers in the Ebro depression and several of the Catalan catchments, while Class 6 is represented by streams situated in the southern section of the Iberian massif.

5.2.2.2 Generalized Additive Models (GAM)

The Generalized Additive Models (GAM) are semi-parametric models (Hastie and Tibshirani, 1986). They differ from multiple linear regressions in two major respects: (1) Predictor variables are related to the dependent variable through a link function and (2) the simple terms of the linear equation β_i*X_i are replaced with $f_i(X_i)$ where f_is are a non-parametric function or smoother of the predictor X_i. In other words, instead of a single coefficient for each variable in the model, in GAMs an unspecified (non-parametric) function is estimated for each predictor to adapt it to the local behaviour of the regression function almost independently in several regions (Venables and Dichmont, 2004). In the present study the data did not adjust to any of the common link functions (i.e. Poisson, Gamma, Binomial). Hence, it was decided to apply the identity link function of the Gaussian family to the transformed variables given that they were assumed to be normally distributed. This allowed isolating and focusing on the use of smother functions to deal with the non-linearity of the relationships between hydrological indices and the environmental variables.

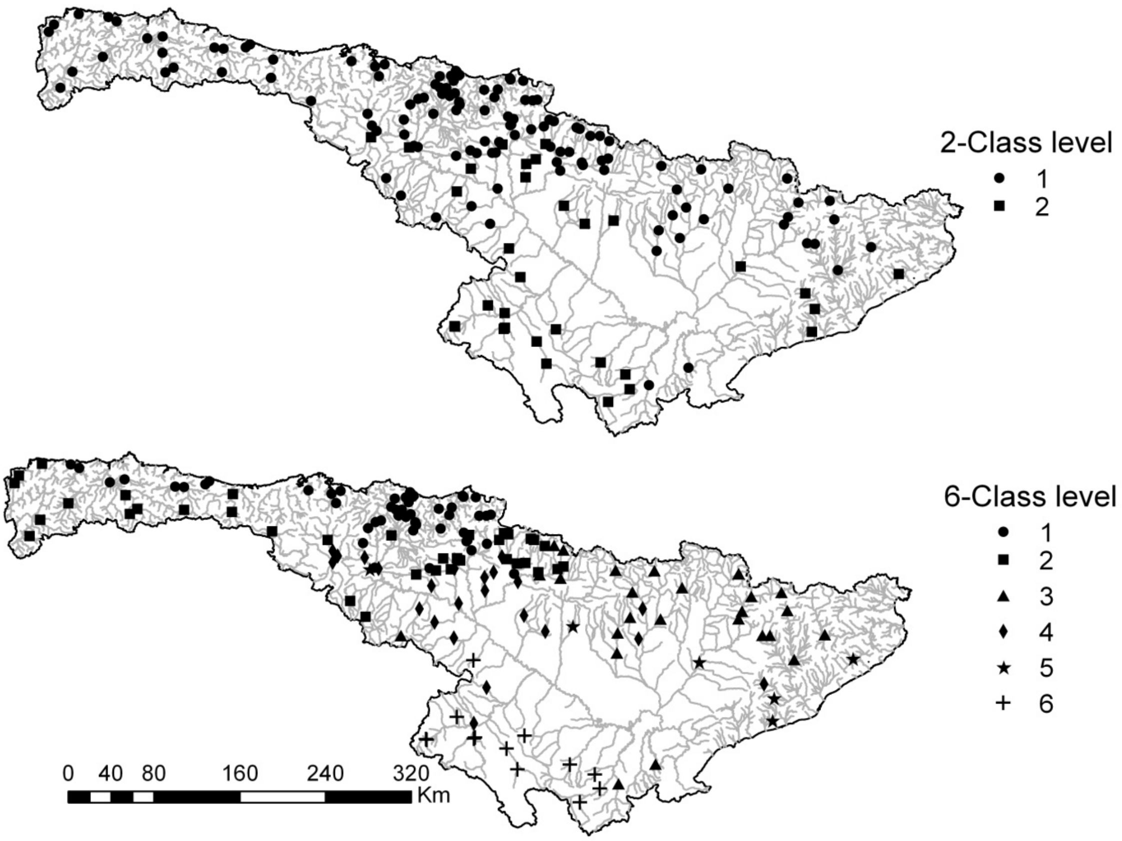

Figure 5.1 - Spatial distribution of gauges in the 2 and 6-Class level classifications developed through the Predict-Then-Classify strategy.

Thin plate regression splines smothers were used with a maximum of 3 degrees of freedom. In the case that the estimated degrees of freedom of a specific environmental variable were 1 or close to 1, i.e. the relation between predictor and response variables is almost linear, but it still contributed significantly to the model, we replaced the smooth with a parametric linear term. Parallel to MLR, the relative importance of each variable was established based in the comparison of the regression test statistic T value and its associated p-value.

5.2.2.3 Random Forest (RF)

A Random Forest (RF; Breiman, 2001; Cutler et al., 2007) comprises an ensemble of individual Classification and Regression Trees (CART; Breiman *et al.*, 1984) and can be used with both categorical and continuous response variables. CART split the dimensional space defined by the predictors into groups that are as homogeneous as possible based on series of binary rules. CART has been widely applied because of their simple interpretation, high classification and regression accuracy and ability to characterize complex interactions among variables (Cutler et al., 2007). Nevertheless they have the limitation of not searching for optimal tree structures and being sensitive to small changes in input data (Hastie et al., 2001). This flaws are overcame by RF which introduces random variation to CART by growing a defined number of trees with a bootstrap sample of the training data and only using a small random sample of the predictors to define the split at each node. Independent predictions are made for each CART from observations that were excluded from the bootstrap sample (OBB samples) obtaining a coefficient of determination (R^2) of the regression. The final prediction accuracy of the RF model is the averaged prediction over all trees. In addition, the importance of the predictor variables is evaluated by randomly permuting each predictor variable in turn and predicting the response of the OBB observations. The decrease in prediction performance is the measure of importance of the original variable.

5.2.2.4 Artificial Neural Networks (ANN)

Artificial Neural Network (ANN) are nonlinear mapping structures based on the functioning of the human brain and have been shown to be a promising area for predictive modelling (Lek and Guegan, 1999). In this study we developed for each hydrological index a multi-layer feed-forward ANN trained by back propagation algorithm (Rumelhart et al., 1986). The architecture of this type of ANN comprises non-linear elements (neurons) arranged in successive layers in which the information flows through a hidden layer from the input layer (environmental variables) to the output layer (hydrological index) (Figure 5.2). Nodes from one layer are connected to all nodes in the adjacent layer, but neither lateral connections within any layer, nor feed-back connections are possible. Input layer and hidden layers can include a constant neuron relating to intercept synapses, i.e. synapses that are not directly influenced by any covariate (bias). Neurons are connected by weight links that were modified during successive iterations (1000 in this study) according to the back propagated error computed between the observed and the predicted output values (Lek et al., 1996). In this study the logistic function, a differentiable function of the neuron's total incoming signal from the precedent neurons to produce the state of the subsequent neurons (Olden and Jackson, 2001), has been used.

One important task regarding ANN model is the selection of the network architecture, i.e. number of neurons in the hidden layer, which optimizes bias and variance while avoiding data overfitting. To define the number of neurons in the hidden layer a 5-fold cross validation procedure was applied. According to these results the ANN with highest performance was selected for subsequent analysis. In addition, the initial weight link for each connection was randomly selected. To avoid the effect that this randomness could produce in the final weight adjustment, each neural network was run 100 times. The contributing importance of each environmental variable in the final model was determined by calculating the product of the connection generalized weights (i.e. input-hidden x hidden-output weights) between its input neuron and the output neuron and then summing the products across all hidden neurons (Olden and Jackson, 2002).

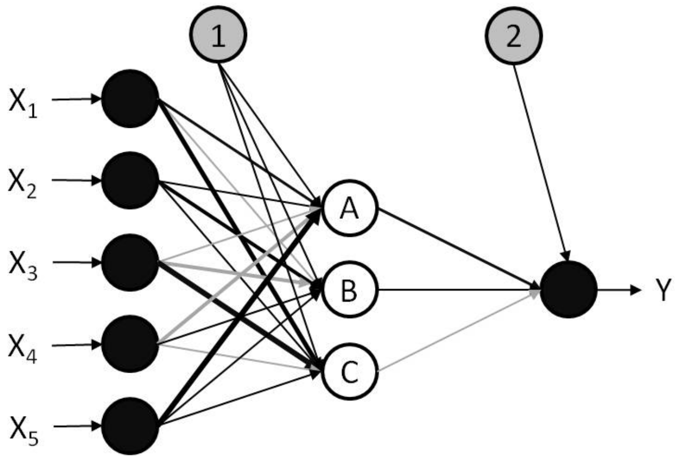

Figure 5.2 - Diagram of a multi-layer feed-forward neural network with 5 input neurons (X_i), one output neuron (Y), one hidden layer consisting of three hidden neurons (A-C) and a one constant neuron for each layer (1 and 2). The thickness of the lines joining neurons is proportional to the magnitude of the connection weight and the shade indicates the direction of the interaction: black connections are positive and gray connections are negative (adapted from Olden and Jackson, 2002).

5.2.2.5 Adaptative Neuro Inference Systems (ANFIS)

Adaptative Neuro-fuzzy inference system (ANFIS) combine qualitative aspects of the human knowledge employing if-then rules, typical from the Fuzzy Inference Systems (FIS), with effective and advanced machine learning method (neural networks) to adjust and tune these rules so as to maximize model performances (Jang, 1993).

A FIS is base mainly on the fuzzy decision rules and the fuzzy reasoning unit (Jang, 1993; Jang and Sun, 1995). The fuzzy decision rules or if-then rules are the way a FIS relates an input variable (X) to an output variable (Y). There are rules expressed in the form: if *X* is A then *Y* is B where A (premise) and B (consequence) are labels of fuzzy sets, i.e. linguistic values, characterized by appropriate Membership Functions (MF). The Fuzzy reasoning is an inference procedure used to derive conclusions from a set of fuzzy decision rules. The steps of fuzzy reasoning performed by a FIS are (Jang, 1993; Figure 5.3):

1. Compare the input variables with the MFs on the premise part of the fuzzy rules to obtain the probability of each linguistic label (fuzzification).
2. Combine (through logic operators) the probability on the premise part to get the weight of each rule.
3. Generate the qualified consequent of each rule depending on their weight.
4. Aggregate the qualified consequents to produce a crisp output (defuzzification).

Given an input-output problem, the construction of a FIS has two fundamental steps: the specification of an appropriate number and type of input and output MFs (structure identification), and the specification of the shape of the MFs (parameter estimation). Whereas the structure identification is solved by human expertise or trial-and-error, numerical methods have been proposed to solve the parameter estimation step. In this paper, we used an approach, which takes advantage of adaptive neural networks algorithms during fitting procedures.

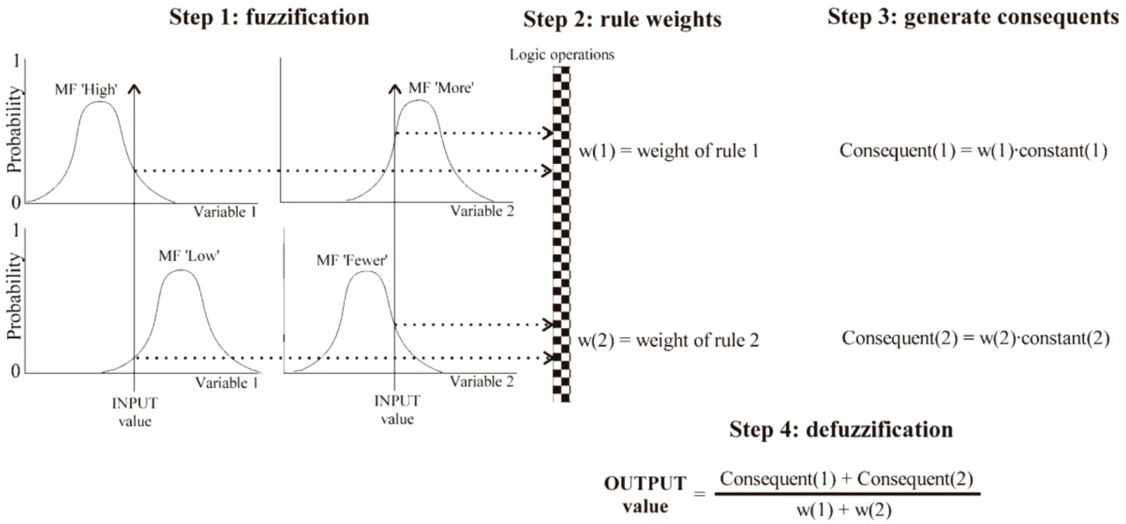

Figure 5.3 - Steps in the fuzzy reasoning. The example contains two input variables, one output and two if-then rules for each input. (source Marce et al., 2004).

The structure identification was solved applying a trial-and-error procedure and a conservative criterion (i.e. minimum number of parameters to the best fit). Moreover, since the number of parameters to be fit increase exponentially with the number of variables and MF and the total number of parameters should not exceed 1/6 the number of cases (Marce et al., 2004), a maximum of 6 predictor variables and 3 MFs for each variable was established. Once the structure was defined, the parameter to be estimated (Gaussian input MF parameters and output constants) was defined by the hybrid learning algorithm. To avoid overfitting problems during the estimation of these parameters, the data set was randomly split into a training set (2/3 of the data set) used to fit the values and a trial set (1/3 of the data), which was not used by the hybrid learning algorithm. The splitting procedure was repeated 200 times and each time the parameters were adjusted individually. This procedure was implemented in a jacknife-cross validation procedure (presented below) in which each observation is left out during the hybrid learning process. Then the parameters estimated in each of the 200 iterations are used to predict the value of the specific hydrological index, obtaining 200 different values. The final predicted value for the site corresponds to the mean value of the 200 predictions. Finally, to obtain the importance of the predictors in each model, environmental variables were removed from the model one at a time while holding all other predictor variables. The larger the decrease of predictive performance the larger importance is assumed for that variable.

For the 5 modelling techniques, Backward Stepwise Regression (BSR) technique was used to define a final model that contains uniquely the actual contributing variables. In BSR the first model includes all predictor variables, and then they are deleted one at a time until removing variables degrade the quality of the model. Akaike Information Criteria (AIC; Akaike, 1973) was used to evaluate the trade-off between degrees of freedom, i.e. number of explanatory variables included in the model, and the fitting of the model when explanatory variables are added or removed. Models with smaller AIC values (indicating adequate fit with fewer parameters) are preferred.

5.2.3 Validation and evaluation of model performances

A jack-knife cross–validation procedure (Efron, 1982) was used to test the predictive performance of each modelling technique for the 16 hydrological indices. This cross validation procedure was applied by leaving out one gauge at a time, developing a new model based on the remaining 155 observations and finally estimating the hydrological index for the left-out gauge. The results from this procedure produced estimates of each hydrological metric as if the gauging station was an ungauged site. The variation between observed and predicted values represents the uncertainty with which the model would be applied to predict index values at ungauged sites (Carlisle et al., 2010) and allow an assessment of the robustness of each method for estimating hydrological indices.

After having estimated the jack-knifed values, we employed the root-mean-square-deviance (RMSD) and the adjusted-R^2 for assessing the correspondence between observed and estimated values and as a relative performance of each model (Van Sickle et al., 2006). Hence, models producing the lowest RMSD and the highest adjusted R^2 were deemed superior.

5.3 Results

5.3.1 Model performances and predictor variables

Model performance was higher when predicting flow magnitude (MA, MH and ML) and frequency indices (FH: FRE7), than when predicting timing (T: JMax; JMin and Pred), duration (DH: dPHigh and DL: dPLow) and rate of change (RC: nPos and nNeg) indices (Table 3.3; Figure 5.4). MA (except for M9) and MH indices were predicted with excellent accuracy showing adjusted R^2s that commonly exceeded 0.8. In contrast, models of 30LF and X95 registered reductions of adjusted R^2 ranging from 15 to 25% relative to MA and MH indices.

Are and annual (Pre), quarterly (PreQ7) and monthly precipitation (Pre4) were the most important variables in practically all these models, especially those developed for MA and MH (Table 5.4). On the other hand, when predicting M9 and ML indices other environmental variables, such as gra, EvMx and QPrRn, presented high contribution rates to the models. Models of timing indices showed the lowest predictive performances (Table 5.3), i.e. the highest deviations of predicted values relative to observed (Figure. 5.4). In general, adjusted R^2s for JMax and JMin indices were not greater than 0.2, while the best model for Pred reached 0.4 (Table 5.3). Pre and MPrRn were selected in all models for Jmax. MPrRn, Eva and Ele were commonly included in the models for JMin, while three of these models also included MPrMn as the most contributing variable. Pred was related mainly to PreMx and Gra (Table 5.4). FRE3 could be predicted with a maximum adjusted R^2 of 0.71 and the most influential variables were Ele, PrMx and QPrRn. Models for predicting dPHigh and dPlow rarely reached adjusted R^2 over 0.3 and PrMx and PrMn were the most contributing variables, respectively. Finally, models for nPos and nNeg showed adjusted R^2 close to 0.5 (Table 5.3). Pre, Ele and MPrRn were the most influential variables in all of these models (Table 5.4).

