UNIVERSITAT POLITÈCNICA DE CATALUNYA
BARCELONATECH
Department of Civil and Environmental Engineering

PhD programme in Environmental Engineering

Doctoral Thesis

Data–driven Bayesian Networks modelling to support decision–making: Application to the context of Sustainable Development Goal 6 on water and sanitation

by

DAVID REQUEJO CASTRO

Advisors:

Dr. AGUSTÍ PÉREZ FOGUET
Dr. RICARD GINÉ GARRIGA

Barcelona, April 2021

ABSTRACT

We live in a complex and interconnected world which permeates different scales, sectors or decision problems. This fact is acknowledged by the United Nations 2030 Agenda for Sustainable Development, which underscores current global challenges, recognizes their interconnectivity and calls for international action. It is recognized that the connected nature of the issues we currently face have been tackled by “silo” approaches, separating the complexities of the real–world into specialized disciplines, fields of research, institutions and ministries, each one focused on a fraction of the overall truth. Similarly, it is widely recognized the need of a major shift in decision–making processes towards more holistic and integrated approaches. Evidence–based decision–making involves complex processes of considering a wide range of information of different nature. Nowadays, available data can support these processes, but methodologies to effectively integrate these data are lacking.

With the aim to contribute in this direction, this thesis focuses on the increasing use of Bayesian Networks (BNs) modelling as an approach to accommodate complex problems and to support decision–making. Common practice employs separately expert knowledge and empirical data to build and apply associated models. Despite of the demonstrated utility of this practice, in an era where the data are bigger, faster and more detailed than even before, there is still room for further exploration. Thus, this dissertation proposes a data–driven Bayesian Networks approach to combine expert opinion and quantitative data to support informed decision–making.

We propose two systematic methods to this end. First, we use our approach to replicate composite indicators (CI)–based conceptual frameworks, which represent expert knowledge, through the use of structure learning algorithms, which characterizes this data–driven Bayesian Networks approach. Second, we use our approach to identify interlinkages associated with a complex context, coupled with a statistical technique (i.e. bootstrapping) to reduce results uncertainty and with a comprehensive result robustness analysis (i.e. expert knowledge).

For testing and validating the proposed approach, this thesis takes the Sustainable Development Goal 6 embedded on the 2030 Agenda as a reference point, with particular attention to the water, sanitation and hygiene sector.

Our results emphasize the likely utility of the data–driven Bayesian Networks approach adopted. First, it allows the integration of both expert knowledge and data availability when dealing with BNs modelling and it accurately replicates (CI)–based conceptual frameworks. As added values, this combination improves model inference capacity, it reduces and quantifies the key variables that explain a pre-defined objective variable (implying important advantages in data updating), and it identifies the interlinkages among the variables considered (which might enhance more integrated actions). Second, the approach adopted is useful to accommodate a thorough analysis and interpretation of the complexities and interdependencies of any context at hand. As added values, interlinkages identification is spurred on by the available data and this identification makes the

approach more suitable than the use of composite indicators. Third, the systematic nature of the methodological contributions associated with the proposed approach can be adapted to different complex problems. Thus, it might expand and deepen the knowledge about the validity, reliability and accuracy of using BNs modelling.

RESUMEN

Vivimos en un mundo complejo e interconectado que impregna diferentes escalas, sectores o problemas de decisión. Esta visión es destacada por la Agenda 2030 para el Desarrollo Sostenible de las Naciones Unidas, que además pone de manifiesto los desafíos globales actuales, reconoce su interconexión y hace una llamada a la acción internacional. Por otro lado, es ampliamente reconocido que la naturaleza conectada de los problemas a los que nos enfrentamos actualmente se ha abordado mediante enfoques "estancos", separando las complejidades del mundo real en disciplinas especializadas, campos de investigación, instituciones y ministerios, cada uno centrado en una parte de la verdad. De igual manera, es reconocida la necesidad de un cambio de paradigma en los procesos de toma de decisiones hacia enfoques más holísticos e integrados. La toma de decisiones basada en evidencias lleva implícita procesos complejos en los que se integran una amplia gama de información de diferente naturaleza. Hoy en día, los datos cuantitativos disponibles pueden respaldar estos procesos, pero faltan metodologías para integrar estos datos de manera efectiva.

Con el objetivo de contribuir en esta dirección, esta tesis se centra en el uso de modelos de Redes Bayesianas (BNs), como un enfoque válido para abordar problemas complejos y, en última instancia, para apoyar la toma de decisiones. En la práctica, se emplea comúnmente por separado el conocimiento de expertos y los datos empíricos para construir y aplicar estos modelos. A pesar de la utilidad demostrada de esta práctica, en una era en la que los datos son más numerosos, más rápidos y más detallados que antes, hay espacio para explorar hasta dónde pueden llegar estos datos. En este sentido, esta tesis propone un enfoque de Redes Bayesianas basadas en los datos que permite combinar el conocimiento experto y la información cuantitativa existente para, en última instancia, apoyar la toma de decisiones.

Se proponen dos métodos sistemáticos para tal fin. En primer lugar, se emplea dicho enfoque para replicar marcos conceptuales basados en indicadores compuestos (IC), que representan el conocimiento experto, mediante el uso de algoritmos de aprendizaje de estructuras, que caracteriza este enfoque de Redes Bayesianas basado en datos. En segundo lugar, se utiliza el enfoque propuesto para identificar las interrelaciones existentes dentro de un contexto complejo, junto con una técnica estadística (bootstrapping) para reducir la incertidumbre de los resultados y con un análisis bibliográfico exhaustivo (conocimiento experto) para demostrar la robustez de los resultados obtenidos.

Para testear y validar el enfoque propuesto, esta tesis toma como punto de referencia el Objetivo de Desarrollo Sostenible 6 que forma parte de la Agenda 2030, con especial atención al sector del agua, el saneamiento y la higiene.

Nuestros resultados ponen de manifiesto la potencial utilidad del enfoque adoptado de Redes Bayesianas basadas en los datos. Primero, este enfoque permite la integración de conocimiento experto y de información cuantitativa a la hora de construir las RBs, y replica con precisión los marcos

conceptuales basados en IC. Como valor añadido, esta combinación mejora la capacidad de inferencia del modelo, reduce y cuantifica las variables clave que explican una variable objetivo predefinida (lo que implica importantes ventajas en la actualización de datos) e identifica las interrelaciones entre las variables (lo que podría potenciar acciones más integradas). En segundo lugar, el enfoque adoptado es útil para dar cabida a un análisis e interpretación exhaustivos de las complejidades e interdependencias de cualquier contexto en cuestión. Como valor añadido, la identificación de las interconexiones se realiza exclusivamente en base a los datos disponibles. Además, el considerar dichas interconexiones hace que este enfoque sea más adecuado que el uso de IC. En tercer lugar, la naturaleza sistemática de las contribuciones metodológicas asociadas al enfoque propuesto puede adaptarse a diferentes problemas complejos. En este sentido, se considera que se contribuye a ampliar el conocimiento sobre la validez, fiabilidad y precisión del uso de modelos de Redes Bayesianas.

PUBLICATIONS AND PROJECTS

Papers published in journals indexed in the Web of Science:

Requejo-Castro, D., Giné-Garriga, R., Pérez-Foguet, A., 2020. Data-driven Bayesian network modelling to explore the relationships between SDG 6 and the 2030 Agenda. Sci. Total Environ. 710, 136014. https://doi.org/10.1016/j.scitotenv.2019.136014.

Requejo-Castro, D., Giné-Garriga, R., Pérez-Foguet, A., 2019. Bayesian network modelling of hierarchical composite indicators. Sci. Total Environ. 668, 936–946. https://doi.org/10.1016/j.scitotenv.2019.02.282.

Giné-Garriga, R., **Requejo-Castro, D.**, Molina, J. L., Pérez-Foguet, A., 2018. A novel planning approach for the water, sanitation and hygiene (WaSH) sector: The use of Object-oriented Bayesian Networks. Environ. Model. Softw. 103, 1–15. https://doi.org/10.1016/j.envsoft.2018.01.021

Papers published in other journals:

Requejo-Castro, D., Giné-Garriga, R., Flores-Baquero, Ó., Martínez, G., Rodríguez, A., Jiménez Fdez. de Palencia, A., and Pérez-Foguet, A., 2017. SIASAR: A country-led indicator framework for monitoring the rural water and sanitation sector in Latin America and the Caribbean. Water Pract. Technol. 12, 372–385. https://doi.org/10.2166/wpt.2017.041

Papers presented in international conferences:

Requejo-Castro, D., Giné-Garriga, R., Pérez-Foguet, A., 2018. Exploring the interlinkages of water and sanitation across the 2030 Agenda: a Bayesian Network approach. In: 24th International Sustainable Development Research Society Conference. Messina, Italy.

A. Pérez-Foguet, A., **Requejo-Castro, D.**, Giné-Garriga, R., Martínez, G., Rodríguez, A., 2017. Construction and application of Bayesian networks to support decision-making in the water, sanitation and hygiene sector: A case study of SIASAR initiative in Central America. In: 23rd International Sustainable Development Research Society Conference. Bogotá, Colombia.

Requejo-Castro, D., Giné-Garriga, R., Flores Baquero, O., Pérez-Foguet, A., 2016. A holistic and participatory information system for rural water and sanitation sector in Latin America and the Caribbean. In: 13th IWA Specialized Conference on Small Water and Wastewater Systems & 5th IWA Specialized Conference on Resources-Oriented Sanitation. Athens, Greece.

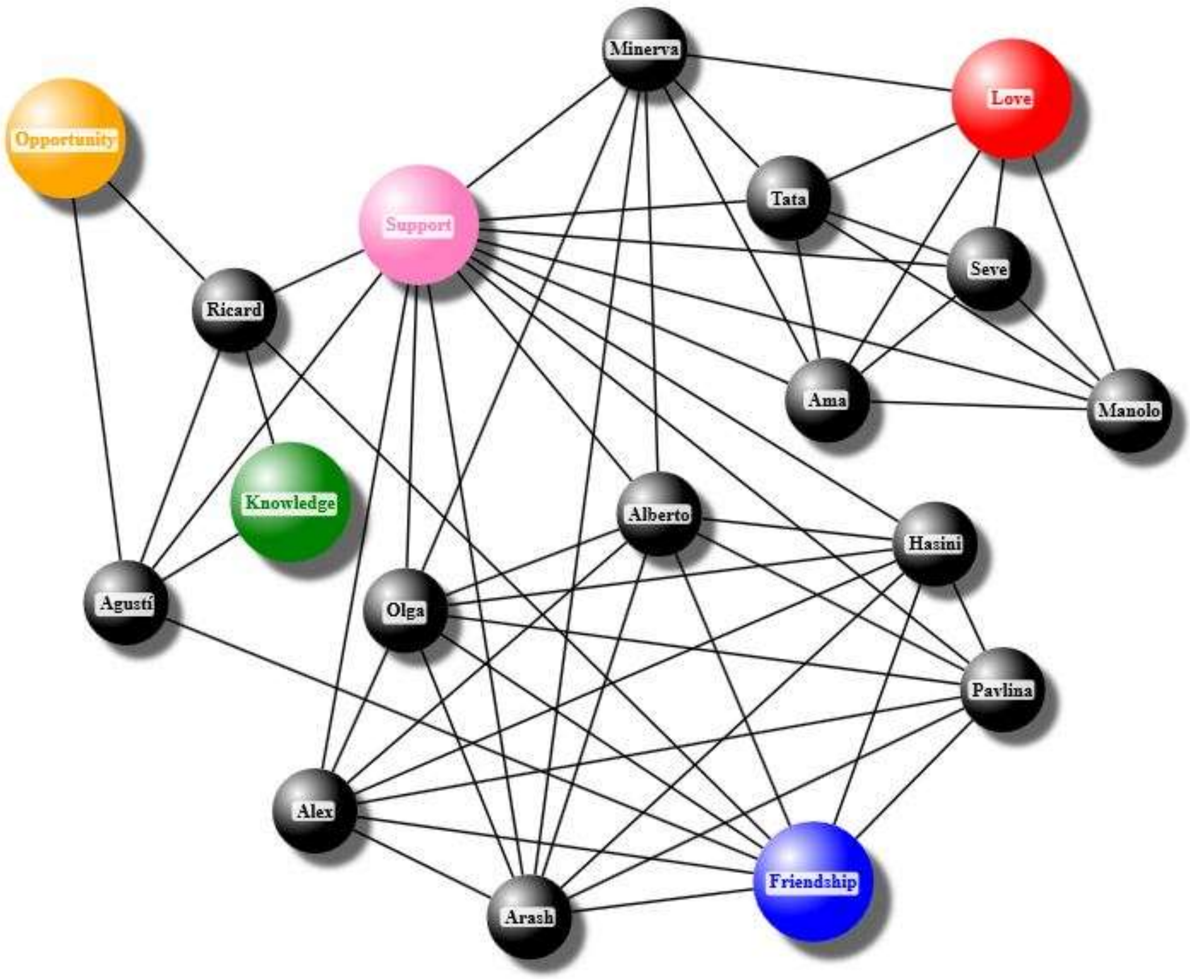
Research projects and consultancy:

Thematic Network on Water Poverty. **Funded by:** Ministerio de Ciencia, Innovación y Universidades bajo la Convocatoria 2017 de Acciones de Dinamización "Redes de Excelencia" del Programa Estatal de Fomento de la Investigación Científica y Técnica de Excelencia, Subprograma Estatal de Generación del Conocimiento (CSO2017-90702-REDT) para el periodo 2018-2020. **Code:** CSO2015-65182-C2-1-P. **Period:** November 2018 - December 2020.

Consultancy to support countries in improving and expanding the use of the Rural Water Supply and Sanitation Information System (SIASAR) as a decision-making tool. **Funded by:** The World Bank. **Reference:** 1205459. **Period:** March 2016 - June 2017.

ACKNOWLEDGEMENTS

Thank you all! Thank you for all!



CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACRONYMS AND ABBREVIATIONS

ACC	Accessibility
ATAG	Air Transport Action Group
AUT	System autonomy
BN	Bayesian Network
CI	Composite indicator
C-Ind	Conditional independence
COM	Community hygiene
CON	Continuity
COV	Community Coverage
CPT	Conditional Probability Table
DAG	Directed Acyclic Graph
DPSIR	Driving force–Pressure–State–Impact–Response
DSR	Driving force–State–Response
DSS	Decision Support Systems
ECO	Economic management
EEA	European Environment Agency
ENV	Environmental management
FA	Factor Analysis
FAO	Food and Agriculture Organization
FOCARD–APS	Foro Centroamericano y República Dominicana de Agua Potable y Saneamiento
GLAAS	Global Analysis and Assessment of Sanitation and Drinking–Water
GWA	Gender and Water Alliance
GWP	Global Water Partnership
HDI	Human Development Index
HSH	Sanitation in Health Centres
HWA	Water Supply in Health Centres
IAMB	Incremental Association Marcov Blanket
IBNET	International Benchmarking Network for Water and Sanitation Utilities
IC	Inductive Causation
ICAO	International Civil Aviation Organization
ICSU–ISSC	International Council for Science–International Social Science Council
ICT	Information and Communications Technology
IEA	International Energy Agency
ILO	International Labour Organization

ILU	Inter–Parliamentary Union
INF	Production infrastructure
INS	Institutional Capacity
INT	Intensity of Assistance
IPCC	Intergovernmental Panel on Climate Change
IQR	Interquartile range
IS	Information system
IUCN	International Union for Conservation of Nature
IWRM	Integrated Water Resources Management
JMP	Joint Monitoring Programme
KBA	Key Biodiversity Area
LAC	Latin America and the Caribbean
MB	Marcov Blanket
MDG	Millennium Development Goal
NTD	Neglected Tropical Diseases
ODA	Official Development Assistance
OECD	Organisation for Economic Co-operation and Development
OECD–IIASA	Organisation for Economic Co-operation and Development–International Institute for Applied Systems Analysis
OPM	Operation & maintenance management
ORG	Operational management
PCA	Principal Component Analysis
PRO	Water catchment protection
PSR	Pressure–State–Response
SD	Sustainable Development
SDG	Sustainable Development Goal
SDSN	Sustainable Development Solutions Network
SEA	Seasonality
SEP	Service provision
SHC	Schools and Health Centres
SHL	Sanitation and hygiene service level
SIASAR	Sistema de Información de Agua y Saneamiento Rural (Rural Water Supply and Sanitation Information System)
SLA	Structure Learning Algorithm
SSH	Sanitation in Schools
SSL	Sanitation service level
SWA	Water Supply in Schools