	MLR		GAM		RF		ANN		ANFIS	
Index	**Adj r^2**	**RMSD**	**Adj r^2**	**RMSD**	**Adj r^2**	**RMSD**	**Adj r^2**	**RMSD**	**Adj r^2**	**RMSD**
I1	<u>0.77</u>	<u>2.99</u>	**0.82**	**2.67**	0.78	2.95	0.79	8.03	**0.87**	**2.21**
I2	<u>0.74</u>	<u>1.79</u>	**0.80**	**1.56**	0.75	1.73	**0.85**	**1.35**	**0.79**	**1.59**
M4	0.74	4.88	**0.80**	**4.32**	<u>0.72</u>	<u>5.02</u>	**0.80**	**4.24**	**0.88**	**3.37**
M9	0.73	1.07	0.76	1.01	0.72	1.09	<u>0.63</u>	<u>1.24</u>	0.74	1.05
30LF	0.58	0.67	0.59	0.52	0.60	0.66	<u>0.49</u>	<u>0.74</u>	**0.63**	**0.62**
X95	0.54	0.55	0.54	0.54	<u>0.52</u>	<u>0.58</u>	0.50	0.57	**0.60**	**0.51**
30HF	0.77	9.05	**0.82**	**8.04**	<u>0.75</u>	<u>9.59</u>	**0.84**	**7.57**	**0.88**	**6.48**
X5	0.75	10.55	**0.80**	**9.27**	<u>0.74</u>	<u>10.73</u>	0.79	9.69	**0.84**	**70.89**
JMax	0.18	21.94	0.18	22.14	<u>0.15</u>	<u>22.14</u>	0.16	22.12	0.19	21.73
JMin	0.19	17.63	0.19	17.65	0.19	17.66	<u>0.11</u>	<u>18.54</u>	**0.25**	**17.01**
Pred	<u>0.16</u>	<u>0.13</u>	**0.33**	**0.12**	**0.32**	**0.12**	**0.25**	**0.12**	**0.41**	**0.11**
FRE3	0.64	1.07	**0.71**	**0.97**	<u>0.62</u>	<u>1.1</u>	**0.69**	**1.01**	**0.69**	**1.02**
dPHigh	<u>0.24</u>	<u>4.94</u>	**0.29**	**4.82**	**0.37**	**4.50**	0.27	4.88	**0.30**	**4.74**
dPLow	0.30	25.29	0.32	24.72	0.28	25.62	0.30	25.27	<u>0.27</u>	<u>25.81</u>
nPos	0.46	12.47	**0.51**	**11.94**	**0.53**	**11.72**	0.46	12.51	**0.54**	**11.50**
nNeg	<u>0.45</u>	<u>12.55</u>	**0.51**	**11.97**	**0.52**	**11.83**	0.47	12.45	**0.50**	**12.13**

Table 5.3 - Predictive accuracy for the 16 hydrological indices using 5 different modelling techniques. The accuracy is estimated by the adjusted R^2 and the RMSD (Root Mean Square Distance). Increases of adjusted R^2 beyond 5% of MLR balues are represented by bold letters. Underlined values indicate the model with the lowest predictive performance. To allow reliable comparisons all the RMSD were calculated after converting the variables to raw variables values.

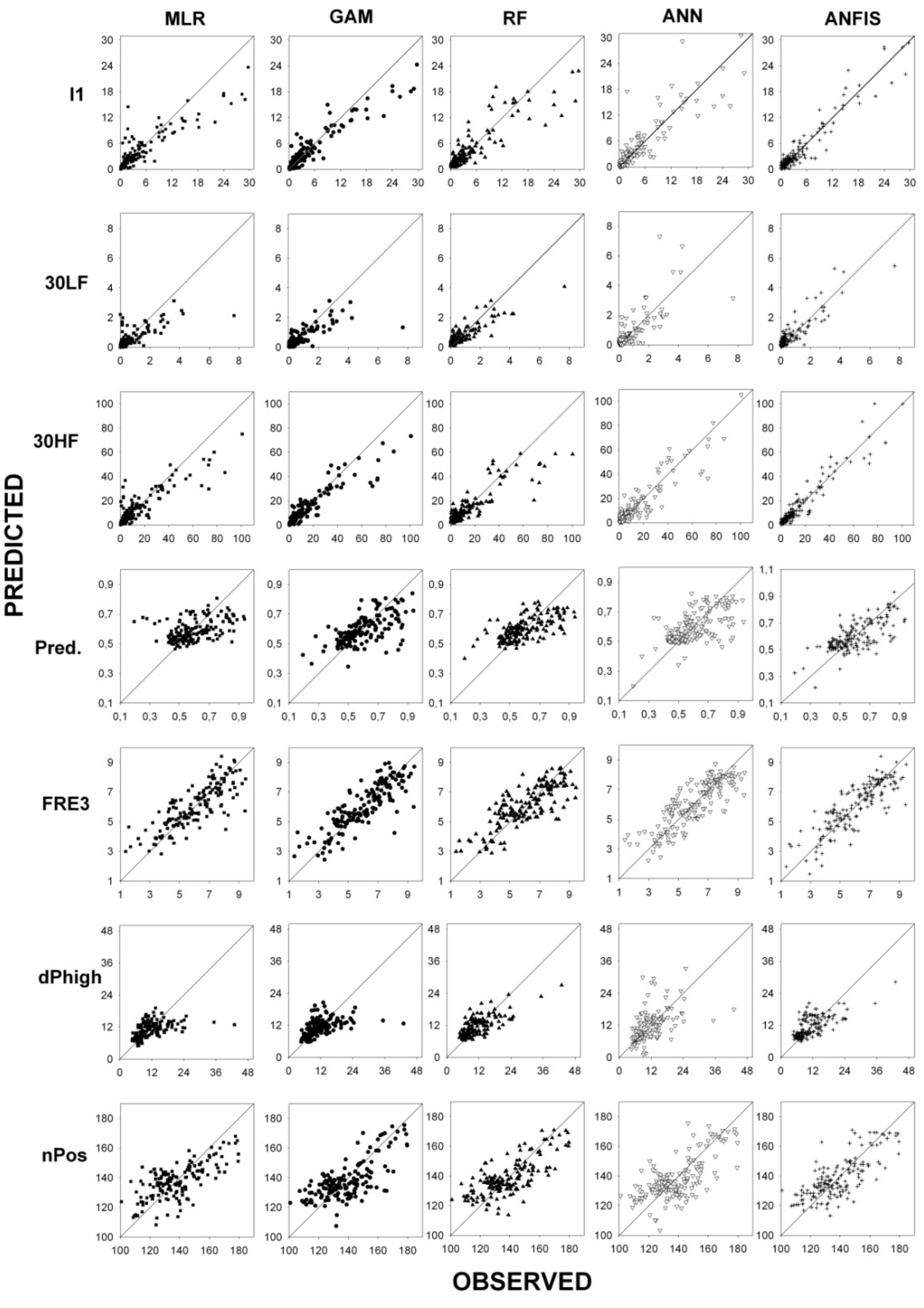

Figure 5.4 - Observed versus jack-knifed predictions of 7 hydrological indices representing the 5 attributes of the flow regime: Magnitude (I1; 30LF; 30HF); Timing (Pred); Frequency (FRE3); Duration (dPHigh); Rate of Change (nPos). Note that for reliable comparisons all variables were transformed to the original raw data distribution.

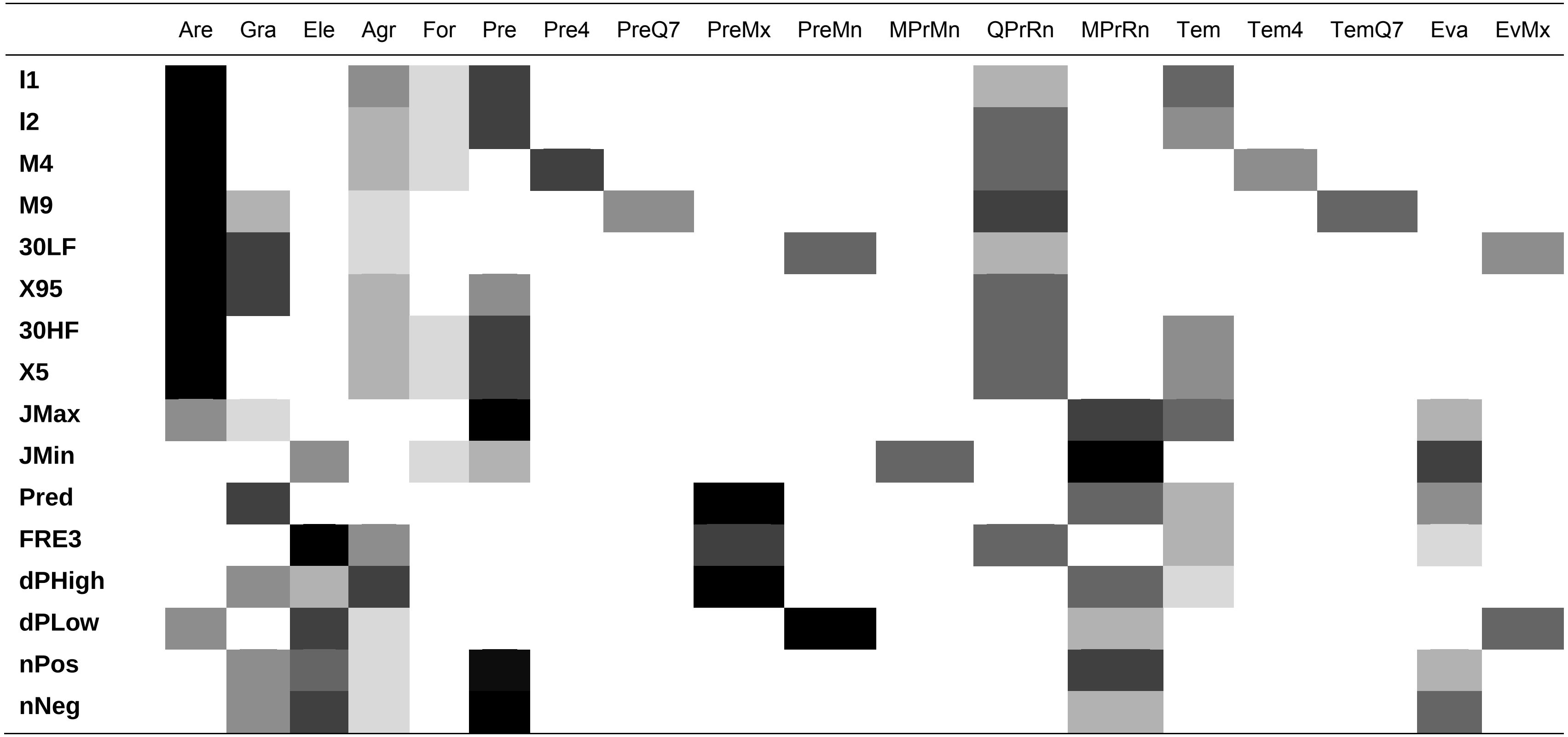

Table 5.4 - Environmental variables contribution to model the 16 hydrologicalal indices. Decreasing darkness shade indicates lower average variable contribution in the models. The overall contribution of variables was computed according to the variables importance in the models developed with the 5 different modelling techniques (MLR; GAM: RF: ANN; ANFIS) for each hydrological index. Each environmental variable was weighted according to the order in the model (6 for the most important variable and 1 for the least important variable) and the results were summed through the 5 different models.

5.3.2 Comparison between modelling techniques

Differences on prediction accuracy obtained by the different modeling techniques were not large (Table 5.3; Figure 5.4). However, it must be remarked that GAM and ANFIS techniques outperformed MLR by more than 5% of the adjusted R^2 in 10 and 13 hydrological indices, respectively. The greatest improvement on predictive performance was observed for magnitude indices. ANFIS supposed a mean increase of 7% of the adjusted R^2 in relation to MLR in all the magnitude indices, while the differences reached up to more than 10% if only MA and MH indices were considered. Differences between MLR and GAM were less marked and improvements in adjusted R^2s beyond 5% were only found for MA and MH indices. In addition, ANFIS and GAM outperformed MLR in one or several of the other indices types (T, F and RC). On the other hand, RF and ANN did not show important enhancements in relation to MLR. Moreover, RF and ANN obtained the least accurate models for 6 and 3 indices, respectively. Nonetheless, MLR did not outperformed RF in more than 2% in most of the cases, while for pred or dPhigh RF outperformed MLR in more than 10%. Similarly, MLR did not outperform ANN in more than 3%. In contrast, for 5 indices ANN obtained adjusted R^2s 5% higher than those obtained by MLR.

5.3.3 The regional regression approach

Class 1 MLR models registered a general increment in predictive performance in comparison to the global model, when using the 2-Class level classification (Table 5.5). Indeed, relationships between hydrological indices and the most contributing environmental variable showed in general less data dispersion after classification (Figure 5.5). On the other hand, models from Class 2, which included streams situated in the aridest zone, showed adjusted R^2s below 0.3 in most of the cases.

	Level 2				Level 6											
	Cl1 (124)		Cl2 (32)		Cl1(50)		Cl2 (38)		Cl3 (26)		Cl4 (23)		Cl5 (6)		Cl6 (13)	
Index	R^2	RMDS	R^2	RMDS	R^2	RMDS	R^2	RMDS	R^2	RMDS	R^2	RMDS	R^2	RMDS	R^2	RMDS
I1	**0.86**	**2.52**	0.34	0.89	**0.89**	**2.32**	**0.90**	**1.92**	0.64	4.48	**0.84**	**1.67**	0.71	0.18	0.39	0.71
I2	**0.81**	**1.61**	0.25	0.55	**0.87**	**2.36**	**0.88**	**1.11**	0.62	2.26	0.77	1.30	0	1.01	0.02	0.40
M4	**0.85**	**4.05**	0.20	1.52	**0.88**	**3.84**	**0.90**	**2.96**	0.71	5.28	0.81	3.80	0	19.50	0.02	0.40
M9	**0.78**	**1.05**	0.07	0.41	**0.78**	**0.82**	0.72	0.90	0.57	0.64	**0.89**	**0.23**	0	0.40	0.45	0.67
30LF	**0.65**	**0.67**	0.02	0.38	**0.79**	**0.36**	**0.67**	**0.63**	0.41	1.30	**0.76**	**0.21**	0	6.53	0	0.57
X95	0.53	0.36	0.04	0.28	**0.59**	**0.37**	**0.70**	**0.49**	0.41	1.00	0.50	0.20	0	0.80	0	0.39
30HF	**0.85**	**7.93**	0.24	3.35	**0.92**	**6.52**	**0.87**	**6.45**	0.62	12.46	0.78	7.10	0	6.70	0.28	2.86
X5	**0.80**	**9.91**	0.28	2.93	**0.84**	**10.29**	**0.87**	**6.97**	0.52	0.60	**0.80**	**6.48**	0.14	0.89	0.38	1.93
Jmax	0.17	21.11	0.10	25.28	0.03	20.16	0.02	16.77	**0.88**	**17.88**	0.19	29.20	**0.46**	**26.27**	0.17	25.05
JMin	0.09	17.71	**0.33**	**18.10**	0	19.67	0.11	11.80	**0.36**	**12.66**	0.09	21.40	0	379.98	0	29.36
Pred	**0.31**	**0.09**	**0.30**	**0.17**	0.04	0.10	0.07	0.09	**0.74**	**0.09**	**0.24**	**0.11**	0.24	0.11	0.07	0.09
FRE3	0.53	1.02	0.32	1.16	0.21	0.77	0.47	0.80	0.62	0.77	0.57	1.08	0	23.30	0	1.38

Table 5.5 - Predictive accuracy of the Multiple Linear Regression Models (MLR) after hydrological classification (2 and 6-Class levels). Increases of adjusted R^2 beyond 5% in relation to the global MLR are represented by bold letters. Decreases of adjusted R^2 beyond 5% in relation to the original MLR are represented by bold letters. Numbers in parenthesis indicate the number of sites per class.

	Level 2				Level 6											
	Cl1 (124)		Cl2 (32)		Cl1(50)		Cl2 (38)		Cl3 (26)		Cl4 (23)		Cl5 (6)		Cl6 (13)	
Index	R^2	RMDS	R^2	RMDS	R^2	RMDS	R^2	RMDS	R^2	RMDS	R^2	RMDS	R^2	RMDS	R^2	RMDS
dPHigh	**0.30**	**3.40**	0	8.22	0.08	1.49	0.24	10.09	0.23	3.96	0.14	6.48	0		0	4.45
dPLow	0.25	24.34	0.05	28.49	0.19	16.90	0.05	29.96	0.19	16.90	0	32.29	0	49.06	0	48.62
nPos	0.23	11.63	0.31	10.80	0	11.89	0.01	10.76	**0.56**	**9.11**	0.01	10.76	0	11.89	0.24	8.67
nNeg	0.24	11.71	0.34	10.49	0	12.31	0,03	10.78	0.05	13.89	0.02	14.72.	0.08	8.91	0.10	10.50

Table 5.5 (*continued*).

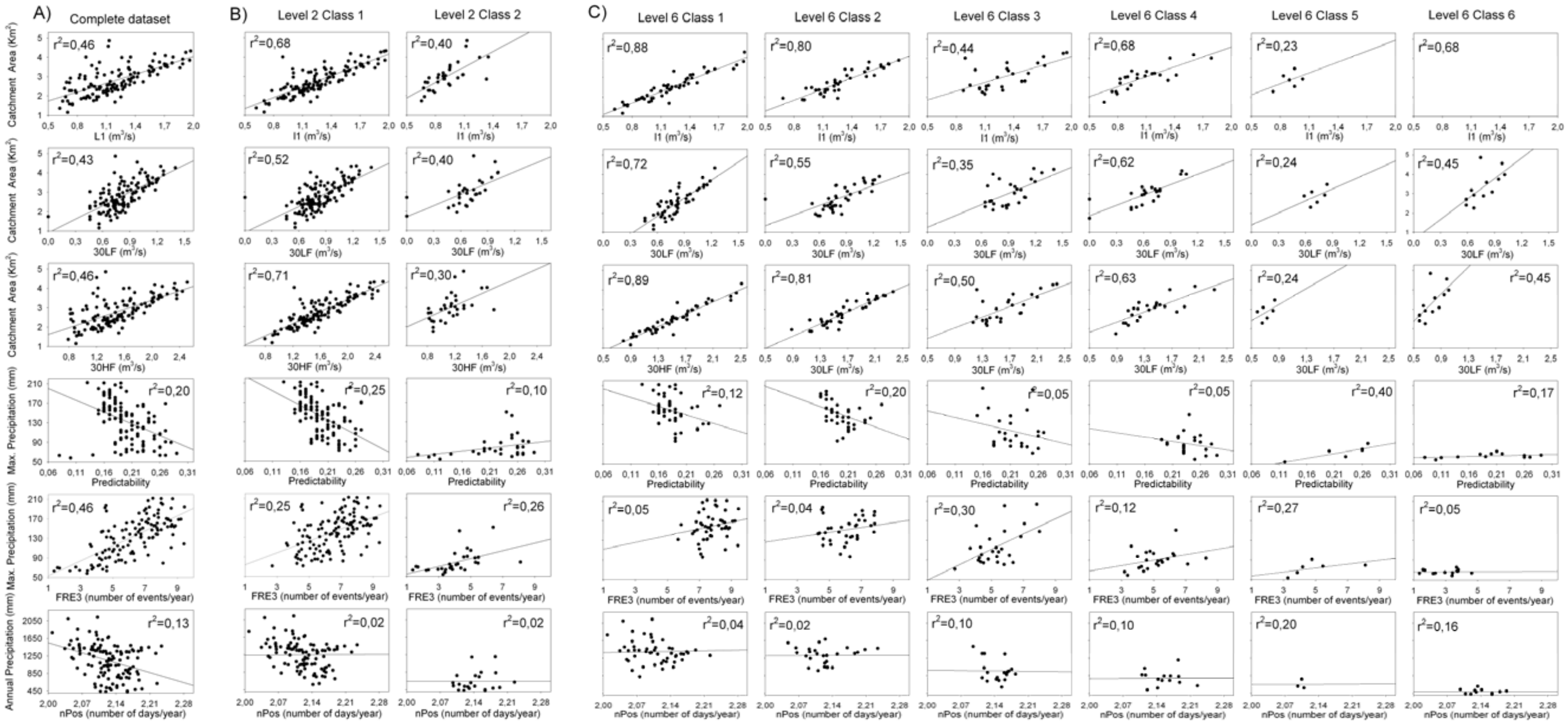

Figure 5.5 - Scatter plot of 7 hydrological indices versus the most contributing predictor variable attending to three different classification schemes: The overall data set (A), the 2-Class level classification (B) and the 6-Class level classification (C). Each index represents one of the ecologically relevant aspects of the flow regime: Magnitude (l1; 30LF; 30HF), Timing (Pred), Frequency (FRE3), Duration (dPHigh) and Rate of Change (nPos). Variables are presented after applying the transformations indicated in Tables 5.1 and 5.2.