TAP	Technical Assistance Provision
TRE	Treatment system
UN	United Nations
UN–DESA	United Nations Department of Economic and Social Affairs
UN–EMG	United Nations Environment Management Group
UN–ESCAP	United Nations Economic and Social Commission for Asia and the Pacific
UN–Habitat	United Nations Human Settlements Programme
UN–IEAG	United Nations Independent Expert Advisory Group
UN–Women	United Nations Entity for Gender Equality and the Empowerment of Women
UNDP	United Nations Development Programme
UNDRR	United Nations Office for Disaster Risk Reduction
UNEP	United Nations Environment Programme
UNEP–WCMC	United Nations Environment Programme World Conservation Monitoring Centre
UNESCO	Unites Nations Educational, Scientific and Cultural Organization
UNESCO–UIS	UNESCO Institute for Statistics
UNICEF	United Nations International Children's Emergency Fund
UNODC	United Nations Office on Drugs and Crime
UNSD	United Nations Statistic Division
WaSH	Water, sanitation and hygiene
WAT	Household hygiene
WB	The World Bank Group
WB–WSP	World Bank Water and Sanitation Programme
WHO	World Health Organization
WPDx	Water Point Data Exchange
WSHL	Water, sanitation and hygiene service level
WSI	Water system infrastructure
WSL	Water service level
WSP	Water and sanitation service performance
WSSI	Water service sustainability index
WWAP	United Nations World Water Assessment Programme

CHAPTER I. INTRODUCTION

The challenges we face in the 21^{st} Century are essentially connected. This fact is acknowledged by the United Nations 2030 Agenda for Sustainable Development, which underscores current global challenges, recognizes their interconnectivity and calls for international action. However, established approaches tend to separate the complexities of the real–world into specialized disciplines, fields of research, institutions and ministries, each one focused on a fraction of the overall truth. Similarly, it is widely recognized the need of paradigm change in decision–making processes towards more integrated approaches. Evidence–based decision–making involves complex processes of considering a wide range of information of different nature. Nowadays, available data can support these processes, but methodologies to effectively integrate these data are lacking.

Within this aim, this thesis focuses on the increasing use of Bayesian Networks modelling as an approach to accommodate complex problems and to support decision–making. Common practice employs separately expert knowledge and empirical data to build and apply associated models. Despite of the demonstrated utility of this practice, in an era where the data are bigger, faster and more detailed than even before, there is still room for further exploration. Thus, this dissertation proposes a data–driven Bayesian Networks approach to combine expert opinion and quantitative data to support informed decision–making.

For testing and validating the proposed approach, this thesis takes the Sustainable Development Goal 6 embedded on the 2030 Agenda as a reference point, with particular attention to the water, sanitation and hygiene sector. In this context, various approaches have been implemented (for different purposes and from different perspectives) that might support evidence–based decision–making. In addition, many academic attempts and proposals have contributed in this direction. Nonetheless, a few attempts to test more complex tools are found, being Bayesian Networks used to a limited extent.

This introductory Chapter is divided into two main sections. The first part describes the rationale where the state of the art is presented. It provides an overview of the approaches proposed to tackle complex problems associated with the sector on which this thesis focuses. It presents as well the approach selected and the current use within the sector. The second part describes the research problem in more detail, as well as the methodology implemented, and outlines the structure of the remainder of the thesis.

1.1. RATIONALE

"Globalized", "interconnected", "interdependent", "complex", "systemic". These are just few adjectives that define the world we live in. These apply to different scales, sectors or decision problems. At global level, the 2030 Agenda for Sustainable Development (SD), which underscores the current challenges human–kind is facing, describes the Sustainable Development Goals that it comprises as integrated, indivisible and mutually reinforcing (United Nations General Assembly, 2015). As highlighted, one major goal seeks to build a sustainable future in a recognized interconnected world (United Nations General Assembly, 2015). This requires covering and balancing the three dimensions of SD – environmental, social and economic – and their institutional/governance aspects (Costanza et al., 2016). Lack of integration across these dimensions in development strategies, policies and implementation has long been perceived as a major weakness in previous attempts towards SD (Le Blanc, 2015; Liu et al., 2018; Obersteiner et al., 2016). This weakness has been widely related to the "silo" approaches in which governments and international agencies, as well as sectorial policies and institutions, operate (Nhamo et al., 2018; Weitz et al., 2014). Similarly, it is widely recognized the need of a major shift in decision–making processes towards more holistic and integrated approaches (Rasul, 2016). In other words, there is the need to pull each part of the overall truth together in order to organize effective policy responses (OECD–IIASA, 2020).

From this global context, a parallelism can be built around the water, sanitation and hygiene (WaSH) sector. The main challenge across this sector is to enable and accelerate progress towards achieving Sustainable Development Goal (SDG) 6 "to guarantee the availability of water and its sustainable management and sanitation for all" (United Nations, 2018a; United Nations General Assembly, 2015). Similarly, there is a growing acknowledgement that existing "silo" approaches will not be sufficient on their own to meet sectorial targets (Valcourt et al., 2020). The WaSH sector is struggling to increase the access and quality of WaSH services. Some of the many challenges are practical actions that provide the "visible" side of water (United Nations, 2018a). To cite some examples, these actions fall on installing taps and toilets, building water storages, drilling boreholes, and treating and reusing/recycling wastewater. The term "sustainability" associated to these services has been broadly used in a wide variety of contexts, and lacks a precise definition (Fisher et al., 2015). Thus, while recognizing the importance of many of the connotations of sustainability, a fair starting point might be those services that offer long term prospects (e.g. in terms of functionality, continuity, manageability, etc.). However, some actions are much less visible. They are complex and challenging, and yet they underpin the visible side of water (United Nations, 2018a). These actions include, for instance, the need for good "water governance". Although water governance lacks as well an accurate definition (see detailed overview in Jiménez et al., 2020), a reference point might be established at the political, institutional and socio–economic settings that influence water's use and management. In other words, the systems that determine who gets what water, when and how, and who has the right to water and related services and their benefits (Allan, 2001).

Water governance includes, among other processes, monitoring and learning. It is a common vision that what it is not measured, it is not manageable. In the WaSH sector, there are a number of global initiatives, from different purposes and from different perspectives, all aimed at better understanding WaSH performance and, ultimately, support decision–making based on evidence. In this sense, various approaches have been implemented, for different purposes and from different perspectives. For the global monitoring, the WHO and UNICEF Joint Monitoring Programme (JMP) for Water Supply, Sanitation and Hygiene reports at the international level on the status of access to water and sanitation, shifting from technology–based indicators to multidimensional measures of the level of service delivered (JMP, 2000; 2008; 2017a; 2019; 2020). In parallel, the UN–Water Global Analysis and Assessment of Sanitation and Drinking–Water (GLAAS) provides a global update on the policy frameworks, institutional arrangements, human resource base, and international and national finance streams in support of drinking–water and sanitation (GLASS, 2019). For inter–utility performance benchmarking, the International Benchmarking Network for Water and Sanitation Utilities (IBNET) is an initiative to encourage water and sanitation utilities to compile and share a set of core cost and performance indicators. For the assessment of WaSH service sustainability, the initiative Water Point Data Exchange (WPDx) gathers and harmonizes data from rural areas at the water point or small water scheme level, and facilitates further assessments through its decision support tools. A further initiative, the Rural Water and Sanitation Information System (SIASAR, by its acronym in Spanish) shares a similar principle of free data access and includes a comprehensive framework for data collection, analysis and dissemination that simultaneously fulfils different stakeholder needs (Requejo-Castro et al., 2017; WB, 2017). In this case, collected data is expanded from the rural water schemes to sanitation services, hygiene–related issues and service and technical provision performance.

In addition to these implemented global monitoring mechanisms, and from a more academic perspective, WaSH–related aspects have been assessed from many disciplinary perspectives and conceptual frameworks: these have tackled issues that are water–related (Bordalo et al., 2006; Cho et al., 2010; Cohen and Sullivan, 2010; Giné-Garriga and Pérez-Foguet, 2010, 2011; Sullivan et al., 2010), sanitation–related (Giné-Garriga et al., 2011; Giné-Garriga and Pérez-Foguet, 2019; WB–WSP, 2015) or hygiene–related (Giné-Garriga and Pérez-Foguet, 2013; Webb et al., 2006). Additionally, more integrated approaches have addressed WaSH–related issues from a human rights perspective (Flores Baquero et al., 2016a; Luh et al., 2013) as well as from a more sectorial–focused one (Giné-Garriga and Pérez-Foguet, 2013; Godfrey et al., 2014).

From all the approaches introduced above, a common factor is the use of indicators and/or composite indicators (CIs). Despite the likely use of these approaches to inform decision–making processes, these suffer from a number of common weaknesses (Giné-Garriga et al., 2018). First, indicators and CIs tend to induce a somewhat narrow, issue–centered perspective on the problem at hand, which is not conducive to a good understanding of the interrelationships within considered variables. Second, in CIs, results are generally expressed in a measure of central tendency (instead of using the distribution variability of the variables at hand), which jeopardizes an adequate identification of the neediest (Flores-Baquero et al., 2016b; Giné-Garriga, 2015). Third, desirable impact assessment of different scenarios is not straightforward in CI–based conceptual frameworks, as relationships between policy initiatives, remedial actions and their impact are not correctly integrated (Pérez-Foguet and Giné-Garriga, 2011).

It is acknowledged as well that previous assessments need to be complemented with analyses that enable interlinkages among the variables at hand to be assessed (Allen et al., 2018; Le Blanc, 2015). Recent publications have proposed different approaches to this end. From a more conceptual and qualitative perspective, the variables at hand have been read as an interconnected network (Le Blanc, 2015), or have been analyzed and presented as a list of relationships (ICSU–ISSC, 2015). They have been also organized through a grading system of interactions (Nilsson et al., 2018), with specific focus on one specific issue (Bangert et al., 2017; Hall et al., 2018; Herrera, 2019), or on a "nexus approach" (e.g. water–energy–food nexus) (Fader et al., 2018; Pahl-Wostl, 2017) with the aim to understand connections, synergies and trade–offs (Liu et al., 2018). On the other hand, from a quantitative point of view, existing relationships among the variables at hand have been assessed by applying more sophisticated modeling approaches.

It is in this last group of approaches the focus of this thesis. Indeed, models are identified as important management tools, since they are descriptions of a real–world system that simplify the calculation and prediction of outputs, given a set of inputs and parameters that characterize the model. However, although these models are very useful for studying a wide range of problems and related impacts, in most cases they are not designed to address and integrate issues such as socio–economic, environmental and cultural issues. In response to the need for more integrated approaches, and complementary to these models, Decision Support Systems (DSS) appear as an alternative instrument. A DSS is a means of collecting data from different kinds of information sources to support a decision. The information might include experimental or survey data, results of functional models, or, when data are sparse, expert knowledge (Bromley, 2005). In other words, a DSS can help to structure decision–making processes and support the analysis of the impacts of possible decisions, making the data easily accessible and allowing analysis of "what if ..." (Cain , 2001). Specific benefits cited in last study in relation to DSS include i) an increase in the quantity and quality of the information identified as relevant to the decision, ii) an increase in the number of alternatives examined, iii) a better understanding of the system management, iv) better use of data resources, and v) better communication and documentation of the issues and justification of the decisions made.

Specifically, the interest of this thesis is narrowed to the use of Bayesian Networks (BNs). BNs have gained popularity among practitioners (Aguilera et al., 2011; Marcot, 2017; Marcot and Penman, 2019) for exploring the interdependencies and cause–effect relationships, simulating complex problems that involve a large number of variables that are highly interlinked. Briefly, a BN is a DSS based on probability theory where each node of the model is associated with one variable of the dataset, where the links connecting the nodes represent informational or cause–effect relationships, and where these dependencies are quantified by the conditional probability tables (CPTs), which represent the extent to which one node is likely to be affected by the others.

Furthermore, some of the features that position BNs as a tool to support decision–making are following detailed. First, BNs are useful for incorporating data and knowledge from different sources and domains, including the economic, social, physical, and environmental (Bromley et al., 2005; Castelletti and Soncini-Sessa, 2007; Henriksen and Barlebo, 2008). Second, since nodes in BNs are modelled by means of probability distributions, uncertainty can be estimated more accurately than in models where commonly only mean values are taken into account (Uusitalo, 2007). Third, since numeric values are associated to the relationships among the variables of a BN, the probability of a particular hypothesis or scenario can be automatically computed (Ordónez-Galán et al., 2009). Fourth, once the BN is designed, the probability distribution of a variable given another (set of) variable(s) is obtained, which also applies for the way round (Uusitalo, 2007). In other words, BNs allow knowing the effects given the causes and the causes given the effects.

These key characteristics make BNs particularly suited for tackling WaSH–related issues in an interdisciplinary, holistic way (Alok and Mazumdar, 2002; Fisher et al., 2015). While BNs have been successfully applied to address environmental issues (Bromley, 2005) and water issues (Phan et al., 2016), their application to the WaSH sector is less common (Alok and Mazumdar, 2002; Chan et al., 2020; Cronk and Bartram, 2017, 2018; Dondeynaz et al., 2013; Fisher et al., 2015; Giné-Garriga et al., 2018). For instance, Cronk and Bartram (2018) applied BNs to define the factors that influence 24–hour water service availability, and to explore which variable was more influential in water discontinuity. Giné-Garriga et al. (2018) developed a BN system to monitor WaSH national programmes, taking as a reference point a WaSH–related multidimensional index (Giné-Garriga and Pérez-Foguet, 2013). Commonly, these contributions agree with the suitability of BNs approach to accommodate the complexities of WaSH issues and their interlinkages. This aspect represents the starting point of this dissertation.

1.2. AIMS AND METHODS

This Section first defines the research problem and then introduces the main objective and the subsequent research questions. It then details the research method employed and provides a brief overview of the topics addressed.

1.2.1. Defining the research problem

Evidence–based decision–making involves complex processes of considering a wide range of information of different nature. Nowadays, available data can support these processes, but methodologies to effectively integrate these data are lacking. As introduced, in the WaSH sector, complex processes are already impacting governance and sustainability of services. In this sense, various approaches have been implemented to support decision–making from different perspectives; global monitoring (e.g. JMP and GLAAS), benchmarking of utilities performance (e.g. IBNET), and service sustainability assessment (e.g. WPDx and SIASAR). In parallel, different academic approaches have been proposed to assess WaSH–related issues. Commonly, these approaches rely on the use of indicators and/or composite indicators, which does not facilitate the assessment of the existing interlinkages among the variables at hand. In this context, BNs appear as a suitable tool to accommodate sectorial complexities and support decision–making. However, BNs use is still limited.

When dealing with BNs modelling, two main tasks are involved: the definition of the structure (encoded in the so–called directed acyclic graph, DAG) and the definition of the conditional probability tables (CPTs). In both cases, the main sources of information to construct these features are expert knowledge, stakeholder knowledge, empirical data and model simulations. Expert and/or stakeholder knowledge refers to the opinion of these actor’s beliefs, mainly expressed as qualitative factors derived from expertise, interviews, survey tools or participatory activities. Empirical data refers to experimental or observational evidence or data. Model simulations refer to outputs obtained by means of other empirical or stochastic models. To this regard, it is of special interest the systematic reviews carried out by Phan et al. (2016), analyzing 111 case studies in the water resources field where the BNs approach was employed. Specifically, it is showed that expert knowledge is the main approach for DAG construction, while empirical data is employed for CPTs population. A similar patter can be found in Aguilera et al. (2011) as regard DAG generation. In contrast, very few studies explored the capacity for automated learning of both constructing DAGs and populating CPT values from empirical data (Phan et al., 2016). In the case of the WaSH studies identified in previous section and which applied a BNs approach, these commonly employ above mentioned methodologies (i.e. DAGs – expert/stakeholder knowledge; CPTs – empirical data; none a pure data–driven approach).

Even with the increasing number of publications applying BNs approach, the task of building model structure remains daunting. The use of expert knowledge and a participatory approach for DAG construction are useful means of ensuring that all dimensions are brought to bear in the problem at hand (Pérez-Miñana, 2016). This approach might be adequate in many instances, particularly in presence of scarce observational data. However, it might imply as well time and cost consuming processes, prone to errors and lacked with a widely accepted interpretation of the processes being studied (Alameddine et al., 2011). The use of empirical data to generate plausible BN model structures appears as an alternative, without being exempt from criticism.

In the 90's, the development of machine learning techniques for BNs gave the possibility to induce automatically BNs from databases (Aguilera et al., 2011). This aspect expanded the potential applications of these models. Specifically, network structures can be obtained through the use of the so–called structure learning algorithms (SLAs). This possibility might tackle above mentioned drawbacks when using expert knowledge to build model structure. However, SLAs are not perfect and several obstacles or critics can be identified in literature. First, learning the structure of the networks purely from data might require important volumes of data (Aguilera et al., 2011; Gama, 2012). Second, these algorithms have been shown to miss dependencies, particularly when dealing with complex models (Alameddine et al., 2011). Third, the network structures automatically generated will be more unwieldy as the logic of the links produced with the algorithm might not be so meaningful (Pérez-Miñana, 2016). Nonetheless, these obstacles might be redefined. First, the world is already experiencing an exponential increase in the volume and types of data available within the so–called "data revolution". Nowadays, data are bigger, faster and more detailed than even before. This fact provides a suitable context for experimentation, innovation and adaptation to the new world of data (UN–IEAG, 2014). Second, SLAs must be considered as aid tools regarding its flexible capacity. SLAs allow specifying known relationships in the study at hand prior to executing the algorithm. Thus, a combination of SLAs along with expert involvement seems to be most promising (Alameddine et al., 2011). However, how to combine them in a systematic way remains elusive. Third, SLAs might identify not so meaningful interlinkages but, at the same time, SLAs might identify further relationships spurred on by the data (i.e. not identified by experts). Thus, testing result robustness and validating them are essential when applying a data–driven approach. In brief, operationalizing both data and expert knowledge and analyzing to which extent data–based solutions are robust deserve further exploration.