When using the 6-Class level classification, a linearization and reduction of data dispersion regarding magnitude indices was observed for Class 1 and 2 (Figure 5.5). These models got an increase of 15% in their adjusted R^2 values relative to the global model. Class 4 models produced the most similar results to those obtained with the global model, while Class 3 models performed worse than the global model for all the magnitude indices (Table 5.5). Class 5 and 6 models also reduced their performance when compared to the global model. It should be note that both classes presented an extremely low number of sites to fit these models, which may have an important influence in these results. In relation to the remaining indices, no clear pattern was observed but in most cases lower prediction performance in comparison to the global model was recorded (Table 5.5; Figure 5.5).

5.4 Discussion

Our results denoted firstly, that predictive performance varied greatly according to the flow attribute been modelled. Magnitude indices were predicted with an excellent accuracy while timing indices were poorly predicted by all techniques. Second, not all complex statistical techniques outperformed MLRs and no single approach was optimal for all indices. However, GAM and ANFIS techniques generally improved the predictive performance of MLR for all indices, while most of the techniques outperformed MLR to model frequency, duration and rate of change indices. Finally, the segregation of gauges according to a hydrological classification enhanced the prediction accuracy of MLR only for those indices that explained the major part of the hydrologic variability within classifications, i.e. the magnitude indices. Nonetheless, this result was just observed in those classes that presented the less variable flow regime and retained at least 20 sites.

5.4.1 Model performances and predictor variables

This study confirms the findings of other works that not all the hydrological indices presented the same potential to be predicted (Yadav *et al.*, 2007; Carlisle *et al.*, 2010).

For instance, we found that 75% of the best models (i.e. the model with highest performance over the five techniques) developed for magnitude indices obtained adjusted R^2s greater than 0.7. These represented significantly higher accuracies than those observed for the models of duration, rate of change and timing indices. FRE3, the uniquely frequency index included in this study, also presented predictive accuracy greater than 0.7. Within the magnitude indices, MA and MH performed better than ML indices. As expected, catchment area was the best predictor for all magnitude index models (Muttiah *et al.*, 1997; Dawson *et al.*, 2006; Eng and Milly, 2007). In addition, the high predictive performance of MA and MH indices is related to their dependence on precipitation events and direct catchment runoff (Poff et al., 1996; Tisseuil et al., 2010). These environmental variables were derived from a 25 m DEM and 1x1 km precipitation grids, respectively, and it was demonstrated that they were precise enough to produce reliable models.

In most instances, the errors associated to the models of the ML indices have been relatively high (Smakhtin, 2001). Low flows are highly dependent on subsurface runoff and groundwater storage and circulation (Gordon *et al.*, 2004; Harper *et al.*, 2008) which are governed by complex physiographic functions. Given the lack of proper data bases and the difficulty to accurately calculate these processes (Kroll et al., 2004; Eng and Milly, 2007), predictor variables referring this attributes have been rarely included as predictor variables. On the other hand, several works have established significant correlations between ML indices and soil and geology characteristics (Gustard and Irvin, 1994; Clausen and Pearson, 1995; Kroll *et al.*, 2004). The inclusion of these variables allowed obtaining prediction performances comparable to those showed by MA and MH indices (Sanborn and Bledsoe, 2006; Knight *et al.*, 2011). In contrast, soil permeability or rock hardness were not included in the models developed in this study. It is likely that the little contribution of these variables was due to the precision of the geology and soil data rather than the lack of causal links. The most detailed soil and geology maps in the study area have a 1:200000 scale, which contrasts with the higher accuracy of the topography (25 m DEM), climatic (1x1 km grid) and land-use (1:25000) data sources. Thus, we believe that improving soil and subsurface geology information should lead to improvements in modelling ML indices.

Lastly, several authors have pointed out the relative influence of land use variables to predict flow magnitude indices (Clausen and Pearson, 1995). Contrary to expected, Agr and For were poorly represented in our models. The little contribution of land use was associated with their relatively low variability in the selected unimpaired gauges. In this regard, 90% of the sites presented Agr below 30% while 50% of the sites showed forest areas that covered more than 40% of the catchment. The Mediterranean character of the study area requires an intense water resource management to sustain the irrigation activity. Hence, most of the unimpaired gauges used to develop the models were situated in headwaters or middle reaches where agriculture activity is not as extended as in the lower areas of the catchments and forest or denuded areas dominate land cover.

Regressions carried out elsewhere (Sanborn and Bledsoe, 2006; Knight et al., 2011) have encountered difficulties to predict accurately frequency indices. In contrast, we could predict FRE3 with a reasonable accuracy. Regressions usually recognized a positive association between frequency indices and elev (Yadav et al., 2007). Rivers in higher altitudes present, in general, smaller size relative to lower altitude rivers. Thus, moderate precipitation events are susceptible to produce flow episodes over a defined threshold (3 times the median flow). In contrast, larger rivers in lower elevations would need more intense or larger precipitations episodes to rise above this threshold. On the other hand, those moderate high flow events accounted in FRE3 usually last several days. The duration of these events contrasts with the time scale of the common available climate database. For instance, in our study area only mean monthly precipitation series were available, which presumably lacked the proper time scale to characterize these events. Hence, the availability of daily precipitation data would suppose a high benefit to predict these indices. In addition, the lack of proper predictor variables has been probably the critical element that hindered the development of more accurate models for the duration and rate of change and timing indices. Even so, predictor variables derived from precipitation series (PreMx, PreMn and MPrRn) were the most contributing environmental variables in the models of the duration and rate of change indices. These relationships indicated that the most humid areas presented longer high flow and shorter low flow events together with a higher rate of flow rise and fall than zones where precipitation is scarce.

5.4.2 Comparison of statistical techniques

Our analysis demonstrated that all the statistical techniques presented similar potential to predict the selected hydrological indices. Moreover, there was not a unique technique that resulted optimal for all hydrological indices. Several works in modelling a variety of ecological and earth science topics have also highlighted that alternative complex techniques did not generally exhibit great differences in their prediction accuracy relative to traditional modelling approaches (Manel *et al.*, 1999; Luoto and Hjort, 2005; Marmion *et al.*, 2008). Nonetheless, results varied according to the modelled variable and its particular distribution pattern (Olden and Jackson, 2002). In contrast, other authors have found that complex statistical techniques outperformed linear approaches to predict hydrological attributes (Tisseuil *et al.*, 2010; Booker and Snelder, 2012), fluvial nutrient load (Marce et al., 2004) or species distribution (Elith et al., 2006; Peters et al., 2007). Most of these authors emphasized the high flexibility of non-linear techniques in capturing complex relationships between predictor and response variables (Elith et al., 2006). However, when the underlying data structure and assumptions are met for a particular statistical method the application of complex techniques do not need to produce significant increments in the model performance (Olden and Jackson, 2002). For instance, when high degree of linearity between predictor and response was achieved, complex models, especially RF and ANN, did not generate much more accurate predictions than MLR. This is the case for magnitude indices (Figure 5.4). However, the four complex statistical techniques usually outperformed MLR in those indices in which linearity was hardly achieved, e.g. pred, FRE3, dPhigh, nPos and nNeg (Table 5.3). Nonetheless, it must be also stressed that GAM and ANFIS outperformed MLR (> 5%) in five and seven out of eight magnitude indices, respectively. GAMs allow for both linear and non-linear additive response shapes (Hastie and Tibshirani, 1986; Wood and Augustin, 2002). Hence, despite the linearity of several relationships, GAM could tune the response more finely in specific sections where relationships were not linear. On the other hand, it is likely that some complex relationships between other environmental variables and hydrological indices were hardly represented by mathematical model (Shu and Ouarda, 2008). Hence, the ability to introduce verbal power through the combination of fuzzy decision rules and fuzzy reasoning process (Jang, 1993) gave a slight advantage to ANFIS models (Chang and Chang, 2006).

The small gains in predictive performance of machine learning techniques can be attributed to the high degree of noise in the data (Moisen and Frescino, 2002) and the low number of training sites (Kampichler et al., 2010). Sources of noise are numerous when using gauged daily series. They include the difference in the length of the series (Kennard et al., 2010), the inclusion of non pristine gauges but the best available (Carlisle et al., 2010; Martinez-Fernandez et al., 2013) and errors associated to the measurement method in the gauges, especially during episodes of extreme high and low flows. Presumably, none of the statistical techniques used in this study was capable to deal with that noisy data better than the others. On the other hand, since machine learning techniques are viewed as data-intensive methods and the spatial availability of hydrological data sets is typically small, their application is limited. In this sense most of the studies in which machine learning methods outperformed linear approaches presented a number of sites ranging from several hundred (e.g. Booker et al., 2004) to more than a thousand (e.g. Prasad et al., 2006), which contrast with the 156 sites used in this work. Therefore, the application of machine learning methods is promising where spatial cover of hydrological data is large.

Beyond the predictive performance, other characteristics such as the computing time and the interpretability of the results, must be taken into account when selecting the optimal statistical technique. For instance, ANNs required the definition of the net structure while ANFIS required the definition of the number and shape of membership functions. In both cases, it is recommended (Lek and Guegan, 1999; Marce et al., 2004) to carry out these processes through an independent cross-validation process, as it was achieved in this work. On the other hand, the application of MLR involves complying with the assumptions of normality, homoscedasticity and linearity which was accomplished through variable transformations. Given the disparity nature of hydrological indices and environmental data, no single transformation could be applied systematically. In contrast, RF was the uniquely fully automated technique. The distribution of the variables do not have to comply any assumption and only the number of tress and the number of explanatory variables tried at each split must be determined (Liaw and Wiener, 2002), which reduces the time and facilitates its application to non-statistic specialists.

The last aspect to take into account is the ability to identify the possible causal relationships between the hydrological indices and the environmental variables. The five techniques agreed in the identification of the most important predictors for most of the models (Table 5.4). However, MLR and GAM allow straightforward insights between predictors and response variables (Manel et al., 1999). In contrast, machine learning methods have been largely seen as "black-boxes". For instance, the development of ANN and ANFIS models and the comprehension of results require a high level of time and knowledge, although huge progress has been recently done to understand the causal relationships underlying these techniques (Olden and Jackson, 2002; Marce *et al.*, 2004). On the other hand, RF results from an ensemble of regression trees and may become also a black box when interpreting the results (Prasad et al., 2006). Nonetheless, the 'RandomForest' package of the R statistical software (R Development Core Team, 2008) incorporates specific functions to numerically and graphically (partial dependence plots) visualize the marginal effect of each predictor variable on the response. These features definitively facilitate the application and understanding of this technique over other machine learning approaches.

5.4.3 The regional regression approach

The hydrological classifications used in this study were markedly dependent on the magnitude of mean, high and low flows and the shape of the hydrograph (Chapter III). This explained why the influence of classification was almost only evident in the models of the flow magnitude indices (Table 5.5; Figure. 5.5).

In this study the RRA produced contradictory results depending on the specific class been modelled. The Class 1 models of the 2-Class level and the Class 1 and 2 models of the 6-Class level classification showed a significant higher predictive performance in relation to the global model, while Class 4 model showed a moderate improvement. In contrast, a loss of accuracy was found in the remaining classes. This result agreed with other authors who found increases or decreases of the prediction accuracy depending on the class been modelled (Gustard and Irvin, 1994; Dawson *et al.*, 2006) while others have highlighted a general improvement after splitting the study domain (Clausen and Pearson, 1995; Laaha and Bloschl, 2006). Our initial hypothesis was that segregating river reaches according to a hydrological classification would reduce intra-group heterogeneity. This was only true for magnitude indices and for a limited number of classes (Figure 5.5).

Sanborn and Bledsoe (2006) related the increase in accuracy for certain classes to the variability of the climatic drivers. For instance, precipitation in classes 1 and 2 in the 6-Class level classification is abundant through the year and represents the main source of flow. Segregating, these two classes allowed that the relationship between area, precipitation and flow magnitude become more linear and straightforward (Figure 5.5). Elimination of gauges situated in more arid zones presenting large areas and low magnitude flows due to the scarce precipitations, might reduce the degree of noise in the analysis. Unlike classes 1 and 2, both snowmelt and rain can be considered the source of flow in class 3 (nivo-pluvial rivers), given that elevations are higher in Pyrenees than in Cantabrian Mountains. However, snowmelt and rains affect differently those rivers situated in the headwater to those in the middle reaches. This variability in the main source of flow together with the lack of predictor variables that account with snow precipitation and accumulation is, presumably, the reason for the limited ability of models to predict flow magnitude indices in this class. However it must be noted that models of timing indices (JMax, Jmin and Pred) of class 3 have significantly outperformed the global model. This is likely associated with the high predictability of peak flows given the simultaneity of snow melting and precipitations in spring (Solans and Poff, 2013). Lastly, results showed that class 2 in 2-Class Level and classes 5 and 6 in 6-Class Level classifications obtained the least accurate models. These rivers are situated in the aridest zones of the study area where river flow is dominated by the high intra and inter annual variability of Mediterranean areas (Vogel *et al.*, 1999; Bonada and Resh, 2013). Moreover, class 6, which is situated in the southern sector of the Iberian Range, could be highly influence by groundwater flow patterns given the presence of soft carbonate rocks in this area (Solans and Poff, 2013).

Therefore, although several authors (Sanborn and Bledsoe, 2006) have suggested the suitability of the RRA for modelling hydrological indices, the results obtained in this study have not showed a general improvement. Moreover, reduction of sites in many classes contributed to decrease the predictive performance in several classes.

5.5 Conclusion

The application of five modelling techniques to predict 16 environmental meaningful hydrological indices evidenced that all techniques might be suitable, since they showed similar prediction ability. Nonetheless, the equal accuracy of machine learning methods to more classical approaches may be associated with the low number of unaltered gauges used to fit the models. Widening this comparison to larger areas with a higher number of unaltered gauges will allow analyzing the actual potential of the most sophisticated methods. ANFIS, represented a slightly improvement over MLR, however the computational cost and the level of knowledge required to apply the method and interpret the results may limit its application. However, it was widely accepted that machine learning are capable to deal with linear and non-linear relationships. Hence, we believe that such approaches must be considered when it did not suppose a significant increment in the required resources and the causal links could be clearly understood.

On the other hand, not all hydrological indices were predicted with the same accuracy. This involves critical implications and limitations depending on the further uses of these predictions. Magnitude and frequency indices were generally predicted with excellent accuracy which opens a promising window to face several freshwater management and ecological interrogates. In contrast, none of the employed techniques was capable of developing precise models for timing, duration and rate of change indices. Therefore, an important effort should be done to improve environmental data bases in order to accomplish with this climatic, geological, edaphological and groundwater information in the appropriate spatio-temporal scale that influence flow regime patterns.

Finally, it was demonstrated that a regional regression approach did not generally improve model predictions, except in some specific classes. The reduction of sites in several classes represented an important handicap that limited the model fitting process. However, the extension of this analysis to larger areas may allow better discerning of the actual benefits of the regionalization approach.

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Chapter VI

Assessing hydrologic alteration: Evaluation of different alternatives according to data availability

Chapter IV. Assessing hydrologic alteration: Evaluation of different alternatives according to data availability

This study is under preparation to be submitted for publication in a SCI journal.

Abstract

The natural flow regime has been largely modified in rivers around the world. Understanding the extent to which flow regime deviates from natural conditions is a mandatory task to propose sound management and restoration measures. In this regard, “Indicators of Hydrologic Alteration” is currently seen as one of the most effective approaches for assessing the hydrologic alteration (HA). However, several factors such as the climatic variability between the pre and post-impacted series and the scarcity of hydrological data in many impaired rivers represent generalized drawbacks that should be addressed. In this study we present a protocol that provides 5 alternative designs to evaluate hydrological alteration in relation to data availability: (1) Paired-Before-After-Control-Impact (BACIP), (2) Before-After (BA), (3) Control-Impact (CI), (4) Hydrologic Classification (HC) and (5) Predicted Hydrologic Indices (HP). BACIP allows comparing the status of the impacted gauge before and after start-up of the perturbation, as well as it controls for natural climatic changes. Hence, it has been considered as the reference benchmark for all other designs. The application of the protocol to 11 reservoirs situated in the northern third of the Iberian Peninsula highlighted that BA correctly evaluated 75% of the HAs when it was compared with BACIP. This indicated the little influence of climate variability between the pre- and post-impact series. Similarly, BACIP and CI showed an agreement over 70% which meant the suitability of hydrological classification for the selection of control gauges. In addition, our results pointed out that critical thresholds for the HA varied depending on the hydrological index been considered. This range went from less than 5% for the number of days with increasing and decreasing flows and over 64% for the duration of low flow pulses. This thresholds indicated when a hydrological alteration should be considered significant and the are very valuable for focusing further impacts on

ecological processes. Finally, the application of HC and HP designs revealed a significant degree of uncertainty related with the intra-class variability and the predictive error of the models. This inhibited the evaluation of 25% of the analysis. However, in the evaluable cases HC and HP designs correctly assessed over 75% of the HA which highlighted the potential usefulness of this methods where streamflow data is scarce.

6.1 Introduction

The natural flow regime of streams in the five continents have been largely altered by the construction of more than 25.000 dams during the last century (Tharme, 2003; Poff et al., 2007). Reservoirs represent essential infrastructures to face the current and expected societal demand of water resources for irrigation, industry, energy production or drinking. On the other hand, the impairment of flow regimes seriously compromise not only the integrity of freshwater ecosystems but the ecosystem services they provide (Naiman et al., 2002). The influence of the natural flow regime on ecosystem processes and functions is well known (Richter *et al.*, 1998; Snelder and Lamouroux, 2010) and research focused on the ecological implications of altered flow regimes (Bunn and Arthington, 2002; Poff and Zimmerman, 2010) has increased rapidly since late 90s.

It is now widely accepted that maintaining some degree of similarity to the various pre-impacted combinations of flow magnitude, timing, duration, frequency and rate of change is required to maintain river processes and functions (Galat and Lipkin, 2000; Arthington *et al.*, 2006; Schneider *et al.*, 2013). In this regard, the first step through the adoption of appropriate conservation and recovery measures is identifying the extend that the flow regime deviates from natural conditions (Black et al., 2005). Reservoirs vary in size, level of impoundment, function and operational rules, so generalizations of their potential hydrologic alteration (HA) and ecological impact are difficult (Magilligan and Nislow, 2001). Hence, one of the most robust approach to determine the HA is the site specific comparison of pre- and post-regulation flow series (McManamay et al., 2012). In this regard, the “Indicators of Hydrologic Alteration” (IHA) method developed by the Nature Conservancy (Richter et al., 1996) has been used worldwide (e.g. Maingi and Marsh, 2002; Magilligan and Nislow, 2005; Yang et al., 2008; Fernandez et al., 2012) and is currently seen as one of the most effective approaches for assessing the HA. The IHA method summarises pre and post-impact series in a number of hydrologic indices (HIs). Then, the IHA is defined for each HI as the magnitude of change between the two periods. Despite its widespread application and acceptance, the IHA presents several drawbacks that should be embraced to completely understand and determine the degree of HA of a river.

Firstly, the results in the IHA are originally presented in terms of the magnitude of the impacts rather than as a statistical value for the null hypothesis that the pre- and the post-impact conditions are the same (Richter *et al.*, 1996). Indeed, most of the applications of the method lack the definition of critical IHA thresholds that produce significant HA (Magilligan and Nislow, 2001; Hu *et al.*, 2008). In other applications thresholds have been defined arbitrarily (e.g. IHA > 50%; Yang *et al.*, 2008; Fernandez *et al.*, 2012; Caruso, 2013). Contrary, the definition of critical IHAs based on objective statistical methods is an essential issue since it would reduce the scientific uncertainty that would guide management decisions. In this regard, given the structure of the data of the IHA method, quantitative and statistical analyses are not mutually excluding and beyond the magnitude of the difference, the statistical significance can be easily estimated (Magilligan and Nislow, 2005; Small *et al.*, 2009).

On the other hand, the natural climatic differences between the pre- and post-impact periods may exert a significant influence in the IHA outcomes (Zhao et al., 2012). Moreover, in the last decades, it has been observed a worldwide increasing trend in the Earth's surface temperature which may cause changes in global atmospheric circulation, inducing changes in precipitation patterns (Suen, 2010; IPCC, 2013). These changes would be reflected ultimately in the flow regime. Hence, climate change constitutes another factor that may interact with other hydrologic perturbations (Naik and Jay, 2011; Schneider *et al.*, 2013). In this regard, the application of the IHA method either from a quantitative or a statistical perspective would uniquely indicate whether a change in state has occurred. However, it would not allow us to distinguish a change caused by the reservoir operation from a change that would have occurred even if the activity had not begun (Downes et al., 2002). Therefore, the actual HA caused by a dam can only be totally unmasked if a control site, uninfluenced by any perturbation, is used as a climatic control. Using the year values of the HIs at the control site as a measure of the state of the system through time, it is possible to statistically compare what it would have occurred in the impact site in the absence of the perturbation. This represents the basis for the Paired-before-after-control-Impact (BACIP) design (Stewart-Oaten *et al.*, 1992; Downes *et al.*, 2002). BACIP design allows testing for significant differences in a variety of possible situations, i.e. when there were not (Figure 6.1A-C) and there were (Figure 6.1D-F) actual changes in the series attributable to the perturbation. Moreover, BACIP designs allow for natural differences between the Control and Impact sites (Figure 6.1B and F).

Another significant factor that can hamper the application of the IHA method is the availability of proper flow records (Carlisle et al., 2010) provided by gauging networks. Many times these networks lack appropriate pre-impact series or are restricted to small fractions of the river network (Eng et al., 2013). Thus, strategies that provide alternative means to assess HA are needed. For instance, several authors have used statistical approaches to estimate HIs of the unimpaired flow conditions to complete river networks based on climate, catchment spatial configuration, geology and land uses (Sanborn and Bledsoe, 2006; Knight et al., 2011). Statistical approaches are generally simpler than watershed rainfall-runoff modelling (Eng et al., 2013) and Carlise et al. (2010) highlighted promising results in quantifying the HA using them. In addition, in the last years it has been demonstrated the suitability of hydrological classifications to provide a sound context for evaluating natural hydrologic variability (Kennard et al., 2010), analysing the spatial patterns in HA (Poff *et al.*, 2007; McManamay *et al.*, 2012) and stratifying rivers in management units for evaluating the HA (Arthington et al., 2006; Poff et al., 2010). Following Arthingthon et al. (2006), hydrological classes may provide the hydrologic baseline from which HA can be assessed. In this regard, to the authors' knowledge no study has accomplished a quantitative comparison between these two alternative strategies and the IHA based on pre and post-impact recorded series.

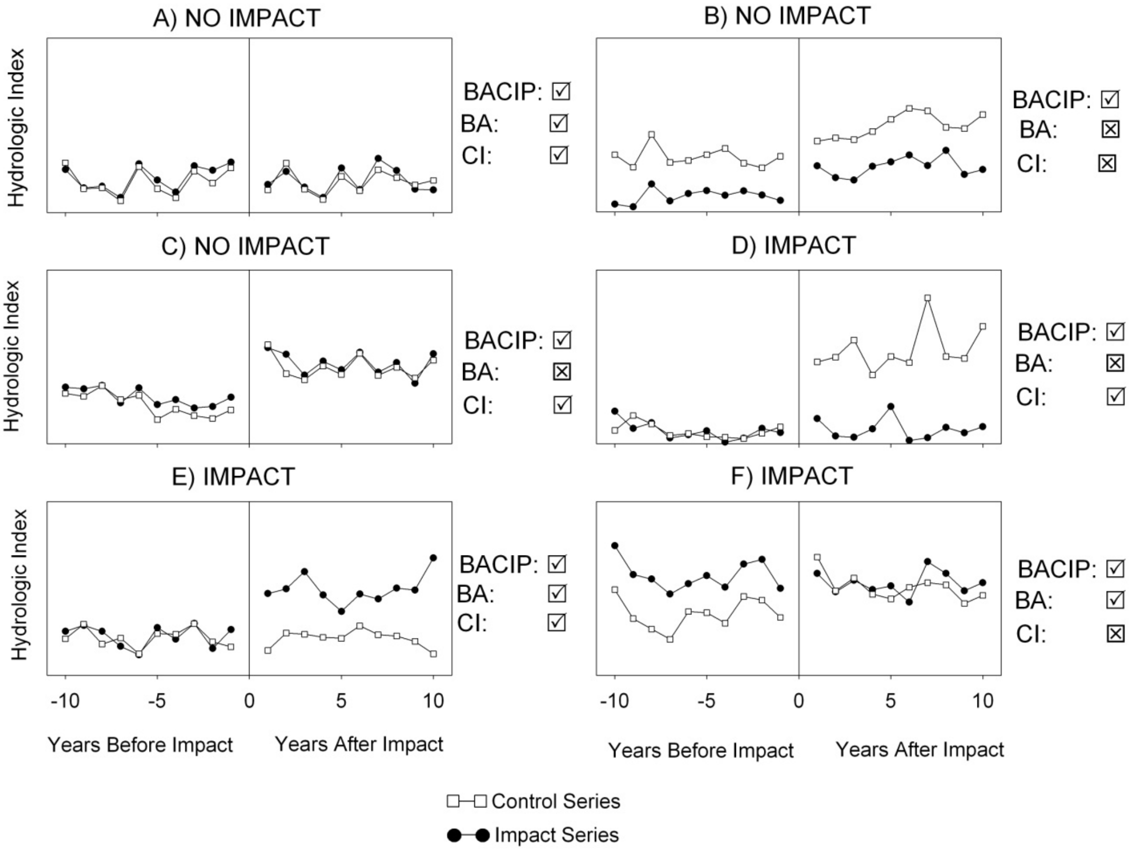

Figure 6.1 - Hypothetical situations regarding relationships between impacted and control gauges and changes between the pre and post-impacted periods. Ticks and crosses in the right side of the graphic indicate whether BACIP, BA or CI designs do well or fail the assessment of the hydrological alteration, respectively.

In this chapter we present a protocol to assess HA using five alternative designs which depend on the availability of hydrological data: (1) Paired-Before-After-Control-Impact (BACIP), (2) Before-After (BA); 3) Control-Impact (CI), (4) Hydrologic Classification (HC) and (5) Predicted Hydrologic Indices (HP). BACIP allows comparing the status of the impacted gauge before and after start-up of the perturbation, as well as controlling for natural climatic changes and other confounding factors. Hence, it has been considered as the reference benchmark for all the other designs.

We applied the protocol at 11 dams situated in the northern third of the Iberian Peninsula aiming to illustrate and evaluate the application of the protocol. Specifically, we (1) assessed the agreement between BACIP and less data intensive designs (BA and CI), (2) determined the critical IHA thresholds that generates a significant HA and (3) evaluated the suitability of alternative strategies to assess the HA in the absence of proper recorded flow data (HC and HP). We hypothesized that BA design would provide similar results to BACIP except for sites subjected to significant climatic changes between the pre and the post-impact periods, while CI would fail in those sites were other confounding factors (e.g. significant shifts in land cover pattern during the analysis period) differed greatly between impact and control sites. Finally, the reliability of HC and HP designs would depend on the uncertainty associated with the prediction accuracy of the models and the intra-class natural variability, respectively.

6.2 Methods

6.2.1 A protocol to assess hydrological alteration

In this study, we developed a systematic protocol to evaluate the HA (Figure 6.2) that enables different analysis and comparisons, taking into account the main drawbacks and principles exposed above:

1. Inclusion of statistical analysis to determine the significance of the changes between the pre and post-impact series.
2. Incorporation of control sites to isolate the HA cause by human perturbations from climatic factors.
3. Proposal of alternative designs to evaluate HA in the absence of proper pre-impact series.

The 5 designs proposed have been already applied to assess the HA in different rivers around the world. However the main capability and novelty of the protocol is that it guides the assessment of the HA depending on data availability and from more robust methods to methods that may present a higher level of uncertainty.

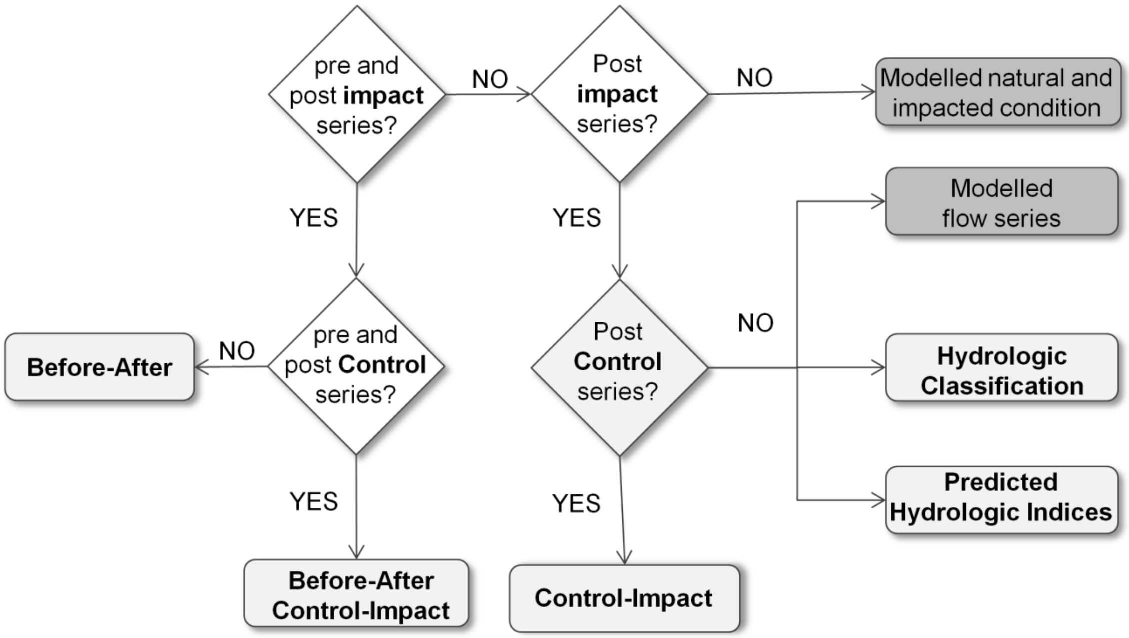

Figure 6.2 - Flow diagram representing the Hydrologic Alteration Assessment Protocol.

6.2.1.1 Selection of impacted and control gauges

The first step in the protocol searches for the most adequate gauge to monitor the target perturbation (impacted gauge; Figure 6.2). The flow series of the impacted gauge has to cover either pre- and post-impact periods or uniquely the post-impact period. This will determine the further analysis to be applied. The impacted gauge should be as close as possible to the perturbation and if possible, situated between the perturbation and the join of tributaries of the same or higher order than the impacted river. If there is not any impacted gauge to monitor the perturbation, several methods have been proposed to simulate synthetic series that reproduce both the natural and the impacted flow conditions (Fitzhugh and Vogel, 2011; Gao et al., 2012; McManamay et al., 2012). However, this kind of assessment is out of the scope of the present protocol and hence, the **modelling of natural and impacted condition** design was not considered.

If both pre- and post-impact periods are available in the impacted gauge, the next step in the protocol is the search for a control gauge. The control gauge must not be affected by any perturbation. In addition, it must be as similar as possible to the impacted gauge. The protocol considers two essential requirements to select the control gauge:

1. Flow series of the control gauge have to match the pre- and post impact periods selected in the impacted gauge.
2. Control and impacted gauge must belong to the same class in a previously developed hydrological classification. This assures a greater degree of hydrological homogeneity between both gauges. There exist many approaches to develop hydrologic classifications (Olden et al., 2012). However, the usefulness of the classification to select control gauges would be only guaranteed if (1) it is based on ecologically meaningful HIs of the natural flow regime, (2) it is based on long-term gauges records for relatively unmodified streams and (3) it is developed from a predictive perspective to define the class membership of ungauged sites (Chapter III).

If these requirements are met, then three extra criteria are applied to select the most optimal control gauge. These criteria were established aiming to reduce the differences between the impacted and control gauges due to local climate variation and the influence of the size of the drainage catchment:

3. Gauges located upstream of the alteration are considered preferably.
4. Gauges situated closer to the impacted gauge are considered preferably.
5. Gauges with the most similar drainage area are considered preferably.

6.2.1.2 Assessment design I: Paired-Before-After-Control-Impact

If a control gauge satisfies all the requirements presented above then, the Paired-Before-After-Control-Impact (**BACIP)** design is applied to evaluate the HA (Figure 6.2). BACIP design assumes that the samples are paired in the sense that the control and impact are measured simultaneously (Stewart-Oaten et al., 1992). In addition, replication comes from obtaining such paired samples at a number of times (years) both before and after the perturbation. Therefore, time series for each gauge (control/impact) must encompass the same collection of years. Moreover, if possible, time series for the pre and post-impact periods must present equal lengths (i.e. equal number of years) to achieve a complete balanced design. Once the time series were defined (i.e. Before-Control, Before-Impact, After-Control and After-Impact), a set of HIs are calculated for each year of the series. Given, that reservoir and other human perturbations can potentially modify flow regime in different ways, HIs covering the 5 ecologically meaningful attributes of the flow regime should be considered: (i) Magnitude of mean flow conditions, (ii) magnitude and duration of annual extreme conditions; (iii) timing of annual extreme conditions; (iv) frequency and duration of high and low pulses and (v) rate of change. For instance, the IHA method considered originally 32 HIs (Richter et al., 1996).

On the other hand, it is assumed that the HIs at the impact and control gauges can present naturally different average values (e.g. Figure 6.1B and 6.1F). Thus, BACIP analysis focuses on changes in the impact gauge relative to the control. In this regard, the variable that is analysed is the difference between control and impact values (Downes et al., 2002). For each year of the series the variable d_{pj}, which is the difference between each HI at the control and impact gauge at a particular year *j*, within either the before and after period (*p*) is computed. Then, the differences in the two periods are compared using a Student's t-test to determine whether the means are statistically different (Downes et al., 2002).

6.2.1.3 Assessment design II: Before-After

When no control gauge meets the established selection requirements and only the impacted gauge is available the **Before-After design (BA)** should be applied (Figure 6.2). This design is equivalent to the original IHA method (Richter et al., 1996) which has been the most extended analysis to evaluate the HA. Hence, it uses the pre (Before-Impact) and post-impact (After-Impact) series of the impacted gauge. According to Richter et al. (1996), values of the HIs are calculated for each year of the pre- and post-impact series and then, the inter-annual statistics (mean and dispersion) are computed. Finally, the HA is calculated as the percentage deviation of each HI of the post-impact series relative to the pre-impact series (IHA_{BA}). In addition, in the present protocol the pre and post-impact periods are compared using a Student´s t-test to determine if the means are statistically different (Magilligan and Nislow, 2005; Costigan and Daniels, 2012).