Having redefined such obstacles, this research aims at enabling a systematic consideration of data and expert knowledge to support decision–making, particularly in the WaSH sector. The hypothesis underlying this thesis is that providing systematic methods within data–driven approaches might expand and deepen the knowledge about the validity, reliability and accuracy of using associated tools (i.e. BNs modelling). As introduced previously, the main motivation falls on shifting traditional assessments towards more holistic and integrated approaches, where the existing complexities of the problem at hand can be accommodated.

1.2.2. Objective and research questions

The overall objective of the research presented in this thesis is as follows:

To improve decision–making processes and the solution of complex problems through data–driven approaches that combine qualitative and quantitative available information

We address this objective from a two–fold perspective. Theoretically, we first review existing approaches within the WaSH sector which tackle the complexities of the context. Then, we provide systematic methodological contributions that might expand the use the proposed data–driven Bayesian Networks approach, by dealing with the valuable knowledge from experts and stakeholders and the increasing amount of data available. Second, and from a more practical point of view, we implement the proposed methodologies in different case studies to assess their validity and usefulness.

Within the outlined objective, this thesis examines the following research questions:

RQ1: How can be combined expert knowledge and data–driven Bayesian Network approaches?

RQ2: To which extent are data–driven Bayesian Network approaches robust in capturing the complexities and interdependencies of a given context?

The first research question tackles the way to systematically combine expert knowledge and empirical data, and to apply it to Bayesian Networks modelling. Operationalizing both sources of information might expand the use of BNs modelling as a tool to support decision–making processes. To answer this question, this thesis proposes the replication of composite indicators–based conceptual frameworks, which represent expert knowledge, through the use of structure learning algorithms, implicit in BNs modelling.

The second question focuses on the identification of interlinkages associated with a complex context. Understanding these linkages enables the full exploitation of synergies, conflict resolution, and trade–offs balances. On the basis of these linkages, integrated planning and management can support decision–making, reduce investment costs and facilitate implementation of a number of strategies that are geared towards sustainable development. To answer this question, we propose a pure data–driven Bayesian Network approach, coupled with a statistical technique to reduce results uncertainty and with a comprehensive result robustness analysis.

1.2.3. Research methodology

To tackle the formulated questions, this thesis integrates three general research steps (see Figure 1.1), which are briefly outlined below. In addition, these steps are complemented by specific methods for each chapter, introduced in next Section.

The first step consists in a literature review with a two–fold objective. On the one hand, this review aims to identify the theoretical and methodological debates associated with the proposed research topic. For this purpose, a wide and diverse array of information resources has been consulted, covering scientific papers, published reports by UN agencies and other organizations, handbooks, and grey literature such as conference proceedings, working papers and project reports. The broad themes addressed include, but are not limited to, BNs modelling, system approaches and monitoring strategies of WaSH and SDGs. The insights from the literature review have informed the theoretical framework of this thesis. On the other hand, this review aims at testing and validating the results obtained. Due to the nature of the analyses carried out along this research, it is remarkable the key role played by the comprehensive reviews.

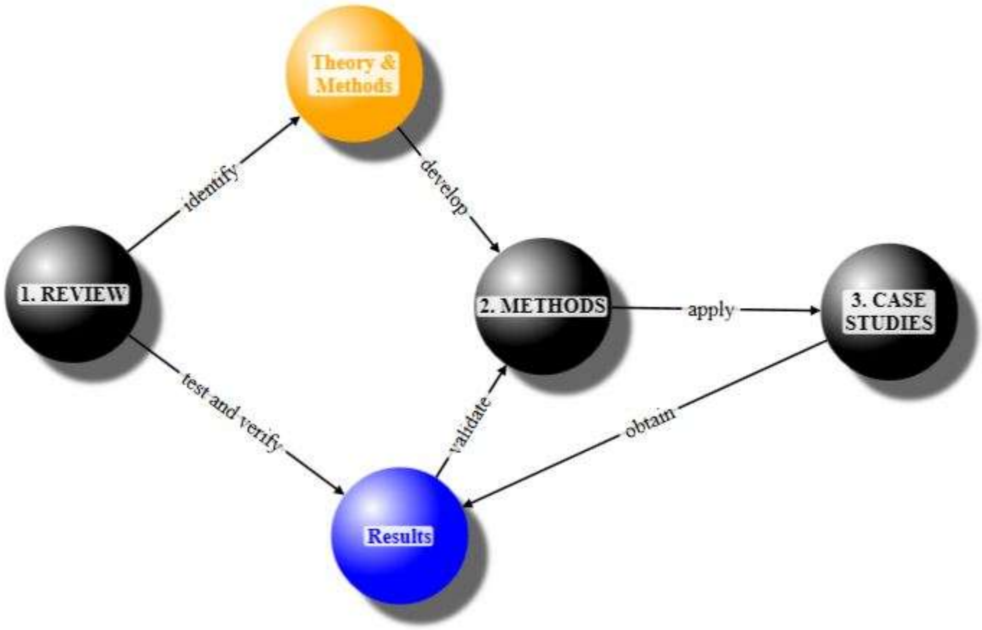


Figure 1.1. Conceptualization of the three general steps followed to tackle the research questions of the thesis.

The second step entails the development of systematic methodologies, based on the use of structure learning algorithms (SLA), for widening the application Bayesian Networks modelling from a data–driven perspective. The underlying philosophy of these methods is "keeping it simple". The main objective is to offer operative mechanisms to deal with existing SLA with a reasonable balance between simplicity, robustness and accuracy. The proposed methods are developed such as they could be replicated by other researches in any context of interest. To this end, all technical details of the methods that this thesis puts forward are publicly available[1].

The third and last step is the implementation of the proposed methods in real–life problems with the aim to assess their validity and usefulness. Two case studies are selected to test the methods and validate the research:

– **The Rural Water Supply and Sanitation Information System** (SIASAR, by its acronym in Spanish). SIASAR is an information system (IS) and a country–led monitoring initiative developed in Latin America and Caribbean (LAC) countries. This initiative seeks to support decision–making of a variety of stakeholders involved in the WaSH sector, as well as to promote evidence–based planning. SIASAR combines data collection from households, water systems and service providers. SIASAR countries have already collected a significant amount of data, which is public available. Specifically, we use data from two different countries, namely Nicaragua and Honduras.

– **The 2030 Agenda for Sustainable Development**. This global Agenda provides an evidence-based framework for global sustainable development planning and programming at different scales (i.e. national, regional and global). This indicator–based framework embraces 17 Sustainable Development Goals (SDGs), 169 targets and 232 indicators. Baselines at national level are already public available, which are gathered by different technical or specialist agencies. Specifically, we select the dedicated goal on water and sanitation (SDG 6).

Data are the lifeblood of this thesis. For the purpose of this research, we cover the two faces of the same coin; large and small datasets. In this sense, we use public available data associated with both datasets (SIASAR and 2030 Agenda, respectively). In addition to this, it is important to emphasize that the contribution of this thesis goes beyond the application to a specific context. Therefore, the proposed methods can be applied to any field of interest.

As mentioned previously, the main feature of the methodological contributions rely on their systematic nature. These are defined by step–by–step processes, making them self–explanatory. Specifically, we provide the guidance to pre–process the data of interest, to select and apply the proposed SLA, and to test and validate the obtained results. However, there are some limitations to take into consideration when applying these methods to any dataset. First, one of the proposed methods is only applicable to composite indicator–based conceptual frameworks that integrate a hierarchical structure. Second, and when dealing with small datasets, there is a constraint associated with the sample size. We establish the minimum size as to obtain reliable results.

[1] All R scripts and datasets used to methods development are available in the Zenodo repository: https://zenodo.org/communities/escgd

1.2.4. Overview of the topics addressed

This thesis includes four additional chapters. First, we provide the qualitatively and quantitatively background of Bayesian Networks modelling, which allow understanding the operational aspects of the algorithms used to obtain BNs from the data, as well as understanding the use of these models within this thesis (Chapter II). Second, we focus on the combination of qualitative and quantitative available data within the WaSH sector (Chapter III). The output is a systematic method to this end based on Bayesian Networks modelling. Third, we expand the use of BNs to the framework of the Sustainable Development Goals, focusing on results consistency and reliability (Chapter IV). In this case, the output is a pure data–driven approach that complements existing studies on interlinkages identification. Fourth, we describe the overall theoretical, methodological and empirical conclusions (Chapter V). Additionally, it identifies the future lines of research.

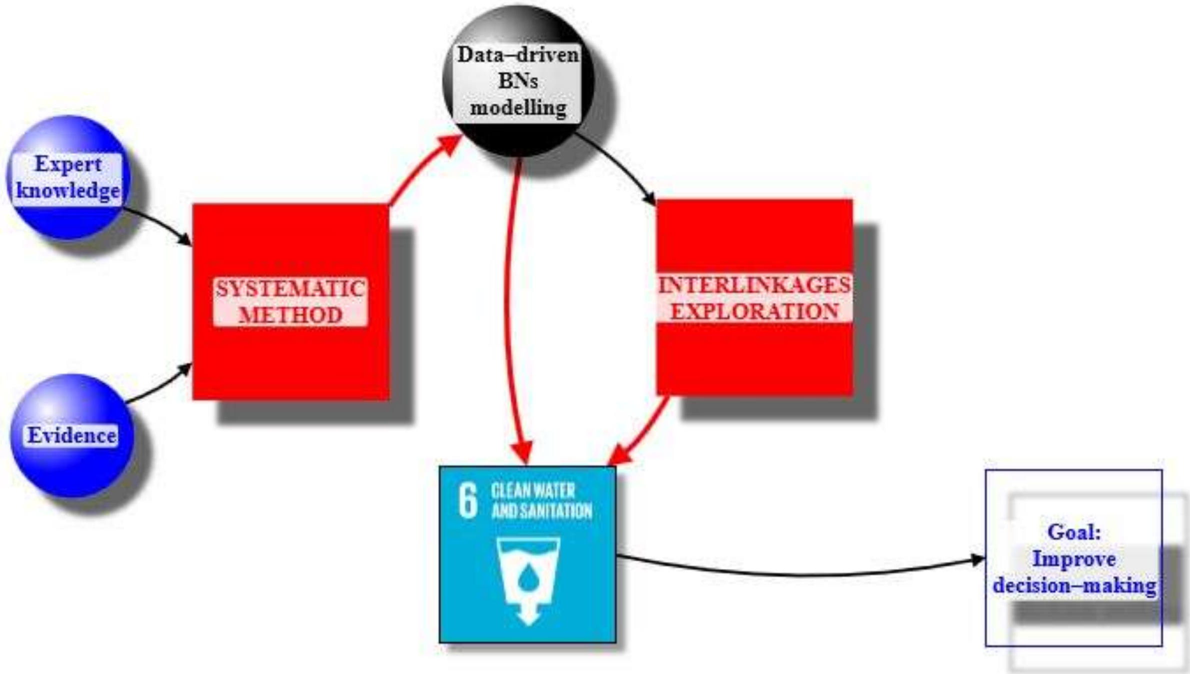


Figure 1.2. Overview of the topics addressed in this thesis. Our goal is to improve decision–making and the solution of complex problems through data–driven approaches that combine qualitative and quantitative available information. We propose a systematic method to this end based on Bayesian Networks modelling. We further apply this approach to test results consistency and reliability in interlinkages identification. For both applications (red solid squares), SDG 6 on “clean water and sanitation” is selected as a case study.

In more detail:

Chapter II. Bayesian Networks modelling and Structure Learning Algorithms

We present the basic concepts associated with BNs, as well as the terms and nomenclature used within this thesis. In addition, we provide the theoretical foundations on which BNs are based. Finally, we present the basic operating principles of the structure learning algorithms (SLAs) employed hereinafter.

Chapter III. Combining expert knowledge and Bayesian Networks modelling

We propose a semi–automatic methodology to combine expert knowledge and data–driven Bayesian Networks approach. Centered on hierarchical and composite indicator (CI)–based conceptual frameworks, which represents expert knowledge, the proposal accurately replicates it, offering great potential for a wider application. It is presented in detail and used as a pilot study the SIASAR initiative.

Chapter IV. Exploring interlinkages between SDG 6 and the 2030 Agenda through a data–driven Bayesian Networks approach

We present a pure data–driven Bayesian Networks approach to identify and interpret interlinkages. The proposal is useful to accommodate a thorough analysis and interpretation of the complexities and interdependencies of the problem of interest, which is ratified by its results robustness and coherency. It is applied to the interlinkages of the Sustainable Development Goal (SDG) 6, related to water and sanitation, across the whole 2030 Agenda.

CHAPTER II. BAYESIAN NETWORKS MODELLING AND STRUCTURE LEARNING ALGORITHMS

In this Chapter, we present the concepts that allow understanding the operational aspects of the algorithms used to obtain BNs from the data, as well as understanding the use of these models within this thesis. First, we introduce the basic qualitative concepts associated with BNs, establishing the terms and nomenclature used in the rest of the thesis, thus facilitating its comprehension. In addition, this background represents the starting point to introduce the quantitative concepts. Second, we present the theoretical foundations and basic quantitative concepts themselves on which BNs are based. Third, we present the basic operating principles of the algorithms that allow building BNs models based solely on the available data. Finally, we end up with a brief of several key aspects.

2.1. BAYESIAN NETWORK DEFINITION

Extending the definition provided in the introductory Chapter, a Bayesian Network (BN) is a statistical multivariate model where its graphical structure allows us to represent and reason about an uncertain domain (Korb and Nicholson, 2004). Each node in a BN is associated with one variable of the domain. A set of directed links connects the nodes representing informational or cause–effect relationships. These dependencies are quantified by conditional probability distributions, which represent the extent to which one node is likely to be affected by the others. The only constraint on the links allowed in a BN is that there must not be any directed cycles. Such networks are called directed acyclic graphs (or DAGs). In brief, BNs are defined in terms of two components: a qualitative one and a quantitative one (Aguilera et al., 2011). We describe the main aspects associated to each component below.

2.2. QUALITATIVE COMPONENT OF A BAYESIAN NETWORK

2.2.1. Nodes and links

On a qualitative level, BNs are graphs with the nodes representing variables and the links representing different kinds of relations among them. Below, we present the taxonomy of these three elements (i.e. graphs, nodes and links) employed in this thesis.

A node represents an exhaustive set of mutually exclusive states, namely the variable domain. This domain can be discrete or continuous (see Figure 2.1).

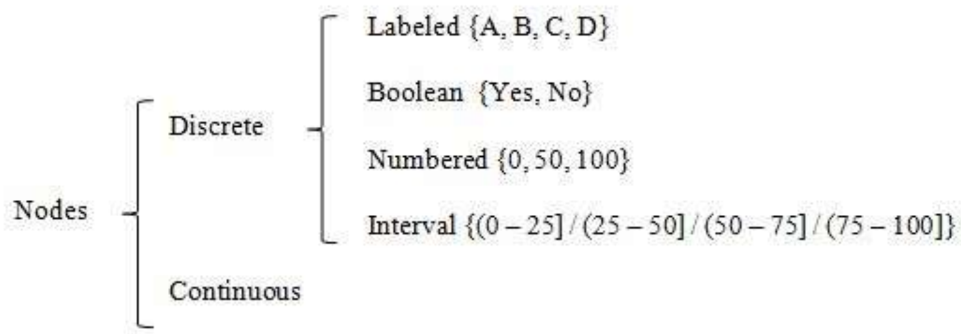


Figure 2.1. Taxonomy for nodes.

The nomenclature of the nodes is summarized in Figure 2.2. We refer basically to three types of nodes: input, intermediate and objective nodes. The graph depicted in Figure 2.2 could be the qualitative component of a BN for variables $X_1 \ldots X_5$. According to the nomenclature, nodes X_1, X_2 and X_3 represent input nodes, X_4 and X_5 intermediate nodes and X_6 an objective node.