6.2.1.4 Assessment designs III: Control Impact

In this study we proposed a set of alternative methods to analyze the HA when only post-impact series at the impacted gauge are available (Figure 6.2). This is a very common situation given that many gauges were installed after the perturbation started or presented very short pre-impacted series. The first approach is the **Control-Impact design (CI)**. It compares the post-impact series of the impacted gauge (After-Impact) with the flow series covering the same period in a control gauge (After-Control; Caruso, 2013). The selection of the control gauge in the CI design considers the same requirements and criteria applied for the selection of controls in the BACIP design. Once the Control gauge is selected, parallel analysis to those performed in the BA design are applied. Hence, the percentage deviation of each HI of the post-impact series in the impacted gauge relative to the control gauge is calculated (IHA_{CI}). In addition, Student´s t-test is applied to determine if the means are statistically different.

6.2.1.5 Assessment designs IV and V: Hydrological Classification and Predicted Hydrological Indices

When none control gauge meets the established selection requirements, there are three alternative approaches to evaluate the HA (Figure 6.2). The first one is based in the development of hydrologic rainfall-runoff models to estimate the natural flow series in the impacted sites. Then, HIs are calculated from these natural flow series. Parallel to the BA and CI designs, in this approach the percentage deviation of each HI calculated from the post-impacted series in the impacted gauge relative to the HI calculated from the modelled flow series are computed (e.g. Black *et al.*, 2005; e.g. Fernandez *et al.*, 2012). However, given the lack of modelled daily flow series in the study area this approach was not considered in this study.

In contrast, the present protocol embraces two different and less common approaches to evaluate the HA when only the post-impact series at the impacted gauge are available (Figure 6.2). The first one is based in the class membership of the impacted gauge regarding a predictive **hydrological classification (HC)**. The conceptual basis for this approach relies in the assumption that the mean value of the HIs in a given hydrological class can be used as a surrogate of the unimpaired natural range of spatial and temporal variation (pre-impact) in all the river segments of that class (Arthington et al., 2006). The hydrological classification must satisfy the three specifications introduced in the second requirement for the selection of control gauges. Once the class membership has been predicted to the whole river network, the mean value of the HIs for each class is calculated from the HIs computed in the unimpaired gauges used to develop the classification. Then, the percentage deviation of each HI calculated from the post-impact series relative to mean HI value of the class HIs are computed (IHA_{HC}). Given that in this case there is a unique pre- and post-impact value, statistical analysis are not applicable.

The last approach, uses the values of **predicted HIs (HP)** for the river segments where the impacted gauge is situated (Figure 6.2). This approach assumes that the predicted HIs are informative of the unimpaired hydrological condition (Carlisle et al., 2010).

Predictive models must be developed from unimpaired gauges coupled with physical and climatic drainage basin characteristics that allow predicting these HI to ungauged sites. Similarly to the HC design, the percentage deviation of each HI calculated from the post-impact series relative to the predicted HIs are calculated (IHA_{HP}).

6.2.2 Application and assessment

6.2.2.1 Study area, selected reservoirs and impacted and control gauge

We selected 11 reservoirs situated in the northern third of the Iberian Peninsula to illustrate and assess the proposed HA assessment protocol (Table 6.1; Figure 6.3). Aiming to compare the results of each design included in the protocol, we only selected reservoirs where all designs could be applied. Therefore, all the reservoirs assessed in this analysis accounted with (1) pre and post-impacted series recorded at an impacted gauge, (2) pre and post-impacted series recorded at a control gauge, (3) mean natural HIs values of the classes provided by a hydrological classification and (4) expected natural HIs values computed through predictive statistical models. In addition, a quality assessment of the pre-impact series of the impacted gauges and the pre- and post-impact series of the control gauges was carried out to retain those gauges with the highest reliability data. Therefore, we eliminated those years with (1) periods of consecutive repeated values, (2) non-natural extreme low flows for short time periods, (3) large periods of zero flow in non- intermittent rivers, (4) non-natural flow magnitude rises and falls or (5) large differences between two periods, probably due to change of flow record method. Then we searched for gaps without data greater than 30 days and removed the years in which gaps occurred. Moreover, a minimum of 7 and a maximum of 10 years length of the pre- and post-impact series were established to allow for reliable comparison between the evaluations of the different reservoirs. The selected reservoirs presented an important range regarding the storage capacity (10-475 hm^3) and were built between 1945 and 1994 (Table 6.1). Most of them are currently used for irrigation or water supply purposes although many times they combine several uses (Batalla *et al.*, 2004; Fernandez *et al.*, 2012).

Reservoir							Impacted Gauge		Control Gauge		Series		
Site num	Hydrol. Class	Name	Area (km^2)	Storage (hm^3)	Year	Use	Code	Area	Code	Area	Pre	Post	Total years
1	1	Ibai-Eder	29	11	1991	D	1109	307	1106	654	1979-1988	1994-2003	10
2	1	Urkulu	15	10	1981	D	1103[1]	449	1196	492	1970-1977	1984-1991	8
3	2	Mansilla	238	50	1960	D/A/O	9034	238	9064	398	1948-1957	1963-1977	7
4	2	Yesa	2186	475	1959	A/H/O	9101	2192	9063	511	1951-1957	1969-1977	7
5	3	Pajares	92	35	1994	D/A	9142	109	9047	428	1975-1992	1997-1998	10
6	3	San Pons	307	24	1957	D/H/O	ACA001	649	ACA025	254	1943-1955	1960-1968	9
7	4	Ullivari	263	139	1957	D/H/O	9107	264	9079	193	1947-1955	1965-1974	9
8	4	Ebro	459	540	1945	D/A/O	9001[2]	5410	9003	1277	1916-1931	1971-1984	9
9	5	Boadella	158	62	1969	D/A/H/O	ACA012	167	ACA026	48	1959-1968	1974-1987	9
10	6	Montegudo	220	10	1982	A	9147	463	9042	1978	1962-1980	1986-1997	10
11	6	Tranquera	1467	78	1959	D/A/O	9009	7587	9010	2712	1950-1957	1962-1980	8

Table 6.1 - Summary of the main characteristics of the 11 reservoirs, impacted and control gauges selected to illustrate and evaluate the Hydrologic Alteration Assessment protocol. (D: Drinking water for population supply; A: Agriculture; H: Hydropower; O: Others). [1]This gauge is also affected by the Aixola reservoir with a storage capacity of 3 hm3. [2] This gauge is affected by several reservoirs. In the table it is only indicated the reservoir with the largest storage capacity and potential impact.

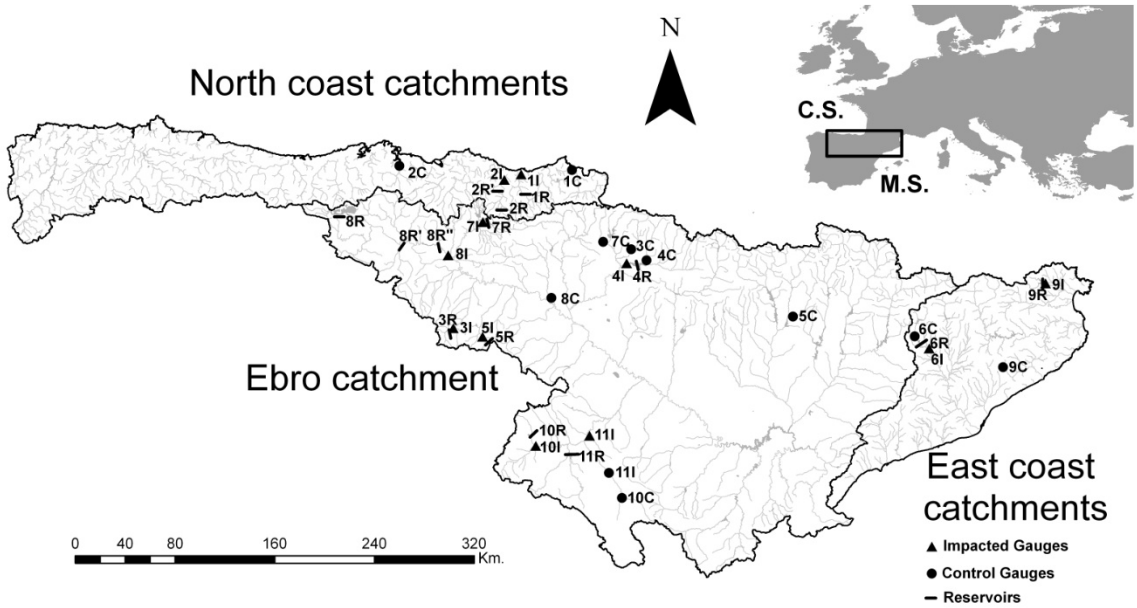

Figure 6.3 - Study area covering the northern third of the Iberian Peninsula, illustrating locations of the 11 reservoirs (R) evaluated in the study and the 11 impacted gauges (I) and corresponding control gauges (C). Reservoirs and Gauges identified by numbers included in Table 6.1 (site number).

On the other hand, it should be pointed out that it was out of the scope of this work to make a complete HA evaluation considering all relevant HIs but to assess the different approaches within the current protocol. Therefore, we selected a reduced set of 14 HIs representative of the 5 ecologically meaningful attributes of the flow regime (Table 6.2): (i) Magnitude of mean flow conditions (3: L1, M4 and M9), (ii) Magnitude and duration of annual low (2: 7LF and 30LF) and high (2: 7HF and 30HF) flow conditions (4); (iii) timing of annual low (1: JMin) and high (1: JMax) flow conditions; (iv) frequency (1: FRE3) and duration of high (1: dPHigh) and low (1: dPlow) pulses and (v) rate of change (2: nNeg and nPos). Although average values at the impact and control gauges can be different in the BACIP all the magnitude indices were standardized by dividing by the catchment area or by the long term mean daily flow (M4, M9, 7LF, 30LF, 7HF and 30HF) to allow for reliable comparisons with the other designs. In addition, annual HIs were transformed when necessary to fulfil the assumptions of normality and homoscedasticity required by two-sample t test.

Index	Type	Units	Description
L1[1]	MA	m^3/s	Linear moment that represents the mean daily annual flow
M4[2]	MA	m^3/s	Mean daily April flow
M9[2]	MA	m^3/s	Mean daily september flow
7LF[2]	ML	m^3/s	Magnitude of minimum annual flow of 7 day duration.
30LF[2]	ML	m^3/s	Magnitude of minimum annual flow of 30 day duration.
7HF[2]	MH	m^3/s	Magnitude of maxima annual flow of 7 day duration
30HF[2]	MH	m^3/s	Magnitude of maxima annual flow of 30 day duration
Jmax	T	Day of year	Julian day of annual maximum
Jmin	T	Day of year	Julian day of annual minimum
dPHigh	DH	Days	Duration of high flow pulses
dPLow	DL	Days	Duration of low flow pulses
nPos	RC	Days	Number of days with increasing flow
nNeg	RC	Days	Number of days with decreasing flow
FRE3	F	Events/year	Number of high flow events per year using an upper threshold of 3 time median flow over all years

Table 6.2 - The 14 hydrological indices selected to illustrate and evaluate the Hydrologic Alteration Assessment protocol (MA: Magnitude Average, MH: Magnitude High, ML: Magnitude Low, T: Timing, F: Frequency, DH: Duration of high flow events, DL: Duration of low flow events and RC: Rate of change). [1]L1 was standardized by dividing by the catchment area. [2]Flow Magnitude indices were standardized by dividing by the mean daily annual flow (L1)

In order to apply the HC design, we used a hydrological classification comprising 6-Class levels developed by means of the Predict-Then-Classify strategy (Chapter III; Provided within the supplementary material included in the DVD.). Briefly, the classes 1 and 2 were distributed throughout the northern coastal catchments and the north-western section of the Ebro basin. Class 3 extended throughout the headwaters and mid reaches of the Pyrenean range, while Class 4 was mainly present in rivers situated in the western most section of the Ebro depression. Class 5 included rivers in the Ebro depression and several of the Catalan catchments, while Class 6 was represented by streams situated in the southern section of the Iberian massif. We selected two reservoirs in each hydrologic class except in class 5 in which only 1 reservoir met the requirements to apply all the designs.

Finally, predictive models of the 14 HIs to assess the HP design were developed using Random Forest (Breiman, 2001; Cutler *et al.*, 2007). Models were based on flow series recorded at 156 minimally impacted gauges and based on climatic and catchment attributes extracted from several data sources (Chapter V; Provided within the supplementary material included in the DVD). In general, model performance measured through the coefficient of determination (adjusted-r^2) was higher when predicting flow magnitude (0.60-0.78) and frequency indices (0.62), than when predicting timing (0.11-0.19), duration (0.28-0.37) and rate of change (0.52-0.53) HIs. Nonetheless, the evaluation of these models also highlighted that timing and rate of change indices were the least variable HIs in the study area. Therefore, although adjusted-r^2s of these models were low, they also presented low root-mean-square-errors (RMSE) relative to the mean value of the HI.

6.2.2.2 Comparison of Paired-Before-After-Control-Impact (BACIP), Before-After (BA) and Control-impact (CI) designs

As exposed before the HA obtained through the BACIP design has been treated as the reference benchmark for all the other designs. Hence, we analyzed the degree of agreement between the BA and the BACIP results and between the CI and the BACIP regarding the significance of the statistical tests (p-values from the student's t-tests). We also compared the agreement between BA and CI. We calculated the total number and percentage of true positives (both significant, $p<0.1$), true negatives (both no-significant, $p>0.1$), false positives (BACIP no-significant and BA/CI significant) and false negatives (BACIP significant and BA/CI no-significant).

6.2.2.3 Estimation of the critical IHA values for the BA and CI designs

As exposed above, in the BA and CI design the Student's t test is used to determine if the means are statistically different as follows:

$$t=\frac{\bar{X}_1-\bar{X}_2}{S_{\bar{X}_1-\bar{X}_2}} \quad (1)$$

where

$$S_{\bar{X}_1-\bar{X}_2}=\sqrt{\frac{(n_1-1)s_1^2+(n_2-1)s_{12}^2}{n_1+n_2-1}\left(\frac{1}{n_1}+\frac{1}{n_2}\right)} \quad (2)$$

The obtained t-value in Eq (1) is then compared with a t-student distribution according to the degrees of freedom and the selected level of significance to determine if differences are significant or not. Hence, the larger the differences are between the impacted and the unimpacted series, the larger the t-value would be. However, given that the significance of the test also depends on the variance of the samples and the number of years the t-test can provide different results for equal overall difference between means (i.e. equal IHA). The relation between the IHA_{BA} and IHA_{CI} and the t-value obtained from the Student's t-test in the 11 reservoirs were analysed to define the thresholds above which IHA should be considered significant. We developed individual analysis for IHA_{BA} and IHA_{CI} using uniquely those true positives and true negatives defined in the section 6.2.2.2. Linear regressions were adjusted for each HI. Since we can calculate the t-value for a given number of degrees of freedom and a given significance level we established two thresholds. The upper threshold considers a 0.05 level of significance and 8 degrees of freedom (i.e. 5 years length series). The lower threshold considers a 0.10 level of significance and 28 degrees of freedom (i.e. 15 years length series). The lower threshold was achieved with lower IHAs, i.e. it is more restrictive than the upper threshold. Using those thresholds and the regression equations derived from the regression developed previously we calculated the critical IHA_{BA} and IHA_{CI} associated with the upper and lower thresholds for each HI.

6.2.2.4 Assessment of the Hydrological Classification (HC) and the Predicted Indices (HP) designs

Finally, we assessed the ability of the HC and HP designs to evaluate the actual HA. For that purpose we compared IHA_{HC} and IHA_{HP} with the results obtained by means of the BA design (IHA_{BA}). Firstly, the uncertainty in the expected natural HIs associated with the intra-classes variability and the error of the predictive models, respectively, must be acknowledged. Therefore, before computing IHA_{HC} and IHA_{HP}, we estimated the 95% confidence intervals of each HI_{HC} and HI_{HP} using Eq (3) and Eq (4), respectively:

$$HI_{HC} + t_{\frac{\alpha}{2},(n-1)} SD > HI_{HC} > HI_{HC} - t_{\frac{\alpha}{2},(n-1)} SD \quad (3)$$

$$HI_{HP} + t_{\frac{1-\alpha}{2},(n-1)} RMSE > HI_{HP} > HI_{HP} - t_{\frac{1-\alpha}{2},(n-1)} RMSE \quad (4)$$

where *t value* was obtained from the t distribution for given interval confidence level (*α=0.10*) and degrees of freedom (*n-1*), *SD* is the standard deviation of each HI calculated for the different hydrological classes and RMSE is the root-mean-squared-error of the Random Forest model developed for each HI. RMSE was calculated through a Jacknife cross validation procedure (Chapter V). The degrees of freedom corresponded to number of gauges in each class or number of gauges used to develop the predictive models for HI_{HC} and HI_{HP}, respectively.

Based on these confidence intervals, 3 IHA_{HC} and the 3 IHA_{HP} corresponding with the central value and each of the confidence limits of the HI_{HC} and HI_{HP} were calculated. The range defined by the maximum IHA_{HC}/IHA_{HP} and the minimum IHA_{HC}/IHA_{HP} is compared with the critical IHA thresholds calculated in the section 6.2.2.3. Therefore, if more than 80% of each range of IHA_{HC}/IHA_{HP} was over or below the critical threshold it was considered that the HI is significantly impacted or unimpacted, respectively. Contrary, if the range intersects with the critical threshold value, the HA was considered as not evaluable. Finally, we compared these results with those obtained through the BA design, taking into account only the true positives and true negatives resulting from the analysis developed in the section 6.2.2.2. Next, we calculated the total number and percentage of true positives (both significant), true negatives (both no-significant), false positives (BA no-significant and HC/HP significant) and false negatives (BA significant and HC/HP no-significant).