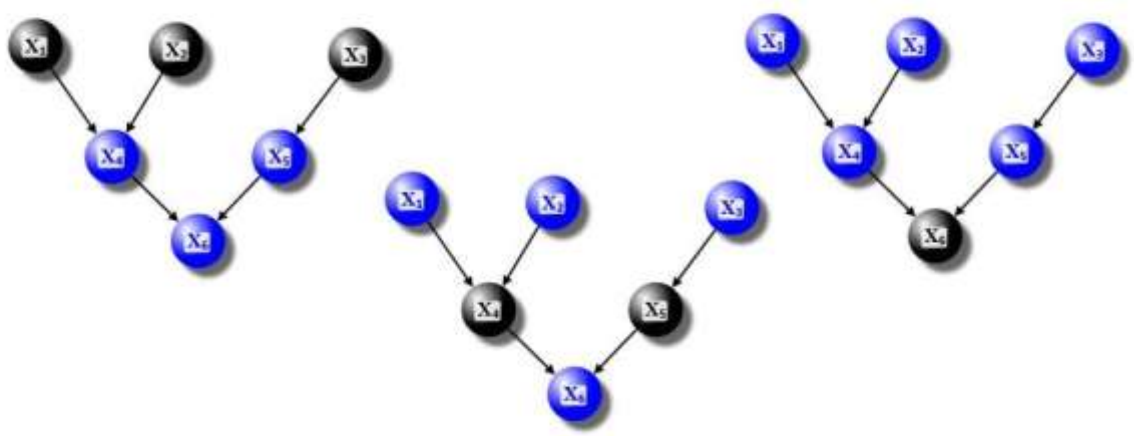


Figure 2.2. Nomenclature for nodes: input (left), intermediate (centre) and objective (right).

In addition to this, it is common to use a family metaphor to refer to nodes. Thus, a node is a parent of a child if there is a link from the former to the latter. For example, node X_3 is the parent of node X_5. Similarly, nodes X_4 and X_5 are parents of node X_6 (see Figure 2.3).

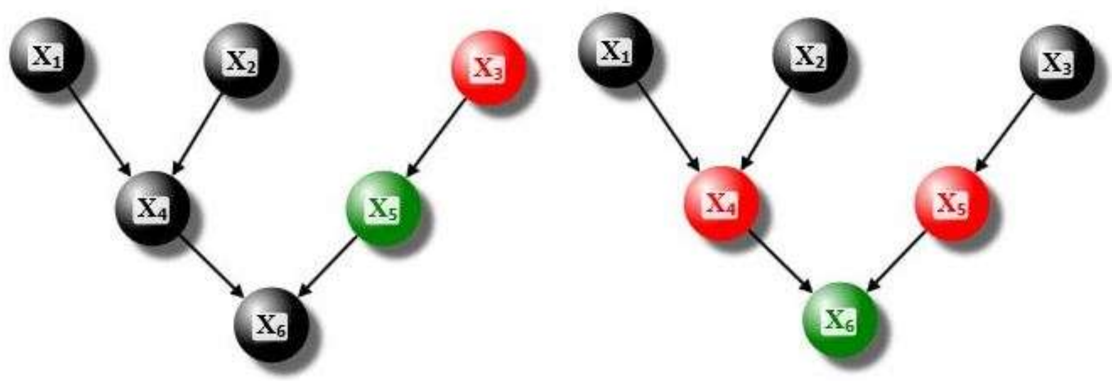


Figure 2.3. Examples for parents (red) and children (green) nodes.

As far as the links, we refer to directed links and undirected links. The former is depicted through arrows from a parent node to a child one. The latter is represented by lines with no direction between parent and child (see Figure 2.4).

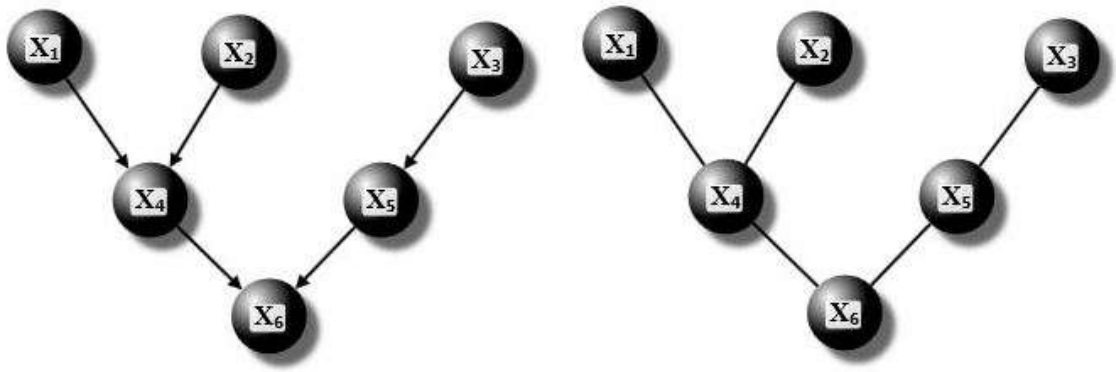


Figure 2.4. Directed links (left) and directed acyclic graph (DAG), and undirected links (right) and skeleton of the graph.

Both nodes and links constitute the graphs. If the graph does not contain undirected links, then the graph is a directed one. Otherwise, it is an undirected graph. Furthermore, if a directed graph does not contain directed cycles is called a directed acyclic graph or DAG. The undirected graph obtained from a DAG by replacing all its directed links with undirected ones is known as the *skeleton* of the graph (see Figure 2.4).

2.2.2. Evidences and types of reasoning

Bayesian networks can be used for updating the values of the nodes when new information is available. This new information is commonly called evidence. This information is received from external sources and is related to the (possible) states/values of a subset of the nodes of the network.

We differentiate and use two types of evidence (Kjærulff and Madsen, 2005). For instance, if the domain of a node is dom (X) = $\{x_1, x_2, x_3\}$, and if the evidence function is $\varepsilon_x = \{1, 0, 0\}$, this indicates that the state of the node is $X = x_1$ with certainty. An evidence function that assigns a zero probability to all but one state is often said to provide hard evidence. On the other hand, if $\varepsilon_x = \{1, 3, 0\}$, then with certainty $X \neq x_3$ and $X = x_3$ is three times as likely as $X = x_1$. In this case, we refer to it as soft evidence.

As BNs provide full representations of probability distributions over their nodes, this implies that they can be conditioned upon any subset of their nodes, supporting any direction of reasoning (Korb and Nicholson, 2004). For example, we can perform diagnostic reasoning (i.e. reasoning from effect to cause). Note that this reasoning occurs in the opposite direction to the network links (see Figure 2.5). We refer to this performance as an *inverse use* of the BN. On the other hand, we can perform predictive reasoning (most common in BNs modelling), reasoning from new information (evidences) about causes to updated knowledge about effects, following the directions of the network links (see Figure 2.5). In this case, we refer to it as a *direct use* of the BN.

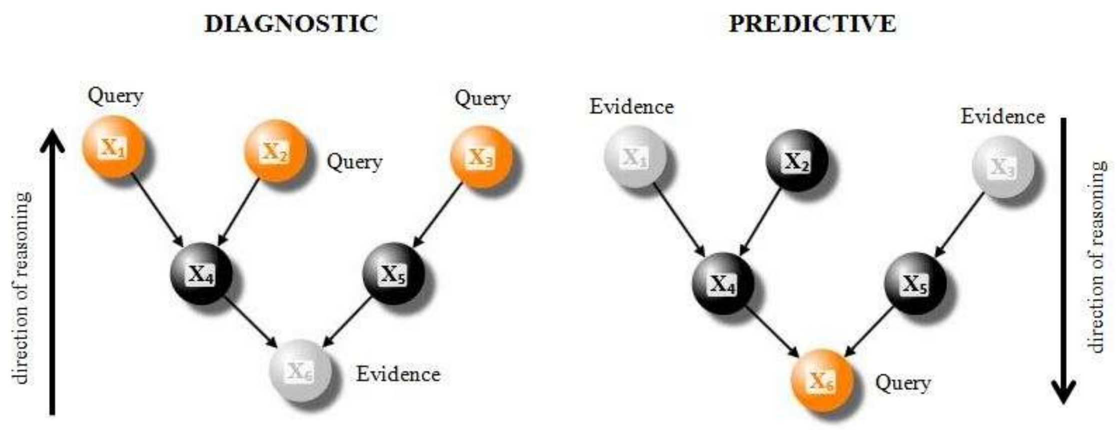


Figure 2.5. Types of reasoning: diagnostic or inverse use (left) and predictive or direct use (right).

2.2.3. The Marcov property

In general, modeling with BNs requires the assumption of the Markov property. This states that there are no direct dependencies in the system being modeled which are not already explicitly shown via links (Korb and Nicholson, 2004).

2.2.4. Flow of information in Bayesian Networks

One of the most important advantages of BNs is that the structure of the associated DAG (which satisfies the Marcov property) determines the independence and dependence relationships among the nodes. The relation between conditional independence and Bayesian network structure is important for understanding how BNs work (Korb and Nicholson, 2004). Thus, it is possible to find out, without any numerical calculation, which nodes are irrelevant (independent) or relevant (dependent) for some other nodes of interest (Aguilera et al., 2011; Kjærulff and Madsen, 2005).