6.3 Results

6.3.1 Overall flow alteration in the selected reservoirs

The evaluation of the available data revealed that almost one half of the 163 reservoirs (storage capability > 1 hm^3) present in the study area had gauging stations downstream (Table 6.3). Monitored reservoirs are susceptible of being assessed with at least one of the designs included in the HA evaluation protocol. 17% of the reservoirs presented pre and post-impact series either in an impacted and a control gauge, so that BACIP and BA designs could be applied. Nonetheless, adequate pre-impact series were missing in most of the impacted gauges. In contrast, CI, HC and HP designs could be applied in almost all the monitored reservoirs.

	Total Dams (>1 hm^3)	**Gauged Dams**	**BACI**	**BA**	**CI**	**HC**	**HP**
Class 1	22	11 (50)	3 (16.6)	3 (13.6)	10 (45.5)	11 (50)	11 (50)
Class 2	25	14 (56)	3 (12)	3 (12)	13 (52)	14 (56)	14 (56)
Class 3	63	31 (49.2)	11 (17.5)	11 (17.5)	29 (46)	31 (49.2)	31 (49.2)
Class 4	17	7 (41.2)	4 (23.3)	4 (23.5)	7 (41.2)	7 (41.2)	7 (41.2)
Class 5	16	4 (25)	1 (6.3)	1 (6.3)	4 (25)	4 (25)	4 (25)
Class 6	19	10 (52.6)	4 (21.1)	4 (21.1)	8 (42.1)	10 (52.6)	10 (52.6)
Total	**163**	**78 (47.9)**	**28 (17.2)**	**28 (17.2)**	**72 (44.2)**	**78 (47.9)**	**78 (47.9)**

Table 6.3 - Total number and monitored dams in the study area. Total number and percentage (in parentheses) of dams in which each design included in the Hydrologic Alteration Assessment protocol could be potentially applied.

BACIP analysis pointed out that there were at least 3 altered HIs for each selected reservoir. Yesa and Ullivarri presented the greatest HAs with significant impacts in 10 out of 14 HIs (Table 6.4). Conversely, San Pons and Monteagudo only produced 3 significantly altered HIs.

Annual low (7LF and 30LF) and flood flows (7HF and 30HF) were the dominant impacts of regulation. 7LF and 30LF were significant altered by almost one half of the analysed reservoirs. In several cases the perturbations supposed inflations over a 50% relative to the unimpaired period although minimum flow decreased in 3 reservoirs. 7HF and 30HF were significantly altered 4 and 7 times, respectively (Table 6.4) and in general, reservoir operation reduced flooding flows. Relative differences between pre and post-impact situations were more pronounced for 7HF than 30HF, ranging from 33 to 62% in the former. Other major downstream effects following regulation was the significant modifications of nPos and nNeg by 7 and 5 reservoirs, respectively. M9 and dPLow were also significantly altered in 5 of the 11 dams. M9 tended to increased from the pre- to the post-impact period with a mean relative difference greater than 50%. dPLow was increased or reduced depending on the reservoir operations reaching mean differences of 50% in both cases. In contrast, other indices such as M4, dPhigh, Jmin and JMax were the least disturbed indices with 3 or less reservoirs producing significant changes.

6.3.2 Comparison of Paired-Before-After-Control-Impact (BACIP), Before-After (BA) and Control-impact (CI) designs

BA design correctly evaluated 75% of the HAs when it was compared with BACIP results. BACIP design revealed 64 significant and 90 no-significant HAs from which BA recognized 68% and 81% of them, respectively (Table 6.4). The greatest discrepancies between BACIP and BA designs were found in L1, Jmin and nNeg where BA produced 3 false positives and 30HF where it produced 5 false negatives. On the other hand the greatest number of failures was found in La Tranquera and Ullivarri reservoirs where BA produced 4 false positives and 5 false negatives, respectively.

Reservoir	Design	Hydrological Index													
		L1	M4	M9	7LF	30LF	7HF	30HF	Jmin	Jmax	dPlow	dPhigh	nPos	nNeg	FRE3
Ibai-Eder	BACIP	0.30	0.27	**0.07**	0.35	0.46	**<0.01**	**<0.01**	0.13	0.70	**0.04**	0.83	0.14	0.16	0.93
	BA	0.18	0.19	**0.08**	0.71	0.55	0.23	0.21	0.14	0.87	**0.09**	0.39	0.58	0.38	0.55
	CI	0.46	0.32	0.71	0.24	0.38	0.49	0.20	0.58	0.97	**0.09**	0.68	**<0.01**	**<0.01**	0.55
Urkulu	BACIP	**0.04**	0.44	0.85	**0.08**	**0.09**	0.82	0.82	0.25	0.73	0.22	0.38	**0.09**	0.14	0.88
	BA	0.18	**0.09**	0.59	**0.05**	**0.01**	0.43	0.41	0.24	0.61	0.24	0.12	0.29	0.34	0.15
	CI	**0.04**	0.92	0.71	**0.04**	**0.03**	0.34	0.27	0.17	0.81	0.14	0.11	**<0.01**	**<0.01**	0.25
Mansilla	BACIP	0.40	0.66	**<0.01**	0.36	**0.02**	0.29	**0.04**	0.22	0.56	**<0.01**	0.21	0.87	0.66	**0.08**
	BA	0.17	0.98	**<0.01**	0.13	**<0.01**	0.15	0.52	**0.10**	0.29	**0.01**	0.23	**<0.01**	**<0.01**	**0.01**
	CI	0.59	0.56	**<0.01**	**0.02**	**<0.01**	0.53	0.92	0.17	0.85	**<0.01**	0.30	**0.10**	**0.09**	**0.01**
Yesa	BACIP	0.37	0.14	**0.04**	**<0.01**	**<0.01**	0.12	**0.06**	**0.01**	0.26	**0.10**	**0.06**	**<0.01**	**<0.01**	**0.05**
	BA	0.26	0.94	**<0.01**	**<0.01**	**<0.01**	0.96	0.71	**0.08**	0.69	**0.02**	**0.07**	**<0.01**	**<0.01**	**0.04**
	CI	**0.05**	0.65	**<0.01**	**<0.01**	**<0.01**	0.78	0.66	0.66	0.75	**0.06**	**0.08**	**<0.01**	**<0.01**	**0.02**
Pajares	BACIP	0.55	**<0.01**	**0.05**	**<0.01**	**<0.01**	**0.04**	0.24	0.68	0.64	0.30	0.55	**0.04**	**<0.01**	0.58
	BA	**0.09**	**<0.01**	**0.01**	**<0.01**	**<0.01**	**0.09**	0.32	0.83	**0.06**	0.20	0.73	**<0.01**	**<0.01**	0.69
	CI	**0.04**	**0.03**	0.74	**0.04**	**0.03**	0.29	0.98	0.89	0.29	0.73	0.36	**<0.01**	**<0.01**	0.44
San Pons	BACIP	**<0.01**	0.41	0.34	0.48	0.20	0.36	0.77	0.57	0.18	**<0.01**	**0.02**	0.19	0.18	0.30
	BA	**<0.01**	0.55	0.57	0.21	0.15	0.34	0.85	**0.07**	0.66	**0.03**	0.39	0.40	0.35	0.80
	CI	**<0.01**	0.82	0.89	0.67	0.34	0.19	0.61	0.44	0.44	0.47	0.73	**0.09**	**0.09**	0.47

Table 6.4 - p-values for the 11 selected dams and 14 selected hydrological indices obtained from the t-student test performed through the BACIP, BA and CI designs. Bold letter indicates significant differences between the pre and post impact series at the 10% level.

Reservoir	**Design**	**Hydrological Index**													
		L1	M4	M9	7LF	30LF	7HF	30HF	Jmin	Jmax	dPlow	dPhigh	nPos	nNeg	FRE3
Ullivarri	BACIP	0.44	**0.09**	**<0.01**	**<0.01**	**<0.01**	**0.01**	**0.01**	0.63	0.39	0.88	**0.05**	**0.08**	**0.07**	**0.08**
	BA	0.22	0.46	**<0.01**	**<0.01**	**<0.01**	**0.02**	**0.02**	0.75	0.51	**0.04**	0.13	0.82	0.81	0.89
	CI	**0.01**	**0.08**	**<0.01**	**<0.01**	**<0.01**	**<0.01**	**0.02**	0.76	0.32	**0.07**	**0.04**	**<0.01**	**<0.01**	**<0.01**
Ebro	BACIP	0.12	0.12	**<0.01**	**0.01**	**<0.01**	**0.06**	**0.02**	0.73	0.41	0.63	0.44	0.13	0.13	0.19
	BA	**0.01**	0.78	**<0.01**	0.16	**<0.01**	0.62	0.35	0.61	0.33	0.61	0.55	**0.01**	**<0.01**	0.69
	CI	0.48	0.22	**<0.01**	**<0.01**	**<0.01**	0.33	0.13	0.74	0.85	0.22	0.36	**<0.01**	**<0.01**	0.22
Boadella	BACIP	**0.01**	0.23	0.32	0.27	0.23	**0.02**	**0.06**	0.96	**0.09**	0.94	0.30	**<0.01**	**<0.01**	**<0.01**
	BA	**<0.01**	0.72	0.64	0.14	0.21	**0.05**	**0.10**	0.38	**0.07**	0.36	0.30	**<0.01**	**<0.01**	**0.01**
	CI	0.15	0.55	**0.05**	0.52	0.38	0.20	0.23	0.78	0.55	0.59	0.41	**<0.01**	**<0.01**	**<0.01**
Monteagudo	BACIP	**0.07**	0.14	0.69	0.71	0.82	0.63	0.56	**0.06**	0.24	**0.08**	0.85	0.85	0.85	0.50
	BA	**<0.01**	0.25	0.80	0.72	0.90	0.63	0.56	0.38	0.67	0.41	0.63	0.14	0.15	0.70
	CI	**<0.01**	0.66	0.20	**<0.01**	**<0.01**	**<0.01**	**0.10**	0.79	0.36	**0.71**	0.46	0.80	0.80	**<0.01**
Tranquera	BACIP	0.13	**0.03**	0.27	0.21	0.16	**0.03**	**0.07**	0.18	0.58	0.23	0.96	**0.04**	**0.04**	0.16
	BA	**0.01**	0.76	0.75	**<0.01**	**<0.01**	**0.07**	0.14	**0.02**	0.73	0.57	0.66	**0.04**	**0.05**	0.14
	CI	0.25	0.57	0.17	**<0.01**	**<0.01**	0.86	0.98	**<0.01**	0.98	**0.03**	0.55	**0.01**	**0.01**	0.51

Table 6.4 (*continued*).

Parallel, the examination of the CI results showed slightly worse results. CI design correctly evaluate 67% of the 64 significant HA and 74% of the 90 no-significant HA (Table 6.4). The major contrast was found in nNeg and nPos where 4 and 5 false negatives were produced, respectively. In addition, for 7HF and 30HF CI produced false negatives over 80% of the times. The worst agreement was found in La Tranquera and Monteagudo reservoirs where 4 false positives were detected while in Boadella reservoir CI produced 4 false negatives.

Finally, the comparison of BA and CI designs pointed out that both analyses agreed in 74% of the analyses. Major differences were found in the evaluation of nNeg where CI produced 4 false negatives and 7HF where it failed in recognizing 4 significant alterations. Moreover, the greatest differences were found in Ullivarri and Monteagudo reservoirs in which CI produced false positives in 6 and 5 HIs, respectively.

6.3.3 Estimation of the critical IHA values for the BA and CI designs

As expected, t-values and IHA either derived from the BA or the CI designs were strongly correlated (Figure 6.4). Therefore, regression analysis showed high fitting values (r^2) ranging from 0.72 (JMin) to 0.99 (nNeg) for IHA_{BA} and from 0.67 (dPhigh) to 0.98 (I1) for IHA_{CI}. This allowed us to obtain accurate thresholds above which IHA_{BA} and IHA_{CI} should be considered significant. Moreover, in most of the cases regression equations for BA or CI designs were similar, so that the thresholds were equivalent for many HIs (e.g. I1, dPlow; FRE3; Figure 6.4, Table 6.5). The critical IHA thresholds calculated for HIs associated with mean flow conditions range between 19 and 32% for I1 and M9 while they were 10% higher for M4 (Table 6.5). Critical threshold values for low flow HIs (7LF and 30LF) were lower (24-37%) than for high flow (7HF and 30HF; 29-55%). Threshold values for timing HIs commonly ranged between 27 and 35% although exceptionally high threshold values were obtained for the IHA_{CI} thresholds of JMax. Regression equations for dPlow and dPHigh produced the less restrictive threshold values, i.e. IHA should be higher than for other HIs to be considered significantly altered. They ranged from 44 to 64% for dPlow and were even higher for dPhigh (51-76%). In contrast, the analysis revealed that exceptionally low modifications of nPos (3.1-5.4%) and nNeg (2.4-4.2%) produced a significant alteration. Finally, critical threshold values for FRE3 ranged between 24 and 37%.

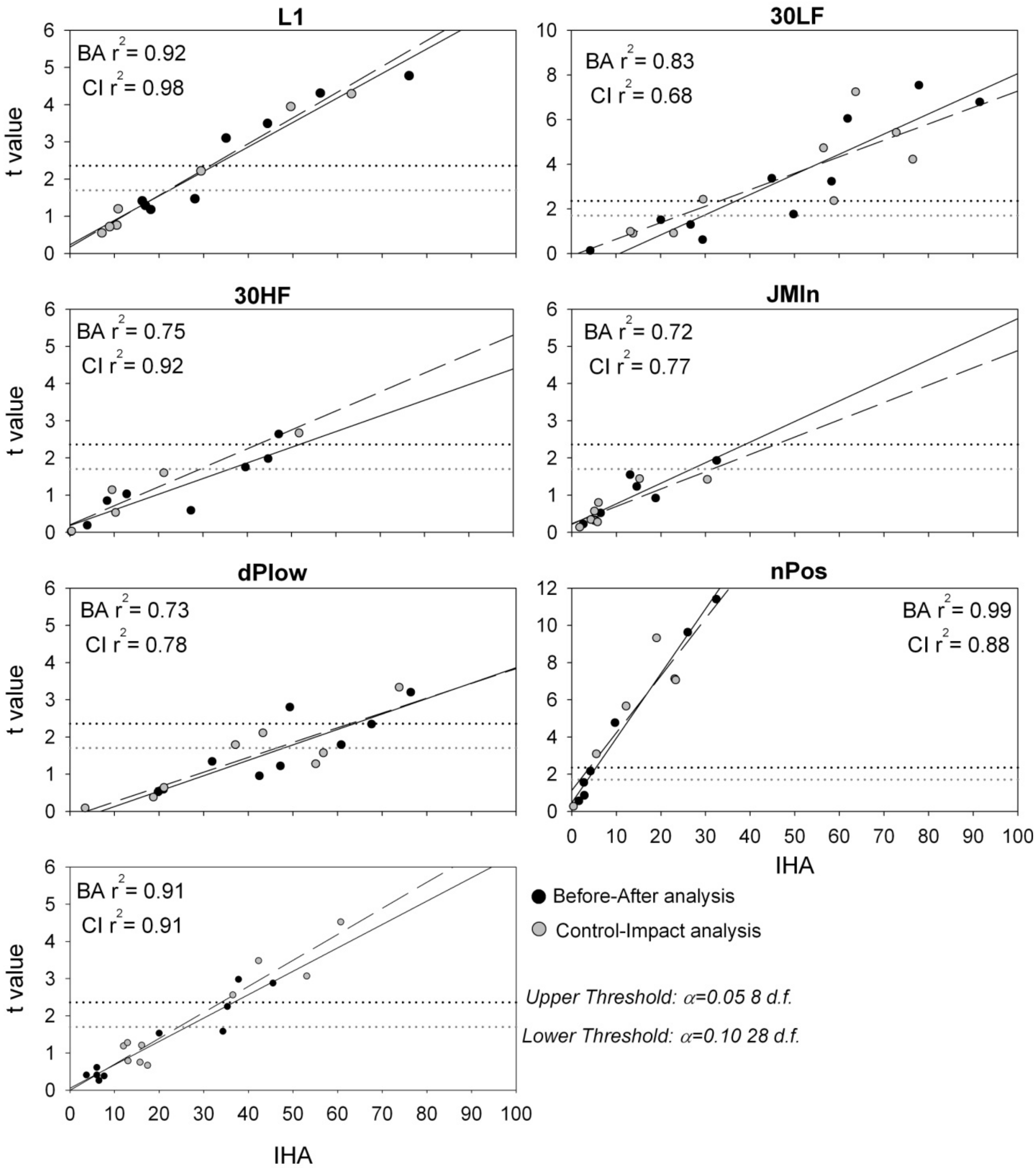

Figure 6.4 - Example of scatter plot and linear regressions of 7 IHA values versus the t-values calculated from the student's t-test of the BA (black circles and solid line) and CI designs (grey circles and dashed line). Dotted lines represent the upper ($t_{1-0.05/2,d.f.=8-1}$ =2,36) and lower ($t_{1-0.10/2,d.f.=28-1}$ =1,701) thresholds calculated for a t distribution.

		Lower IAH threshold	Upper IAH threshold
L1	BA	22.21	32.28
	CI	22	31.5
MeanApr	BA	32.9	41
	CI	36.2	48.7
MenaSep	BA	23.9	29.9
	CI	19.1	28.1
7LF	BA	30	34.8
	CI	25.6	32.5
30LF	BA	29.6	36.9
	CI	24.4	33.3
7HF	BA	40.2	55.1
	CI	32.2	49.4
30HF	BA	32.3	50.5
	CI	39.3	42.2
JMin	BA	27.8	40.1
	CI*	31.5	46
JMax	BA	32.2	45.3
	CI*	43.8	62.1
dPlow	BA	47.7	63.6
	CI	46.2	62.8
dPHigh	BA	51.1	73.3
	CI	51.2	75.5
nPos	BA	3.5	5.4
	CI	3.1	5.3
nNeg	BA	2.8	4.2
	CI	2.4	3.8
FRE3	BA	26.2	37
	CI	24.3	33.7

Table 6.5 - Critical thresholds for the 14 hydrological indices calculated from the linear regressions from IAHBA/IAHCI values versus the t-values. The upper threshold considered a 5% level of significance and 8.d.f. The lower threshold considers a 10% level of significance and 28 d.f. *No true positives (significant altered) were found.

6.3.4 Assessment of the Hydrological Classification (HC) and the Predicted Indices (HP) designs

HIs representing the magnitude of flows and especially M9, 7LF and 30LF, showed the largest ranges defined by the maximum and the minimum IHA, either for the HC and HP designs (Figure 5). Hence, these indices presented a greater proportion of not evaluable situations than the remaining HIs. For instance, it was found that for M9, 7LF and 30LF, 6, 5 and 4 of the 11 reservoirs could not be evaluated through the HC design. Parallel, 3, 4 and 5 of the 11 reservoirs could not be evaluated through the HP design. The number of not evaluable impacts regarding the remaining HIs ranged from 0 (Jmin) to 3 (dPlow) in the HC design and from 0 (Jmin, JMax and dPhigh) to 4 (nNeg) in the HP design.

The comparison between HC and BA revealed that the former correctly evaluated 80% of the 39 significant HAs and 74% of the 56 no-significant HAs. However, 25% of the analyses were not evaluable given the high overlap between the IHA_{Class} range and the critical IHA_{BA} threshold. L1 and dPlow presented the greatest disagreement between HC and BA. Moreover, San Pons and Montegaudo presented the highest rate of failure with 4 and 6 false positive, respectively.

Finally, the assessment of HP design pointed out very similar results to those obtained through HC. Hence, 87% of the significant HA and 77% of the no-significant HA were correctly evaluated while 25% of the HA were not evaluable. Results for M9 and dPlow presented the greatest disagreement with 3 false positive and 3 false negatives, respectively. Once again, the assessment of the Monteagudo reservoir presented the worst result with a total of 5 false positives.

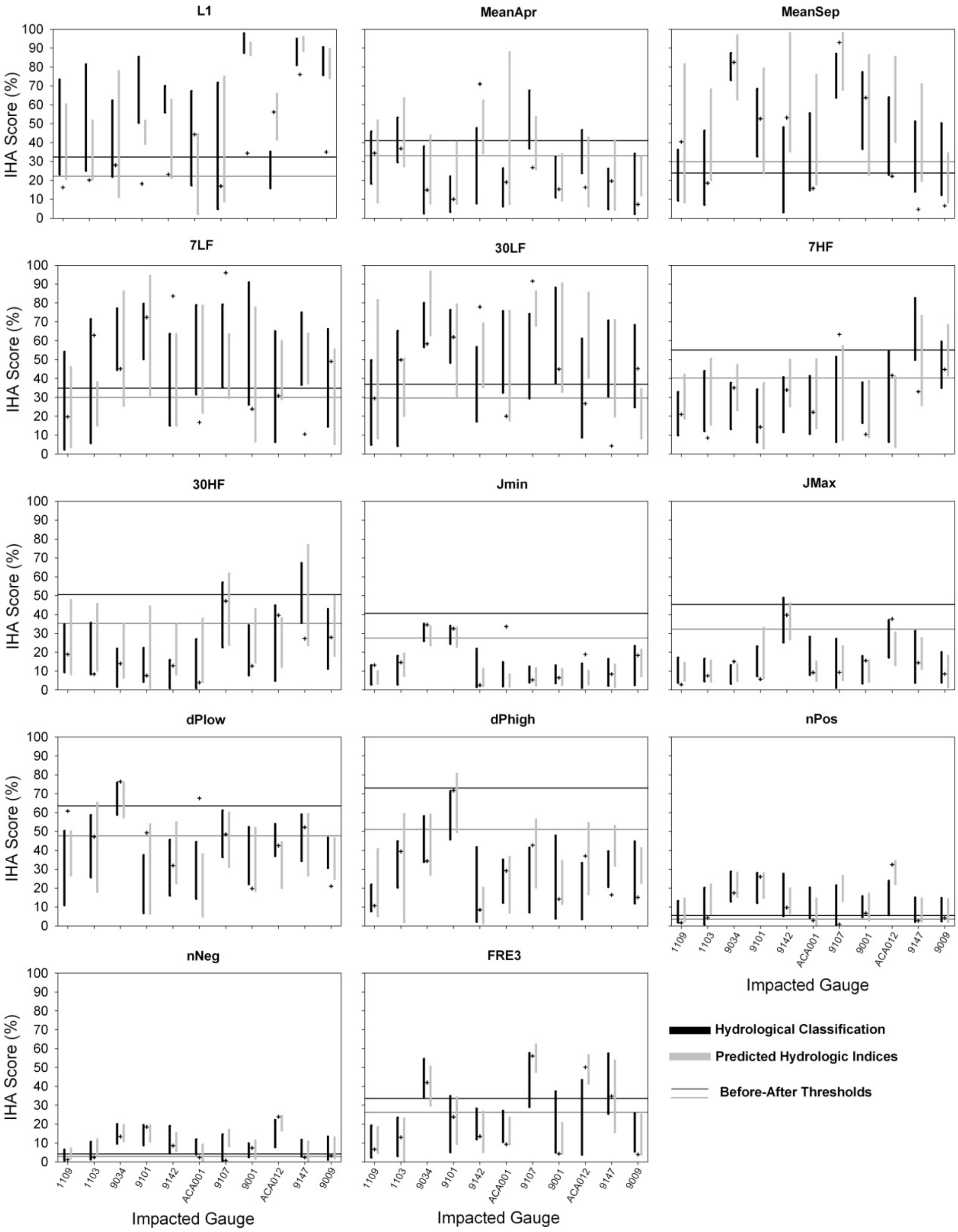

Figure 6.5 - Results of the HC (black boxes) and HP (grey boxes) designs to measure HA. Cross symbols represents the IHA calculated from the BA design. Solid lines represent the critical upper and lower values computed form the IHA_{BA} results.

6.4 Discussion

Application of IHA worldwide has highlighted a generalized flow regime alteration due to dams operation (Magilligan and Nislow, 2005; Döll et al., 2009), modification of catchment land uses (Zacharias et al., 2004; Yang et al., 2010) or climate change (Döll and Zhang, 2010; Schneider *et al.*, 2013). A complete evaluation of the HA was out of the scope of this work. However for several HIs, the HA assessment in the 11 selected reservoirs was consistent with other extensive studies (Maingi and Marsh, 2002; Batalla *et al.*, 2004; Fitzhugh and Vogel, 2011; Gao *et al.*, 2012). The Mediterranean character of the study area, the reservoir function and management schemes mainly explained the principal HAs found in the 11 reservoirs. Nonetheless, it was demonstrated that the evaluation of the HA varied according to the available hydrological data and the HA assessment design applied. Indeed, the HA assessment protocol presented in this study introduced a quantitative comparison of different designs and pointed out their potential benefits and shortcomings.

6.4.1 Comparison of Paired-Before-After-Control-Impact (BACIP), Before-After (BA) and Control-impact (CI) designs

The comparison between BACIP and BA designs revealed good agreement (>75% success evaluation). This indicated that in most of the cases the HA was mainly due to reservoir operations rather than a change in the climatic patterns or other factors, e.g. land cover, between the pre and the post-impact periods. Several studies at the regional (Morán-Tejeda *et al.*, 2011; Naik and Jay, 2011; Zhao *et al.*, 2012), continental (Schneider et al., 2013) and global (Döll and Zhang, 2010) scale pointed out the potential HA due to global climate change. For instance, several works carried out in the Iberian peninsula have highlighted changes in the streamflow evolution not related with flow management (Lopez-Moreno *et al.*, 2011; Morán-Tejeda *et al.*, 2011; Martinez-Fernandez *et al.*, 2013). Moreover, the HA cause by climate change may be equal or even higher than the effect produced by dams (Döll and Zhang, 2010) and may be specially evident in the Mediterranean regions (Schneider et al., 2013). However, it is widely recognized that change in climatic trends have been specially noticeable since 1990's (Döll and Zhang, 2010; IPCC, 2013). This is the most likely explanation for the lack of effect of climate variability in our analyses given that all but two of our post-impacted series covered a temporal window previous to this decade (Table 6.1). Nonetheless, our analyses also highlighted that for several HIs and reservoirs, BA design under or over estimated the HA. These differences might be a response to the climate variability (Magilligan and Nislow, 2005) or to changes in the catchment land uses (Martinez-Fernandez et al., 2013) between the two periods. For example, in Tranquera reservoir equivalent changes in the impacted and control gauges has been observed in four HIs (e.g. Fig. 1B and C). Contrary in the Ullivarri reservoir, the hydrological regime of the control gauge changed between the pre and post-impact series while these changes were masked in the impacted gauge due to dam operation (e.g. Figure 1D and 1F). These changes stressed the advantage of using control gauges. The wrong assessment of the HA using the extended BA design may yield ineffective management measures. Moreover, in the further example of the Ullivarri reservoir, certain restoration actions could even aggravate the HA impacts on the freshwater ecosystem. In this regard, the evaluation of the available data highlighted that it was possible to find a suitable control gauge for almost all the monitored impacted gauges. Hence, it is arguable to encourage the application of BACIP over the BA. This would be especially relevant for those HA assessments in which more recent flow series are to be used given the most probable effect of climate change.

The problem of climatic variability has been normally addressed using the method introduced by Yoo (2006). The method eliminates those years that present values of total annual precipitation or annual runoff over (wet years) or below (dry years) defined thresholds. However, it presents two main drawbacks. Firstly, the technique does not actually eliminate at all the effect of climate variability as the rising or declining trend of climate change would be patent both in high, low and normal years. On the other hand, the removal of a great number of years would greatly reduce the potential gauges that account with a minimum number of years to perform BA analysis. In contrast, in the

BACIP design the control and impacted gauges accounted with the same pre- and post-impacted series so that, they would be homogenously influenced by the climatic trends. Moreover, the differences between the impacted and control series would be maintained constant within each period independently of the type of year (wet, dry, and normal). Consequently, the BACIP design can be applied with a reduced number of years relative to the minimum of 15-year record recommended for the BA (Richter et al., 1996).

CI design overcame the problem of climatic variability as both control and impacted series cover the same time period. However, this design has been infrequently used in other HA assessments. In most cases the CI design has been applied to compare flow regimes recorded upstream and downstream of a target dam (Assani et al., 2006). The application of the upstream control approach may be restricted due to the scarcity of reservoirs with upstream and downstream gauges, as in the present study. In addition, homologous hydrologic character is not assured if control and impacted gauges were far away. For instance, Zhao el at (2012) used control and impacted gauges that were over 250 and 400 kms away. This distance probably induced hydrological changes associated with modifications of local precipitation patterns, catchment physiography and the join of main tributaries. Thus, upstream control approach may be subjected to significant uncertainty.

In contrast with other approaches (Assani *et al.*, 2006; Caruso, 2013), the protocol presented in this study established the hydrological class membership as the critical requirement to select control gauges (Arthington et al., 2006). Inductive hydrologic classifications (Olden et al., 2012) arrange streams into groups that are most similar relative to the characteristics of their flow regime. Therefore, it is arguable that hydrologic classification represents the most effective and objective approach to select control gauges. The good agreement between CI and BACIP and between CI and BA indicated that the selected control and impacted gauges presented equivalent hydrologic character. Hence, it is likely that differences regarding the HA was derived from the influence of reservoirs and not by the dissimilarity between gauges.

Notwithstanding, we also found discrepancies between CI and BACIP for several HIs and reservoirs, which means that class membership do not assure a complete hydrological homogeneity in all the cases. In this sense, contrary to BACIP design, when natural differences exist between the control and impact gauges (e.g. Figure 1B and F) CI failed in detecting the actual effect of the reservoir. Finally, it must be pointed out that the highest discrepancies were observed in reservoirs belonging to classes 5 and 6 where unimpaired gauges were especially scarce. Hence, the selection of the optimal control gauge is subjected to the available gauges in the class. This might hinder the application of the CI design.

6.4.2 Estimation of the critical IHA values for the BA and CI designs

The original IHA method (Richter et al., 1996) did not include any threshold beyond which the HA should be considered significant. It was widely accepted that the higher the IHA the higher the probability that the flow conditions were out of the natural range (Maingi and Marsh, 2002; Batalla *et al.*, 2004; Caruso, 2013). Afterwards, the Range of Variability Approach method (RVA; Richter *et al.*, 1997; RVA; Richter *et al.*, 1998) introduced the analysis of the frequency of non-attainment of fixed targets for each HI (e.g. ± 1 standard deviation). The method also included the categorization of numerical HA into a few qualitative arbitrary classes (little: 0-33%; moderate: 34-66%; high: 67-100%). Following similar rationale, Black et al. (2005) and Martinez and Fernandez (2006) proposed impact severity classifications composed by 5 classes while other works assumed significant alterations when IHA get over 50% (Fernandez et al., 2012). The direct relationship between HA and the statistical significance is evident. However, several studies agreed with our results in that similar IHAs values may cause a significant or no-significant HA depending on the HI (Magilligan and Nislow, 2005; Costigan and Daniels, 2012). Moreover, our results highlighted that IHA below 30% are statistically significant for many HIs which contrast with the widely accepted thresholds described above. This result is especially relevant for the adoption of further restoration measures.

On the other hand, it is clear that the t-test used in this study only provide statistical inference regarding the hydrologic changes. It was not testing if the HA was environmentally important. However, it represents an objective starting point facing further adaptative management based on the development of specific flow alteration-ecological response relationships (Poff et al., 2010).

6.4.3 Assessment of the Hydrological Classification (HC) and the Predicted Indices (HP) designs

As expected, HC and HP designs showed worse results than BA and CI. Analysis revealed that a significant degree of uncertainty rose when these designs were applied. Uncertainty was mainly associated with the 25% of the cases that could not be evaluated. Contrary to expected, the larger HA ranges were found for those HIs that presented the most critical role in the hydrological classification (Chapter III) and the most accurate predictive models (Chapter V), i.e. the magnitude HIs. However, this result was not entirely surprising given the great spatial variability of these HIs. The classification procedure maximized the differences between classes in regard to magnitude HIs but a certain level of dissimilarity within classes still remained. On the other hand, predictive models for the magnitude HIs explained the greatest part of their spatial variability (adjusted-R^2 >0.70). However, given the large spatial variability, the unexplained part of the spatial variability still provides an important degree of uncertainty. This contrasts with the result obtained for timing and rate of change indices. Models of these indices were less accurate than those of magnitude indices but they also presented lower differences between rivers which explained the small IHA ranges found.

Beyond the not-evaluable cases, it must be also pointed out that 75% of the evaluable cases in both the HC and HP designs were correctly assessed. Despite the ability of HC and HP to quantify the HA showed in this and other studies (Arthington *et al.*, 2006; Eng *et al.*, 2013), the development of rainfall-runoff models has been usually chosen as the best option (Murphy et al., 2013). However, the quality of the series may be conditioned by various factors (Eng et al., 2013) and some studies have demonstrated their limitation to be effectively applied in hydroecological studies (Murphy et al., 2013). Moreover, the application of this approach has rarely accounted with the estimation of the uncertainty in the HA (Meile *et al.*, 2011; Fernandez *et al.*, 2012) or it was just used to define the benchmark below which the HA could not be evaluated (Black et al., 2005). Hydrological classifications are currently view as a relevant procedure to guide hydroecological research (Kennard et al., 2010; Snelder and Booker, 2013) but they have been rarely used to establish the baseline condition as proposed by Arthington et al. (2006). Our results highlighted the potential applicability of this design to evaluate HA when data availability is very limited. In addition, the use of hydrologic classification was enhanced given that the degree and direction of alteration would also depend upon the hydrologic characteristics of the impacted river, i.e. its hydrological class (Poff *et al.*, 2007; McManamay *et al.*, 2012). Similarly, in few times the evaluation of the HA has been addressed by means of predictive models (Carlisle *et al.*, 2010; Knight *et al.*, 2011). Awareness of the model error represented a critical issue when applying this design. For instance, Knight et al. (2011) probably overestimated the ability of the models to quantify the HA because model errors were ignored in the assessment process. In contrast, Carlise et al. (Carlisle *et al.*, 2010) considered model error as the threshold below which a specific HA could not be detected. For example, if the model presented a 20% of error they argued that only departures from natural hydrologic condition greater than 20% were evaluable. The fully recognition of the model error might be based in the definition of confidence bands to account for this uncertainty (Acreman et al., 2008), as it was established in this chapter.

6.5 Conclusion

The HA assessment protocol presented in this study may be more important than the results discussed. While individual works worldwide have focused in just one approach to assess HA, this protocol provides different alternatives depending upon the availability of data. Therefore, it represents a valid approach in different situations that may guide future management actions and the implementation of restoration and conservation measures. The assessment of the different designs highlighted that the BA was able to correctly identify most of the significant and no-significant HA. Nonetheless, assuming that the influence of climate and land uses changes will be especially evident for future decades and that most of the impacted gauges account with a control gauge, we emphasize the application of the BACIP design. However, the lack of pre-impact series to monitor the majority of the reservoirs required the proposal of alternative designs. CI design overcame the problem of climatic variability between periods and in general presented an equivalent ability to detect HA as BA design. Moreover, the use of a hydrological classification as the basis to select the control gauges provided excellent results regarding the similarity between control and impact gauges. On the other hand, it was patent that the application of fixed perturbation thresholds for all the HIs may be translated in inadequate restoration measures. It was out of the scope of this study to provide definitive critical thresholds but our results highlighted that a further research in this issue is well needed. For instance, in this study we only presented thresholds obtained from hydrological data and statistical inference. These results are the basis to guide future research that analyse the impact of flow alteration on fluvial processes and communities which would allow to state final restoration measures. Lastly, it was demonstrated the potential utility of HC and HP designs to assess HA in scarce data situation. However, the heterogeneity of hydrological character in the rivers posed a major uncertainty to the application of these methods. Water managers must be totally concerned with the uncertainty issue which must be awarded before management measures are implemented. Finally, the protocol introduced in this paper did not account for these situations in which neither pre-impact nor post-impact series are available. An extra design able to simulate synthetic impacted flow series should be further introduced in the protocol to fulfil all possible situations.

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Chapter VII

General conclusions and future research

Chapter VII. General conclusions and future research

6.1 General conclusions

Classifications, regressions and predictive models are tools that allow us to discriminate the spatio-temporal natural hydrological variability from one caused by specific human alterations. These methodological procedures are subjected to an important level of uncertainty which can significantly influence the assessment of hydrological alterations and other water management issues. Moreover, evaluation of hydrological alteration is exposed to other sources of variability that can only be controlled through the application of proper statistical designs that contrast with more classical approaches. In this regard, water resource management needs to minimize uncertainty in the decision-making process. Providing suitable tools would allow managers recognizing more rigorously the effect that specific water uses would have on fluvial ecosystem and, thus, define consistent measures to minimize impacts. Moreover, quantifying objectively the uncertainty associated to the assessment process is the only way to establish the degree of confidence in the management decisions to be taken.

In this thesis we have compared quantitatively potential sources of uncertainty during the assessment of hydrologic alteration, using a variety of procedures and data for the same study area, which has been rarely done previously. Conclusions extracted from each study chapter provide managers and scientist important insights about the level of uncertainty that they should consider when analyzing the natural hydrologic variability and evaluating the hydrological alteration at the regional scale.

Following, general conclusions are presented for each chapter of the thesis:

Chapter III. The influence of methodological procedures on hydrological classification performance.

- The initial treatment of the flow series greatly influenced the interpretation of hydrological classifications. The use of raw flow series segregated the river network according almost exclusively to the size of the river and the magnitude of flows. In contrast, the hydrological classification based on normalized flow series accounted with a wider spectrum of hydrological features than the former.

- Characterising and segregating rivers based only on flow magnitude provided a significant loss of hydrological information within the classification which limits its use to evaluate the hydrological alteration. Moreover, such limited information would also restrict the development of flow-ecological response relationships to those that are directly influenced by the flow magnitude such as habitat availability. In contrast, segregating rivers according to a larger spectrum of hydrological attributes widens the potential range of flow alterations that can be properly evaluated. Assessment of hydrological alteration carried out worldwide has demonstrated that many other flow attributes different from flow magnitude may be potentially altered by human perturbations. Hence, classify rivers according to normalized flow data is an adequate procedure allowing user to gain a more complete perspective regarding flow alterations.
- The use of the Predict-then-Classify approach enhanced the robustness of the classifications and provided higher ability to discern hydrological attributes than the Classify-then-Predict approach. Predict-then-Classify approach produced classes that presented higher intra-class homogeneity and higher inter-class heterogeneity than those derived with the Classify-then-Predict approach. Those features are very valuable when evaluating hydrologic alteration, as it provides classifications with a greater ability to discern between the actual effect of the perturbation and the natural variability within the class. In addition, the more robust the classifications are the greater ecological difference between classes should be expected. Therefore, classifications developed trough Predict-then-Classify approach represent the best strategy to further detect not only the hydrological alteration caused by human perturbations but the ecological impact associated to this alteration.

- The Predict-then-Classify approach generated more even subdivisions of the river network. It also overcame the limitations of other approaches regarding the over and underrepresented parts of the observed hydrologic space. All of them are desirable characteristics of classification as they represent clear advantages to assess the hydrological alteration. Hence, Predict-then-Classify approach increases the probability that the actual flow regime of a specific river corresponds to the hydrologic character of its predicted class which greatly reduces the uncertainty of further hydrological assessments. It also promotes that control gauges are equally represented for all the hydrological classes, maximizing the number of potential control gauges to be use within a before-after-control-impact design.
- The selection of the most suitable number of classes is difficult to be accomplished from completely objective criteria, as many times, classification with different degree of detail presented similar statistical performance. We recommend the use of classifications with a reduced number of classes in first instance that allows users to overview the general hydrological patterns in the study area. Classification with few classes increases the potential number of control gauges to be found for a specific altered gauge. Results demonstrated that more detailed classifications do not assure a greater homogeneity within classes and hence, gauges in each class are supposed to be equally suitable controls independently of the classification detail. In addition, the classification structure can be adapted and refined in subsequent steps according to further necessities.

Chapter IV. Sources of variation in hydrological classifications: Time scale, flow series origin and classification procedure.

- Contrary to expected, reduction of the time scale detail from daily to monthly date did not seriously compromise classification properties. Hence, if daily gauges do not account with the desirable quality, the use of monthly flow series to develop hydrological classifications represents a very valuable alternative to assess flow alteration and define ecologically similar groups. However, caution should be employed when using monthly classification from those hydrological indices not considered in determining the classification structure.

- Predictive classifications based on empirical relationships between classes and catchment attributes represents a better strategy to those based on flow series derived from rainfall-runoff models. Modelled flow series produced classifications with a significant lower statistical performance and a fairly different spatial arrangement to those based in gauged flow series. Hence, the source of data (raw against modelled) seemed to pose a significant impediment to provide accurate hydrological classifications from which assess hydrological alteration. The selection of control gauges based on these classifications would increase the uncertainty regarding the homogeneity between the control and the impact gauges, i.e. control gauges would not act as actual controls. Parallel, the use of heterogeneous classes would fail in discerning if a hydrological change is actually due to the presence of a perturbation or to the large intra-class variability. Therefore, the use of this strategy must be restricted to regions lacking gauged information in all the hydrological types potentially present in the region. However, if this approach is the unique alternative, further restoration measurements defined from these results must be used carefully.

- This study also demonstrated how the selection of hydrological indices, the criteria and the procedure used to segregate river reaches is the most important feature that influences classification properties. The low performance, the uneven distribution of classes and the lack of ability to differentiate hydrological character in the expert driven classification constitute serious drawbacks for the application of this classification in many water management uses. For instance, the expert driven classification used in this study was based in the hydroregions map at the national scale promoted by Spanish government agencies. It was developed to support the definition of the environmental flows that should be incorporated in the basin management plans. Attending to our results we encourage water managers to review the specific flow aspects defined with base on this classification and establish the degree of uncertainty in the final environmental flow proposals.

Chapter V. A comparison of statistical techniques and strategies to model hydrological indices to ungauged rivers.

- Models developed for hydrologic indices representing magnitude and frequency attributes explained much of the actual spatial variability and obtained accurate predictions. Notwithstanding, due to the large hydrological heterogeneity within the study region, models still failed in explaining an important part of the spatial variability of these flow attributes. The accuracy of models must be acknowledged to define the uncertainty with which predictions can be used in further management applications. Such a critical issue has still been addressed vaguely in the literature.
- Deeper research is needed to develop models capable to explain the spatial variability of other flow attributes such as timing, duration or rate of change attributes and also, to improve models of magnitude and frequency indices. We believe that a first step would be to increase the spatial resolution of attributes related to edaphology and geologic character as well as groundwater dynamics. In addition, providing more detailed climatic variables and the inclusion of other attributes, such as the process related with snow accumulation and melt, would also increment the ability to unravel hydrologic character regarding flow variability, timing or duration of droughts. Improvement of models is an essential objetive that should be accomplished to reduce the uncertainty to asses flow alteration or establish flow-ecological responses. Once these weakness are solved the prediction of hydrological indices approach pose a promising aptitude to carry out these objectives.
- The four complex statistical techniques, in general, outperformed linear models, although the improvement in performance was not as large as expected.

Machine learning techniques need large data bases to fit accurate models, while the relatively reduced gauge network used in this study has likely posed some flaws in their abilities to establish better relationships. If a proper data base is used, we believe that these techniques will provide a higher potential to overcome linear models, as their ability to deal with non-linearity and variable interaction has been largely demonstrated in literature.

- Development of ANFIS and ANN models required high statistical and informatics skills to find the optimal model structure and completely understand the causal relationships between hydrological indices and predictor variables. On the other hand optimal data transformation had to be found for the applications of MLR and GAM, which was not always achieved. All these features together with the prediction accuracy must be evaluated when selecting the most suitable technique. Moreover, providing tools that allow understanding not only the statistical but the physical links between variables is a key aspect to determine management measures and define the expected range of ecosystem response to these measures.
- The segregation of gauges according to their hydrological similarity did not enhance model accuracy for all classes. One of the main reasons by which the RRA did not succeed in all classes was the limited amount of sites to construct each class model. A larger number of gauges to fit the models in each individual class may improve global models. However, this improvement would also rely in the acquisition of more precise predictor variables, as the variability of the hydrological attributes within each class is reduced in comparison to entire gauge domain. Hence, relationships do not respond only to regional patterns but also to local factors.

Chapter VI. Assessing hydrologic alteration: Evaluation of different alternatives according to data availability.

- The combination of control gauges within the extensively applied before-after analysis to evaluate hydrological alteration assured that the observed shifts in the flow regime were exclusively due to reservoir operations. The evaluation with and without control gauges, BACIP and BA designs respectively, showed good agreement. However, we also demonstrated that it was possible to find suitable controls for all the impacted gauges. Hence, we believe that the use of controls must be considered in every assessment as BACIP is the unique design that provides managers the total certainty of the actual hydrological alteration. For instance, it is acknowledged that climate trends have significantly influenced flow regimes in last decades, so control for climatic variability is a critical element to be taken into account for future assessments. This will allow establishing the most scientifically defensible restoration measures and ecological flow regimes, while it would reduce the confrontations between water users due to imprecise definitions of potential alterations.
- Results highlighted that the hydrological classifications represented an optimal tool for the selection of suitable controls. Two gauges belonging to the same hydrological class presented a high degree of hydrological similarity. When this attribute is combined with other criteria (e.g. geographical distance) to control for local variability, the ability of controls to detect changes in the impacted gauges is increased and it could well substitute other approaches, such as the upstream control design. Nonetheless, as it has been pointed out repeatedly, scientists must provide classifications that minimize the uncertainty regarding the hydrological heterogeneity within classes. The use of unsuitable classifications would invalid the selection of controls and yield inaccurate evaluations.
- The definition of thresholds to determine the degree of hydrological alteration must be supported by objective criteria. We demonstrated that critical

thresholds showed large differences depending on the hydrological index considered. In addition, results showed that thresholds established in many previous studies are well above those calculated in this study. This represents a critical aspect regarding water resource management and the establishment of ecological flow regimes, as we might be detecting alterations when there is just large natural variability or not detecting them when they are there.

- Hydrological classifications and predicted hydrological indices from unimpaired gauges are suitable alternatives when other hydrological data lacks. We believe that being able to acknowledge the level of uncertainty for each considered hydrological index is in itself a much desired result when evaluating hydrological alterations.

6.2 Future research

According to the objectives established in this thesis, we identified and evaluated several critical aspects within the ELOHA framework and stated important issues to be taken into account in water management issues. In addition, this work also revealed the existence of certain deficiencies that should drive future research:

- The development of new catchment and climatic variables capable to explain the actual variability of all the attributes of natural flow regime attributes is needed. This task will be very valuable to improve classification procedures and the prediction of hydrological indices and will aid researches to entirely understand the hydroecological patterns of the region. Moreover, more accurate predictions will be very valuable to apply alternative methods to assess hydrological alteration with higher confidence.
- The protocol to assess the hydrological alteration within this thesis was validated uniquely through the analysis of changes caused by dams. It is essential to widen the range of targeted perturbations to completely determine the benefits and drawbacks associated within each design. In this regard, the

effect of land use evolution and the potential impact of projected climate change should also be evaluated.

- The hydrological alteration assessment protocol did not include any alternative to evaluate those cases in which neither pre- nor post-impact series were available. The studies focusing this issue are still scarce in the literature and deeper research is needed to cover all the possible situations in which the assessment of hydrological alteration has to be done.
- The critical thresholds to consider significant hydrological alterations were established based on results of just 11 reservoirs. This analysis must be extended to the whole river network both in our study area and the rest of the Iberian Peninsula to define more robust values. These thresholds could be then incorporated in future water management guidelines at the national scale to reduce levels of uncertainty in the decision-making process.
- Finally, two critical steps within the ELOHA framework and the environmental flows field were not covered in this thesis: The establishment of quantitative relationships between flow regime and ecological responses together with the determination of the consequences of flow alteration over ecological processes. These issues need to be investigated deeply. The current data base developed for the study area covered in this thesis do not account only with hydrological information but with more than 2000 sample sites regarding river physical, physico-chemical and biological information. This represents a superb opportunity to accomplish an important advance in this field of knowledge. The development of this research will provide scientists and managers with robust tools to define objective restoration measures and environmental flow regimes.

Appendix

Hydrological indices used in classifications

APPENDIX: Hydrological indices used in the classifications

Table A1 - Hydrological indices derived from daily gauged data. Overall mean and standard deviation (referred in the manuscript by the prefix sd) of annual values for each index except for I1, I2, lca, lcv, ikur, X5, X25, X75, X95, MxM1-MxM12, MnM1- MnM12, pred, dPHigh,MeanPos and MeanNeg. I1 was not calculated for Normalized flow series.

Flow attributes and indices	Description
Magnitude of annual and monthly flows	
I1	Linear moment that represents the mean of the calculated flow duration curve
I2	Linear moment that represents the variance of the calculated flow duration curve
lca	Linear moment that represents the skewness of the calculated flow duration curve
lcv	Linear moment that represents the coefficient of variation of the calculated flow duration curve
ikur	Linear moment that represents the kurtosis of the calculated flow duration curve
M1-M12	Mean monthly flow.
MxM1-MxM12	Maximum monthly flow
MnM1- MnM12	Minimum monthly flow
Magnitude and duration of annual extremes	
1LF	Magnitude of minimum annual flow of 1 day duration.
7LF	Magnitude of minimum annual flow of 7 days duration.
30LF	Magnitude of minimum annual flow of 30 days duration.
90LF	Magnitude of minimum annual flow of 90 days duration.
X75	Mean magnitude of flow exceeded 75% of the time
X95	Mean magnitude of flow exceeded 95% of the time
1HF	Magnitude of maxima annual flow of 1 days duration
7HF	Magnitude of maxima annual flow of 7 days duration
30HF	Magnitude of maxima annual flow of 30 days duration
90HF	Magnitude of maxima annual flow of 90 days duration
X25	Magnitude of the flows exceeded 25 % of the time.
X5	Magnitude of the flows exceeded 5 % of the time.

Flow attribute and indices	**Description**
Magnitude and duration of annual extremes (cont)	
ZFD	Number of zero flow days
BFI	Seven-day minimum flow divided by mean annual daily flows
Timing of extreme flow events	
JMin	Julian day of minimum flow
JMax	Julian day of annual maximum flow
pred	Predictability
Frequency and duration of high pulses	
FRE1	Number of high flow events per year using an upper threshold of 1 time median flow over all years
FRE3	Number of high flow events per year using an upper threshold of 3 time median flow over all years
FRE7	Number of high flow events per year using an upper threshold of 7 time median flow over all years
nPHigh	Number of high pulses within each year
DPHigh	Duration of high pulses within each year
4) Rate and frequency of flow changes	
meanPos	Mean of all positive differences between days
nPos	Number of days with increasing flow
meanNeg	Mean of all negative differences between days
nNeg	Number of days with decreasing flow
reversal	Number of hydrologic reversals

Table A1 – *(continued)*

Table A2 - Hydrological indices computed from monthly flow series. Overall mean and standard deviation (referred in the manuscript by adding sd to the abbreviation name of the variable) of annual values for each index were obtained except for l2, lca, lkur, MH1-MH12, ML1-ML12, X5, X25, X75, X95, ZFM, FRE3m and FRE7m

Flow attributes and indices	Description
Magnitude of annual and monthly flows	
l2	Linear moment that represents the variance of the calculated flow duration curve
lca	Linear moment that represents the skewness of the calculated flow duration curve
ikur	Linear moment that represents the kurtosis of the calculated flow duration curve
M1-M12	Mean monthly flow.
MH1- MH 12	Mean maximum monthly flows for all months
ML1-ML12	Mean minimum monthly flows for all months
Magnitude and duration of annual extremes	
M2LF	Mean magnitude of 2-month-duration minimum annual flow
M3LF	Mean magnitude of 3-month-duration minimum annual flow
MLF	Mean of the mean minimum flows
X95	Mean magnitude of flow exceeded 95% of the time
M2HF	Mean magnitude of 2-month-duration maximum annual flow
M3HF	Mean magnitude of 3-month-duration maximum annual flow
MHF	Mean of the mean maximum flows
X5	Magnitude of the flows exceeded 5 % of the time.
ZFM	Percentage of months with zero flow
Frequency of High Flows	
FRE3m	Number of high flow events per year using an upper threshold of 3 times the median flow over all years
FRE7m	Number of high flow events per year using an upper threshold of 7 times the median flow over all years

Table A3 – Hydrological indices used in the expert knowledge classification based on monthly modeled flow series. The classification is based on the combination of the mean (intrannual) and the coefficient of variation (interannual) of annual values for each index

Index	**Description**
MI1	Minimum monthly discharge/ mean annual discharge
MA1	Maximum month discharge/ mean annual discharge
MI2	Mean of the 3 Minimum Monthly discharge/ mean annual discharge
MA2	Mean of the 3 Maximum Monthly discharge/ mean annual discharge

Supplementary material

Supplementary material

We provide a DVD with the following supplementary material:

- PhD dissertation in digital format.
- Initial flow series used in classifications and statistical models.
- Derived Hydrological Index from flow series.
- Environmental data used to develop predictive classification and statistical models.
- Results of all the ANOVA analysis performed in Chapters III and IV
- Classifications of the Synthetic River Network using the four approaches introduced in Chapter III
- Predictions of Hydrological Indices for the Synthetic River Network using Random Forest Technique.

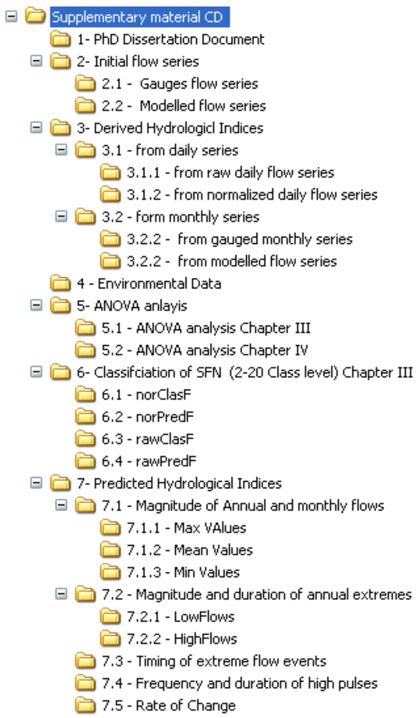

Figure S1 - DVD folder structure