Here, we introduce an adapted "toy" example from Pearl (1988) to illustrate and explain the transmission of information in BNs. The context is as follows: at a rural town of a tropical country, a researcher is carrying out a routine water quality tests, when observes a positive result in pathogens. She concludes that the water treatment system has not been operative due to the previous week storms, as these phenomena cause energy outages which render these systems inoperative. When she is about to contact the energy company to report the incidence, she finds on her way a technician heading to the treatment system. He explains to her that they have indeed communicated a fault in the system. Knowing that mechanical failures are also the cause for the not functionality of the systems, she refuses to call the company.

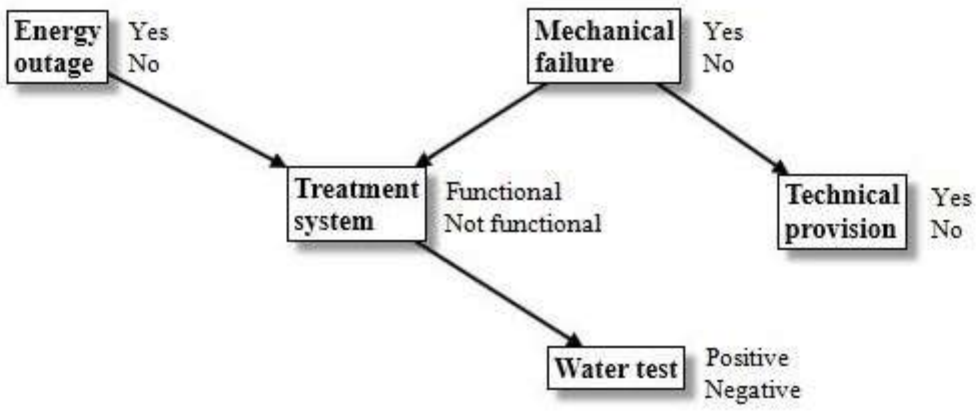


Figure 2.6. Bayesian Network for the example introduced, including the states of each node.

The context described in the example can be represented in terms of a BN (see Figure 2.6). Generally, there are only three types of connections among nodes in a DAG: serial, diverging and converging connections (see Figure 2.7). Therefore, it is enough to explain how information flows for these three connections. We recall the example introduced above to illustrate this.

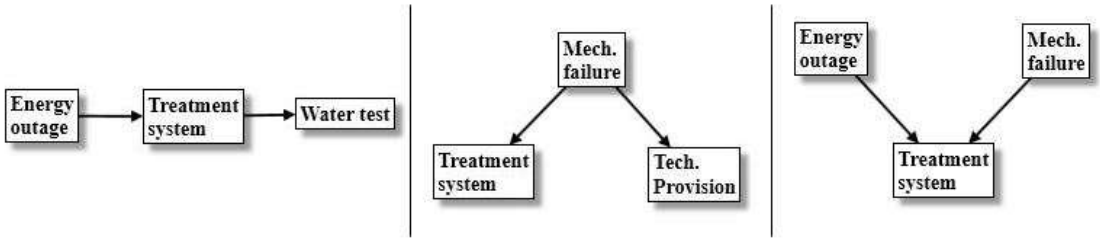


Figure 2.7. Serial (left), diverging (centre) and converging (right) connections.

1. Serial connections: “Energy outage” has a causal influence on “Treatment system”, which in turn has a causal influence on “Water test”. Thus, information flows from “Energy outage” to “Water test” and vice versa, since evidence (new information) associated to one of the nodes provides information about the other. However, if we know about the state of “Treatment system”, any information about the state of “Energy outage” is irrelevant to our belief about “Water test” and vice versa, since once we have certainty about the fact that the treatment system is not operative, the information provided by the water test does not change our state of belief. In brief, information may flow through a serial connection A → B → C unless the state of C is known.

2. Diverging connections: “Mechanical failure” has a causal influence on both “Treatment system” and “Technical provision”. Therefore, information flows from “Treatment system” to “Technical provision” and vice versa, since evidence associated to one of the nodes provides information about the other. Thus, if we only know that the technician is about to repair the treatment system, our belief about the non functionality of the system would increase. On the other hand, if we observe “Mechanical failure” (i.e. we have certainty about that), any information about the state of “Treatment system” is irrelevant for our belief about a contact for “Service provision” and vice versa. Similarly to the previous case, information may flow through a diverging connection A ← B → C unless the state of B is known.

3. Converging connections: “Treatment system” is causally influenced by both “Energy outage” and “Mechanical failure”. However, in this case the last two nodes are irrelevant to each other: if we do not have any evidence about the status of the treatment system, there is no relationship between the other two nodes. However, if we have evidences about “Treatment system” and “Energy outage”, then this will affect our belief about “Mechanical failure”: energy outage explains treatment system failure, reducing our belief that a mechanical failure is the triggering factor, and vice versa. Contrary to serial and diverging connections, information may flow through a converging connection A → B ← C if we know the status of B and the status of one of its descendants.

2.2.5. Dependencies and independencies (d–separation criterion)

In general, applying the three rules detailed above, it is possible to determine the nodes that are relevant to our objective node (Aguilera et al., 2011). Specifically, these three rules comprise the components needed to formulate a general rule for reading off the statements of relevance (dependency) and irrelevance (independency) relations among for two nodes or two sets of nodes, possibly given a third node or set of nodes (Kjærulff and Madsen, 2005). This general rule is known as the *d–separation* (from direction–dependent separation) criterion and is due to Pearl (1988).

The formalism of the d–separation criterion reads “A set of nodes B d–separates two other sets of nodes A and C if every path from a node in A to a node in C is blocked given B” (Korb and Nicholson, 2004). In other words, if A and C are d–separated by B, then A and C are conditionally independent given B (given the Markov property). Some of the d–separation properties observed in the example depicted in Figure 2.6 are:

– Energy outage and Mechanical failure are d–separated (converging connection with no evidence about Treatment system)

– Energy outage and Mechanical failure are not d–separated, given the status of Treatment system (converging connection with evidence about Treatment system)

– Treatment system and Technical provision are d–separated, given the status of Mechanical failure (diverging connection with evidence about Mechanical failure)

– Energy outage and Water test are d–separated, given the status of Treatment system (serial connection with evidence about Treatment system)

2.2.6. Markov Blanket criterion

Another useful concept is that of the Markov Blanket (MB) of a node. Considering the definition introduced by Pearl (1988), in any BN the MB of a node X consists on the union of the node's parents, its children, and its children's parents (see Figure 2.8), which is easily identifiable from the graph.

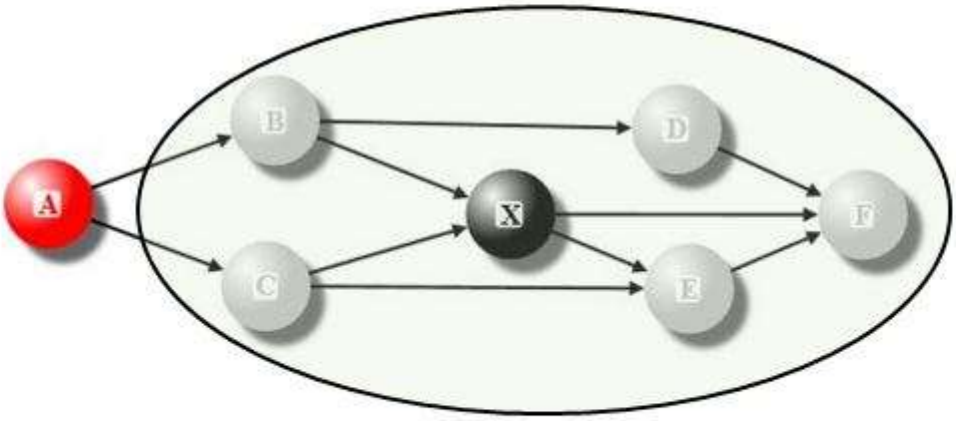


Figure 2.8. Schematic representation of a Markov Blanket with full conditionals. Source: Adapted from Kirchhoff et al., 2018.

Figure 2.8 illustrates the Markov Blanket for node X. It consists on the union of its parents (B, C), its children (E, F), and the parents' children (D). Hence, X = (B, C) U (E,F) U (D) = (B, C, D, E, F). The overall union of X does not include (A). This remarks that X and (A) are conditionally independent given (B, C, D, E, F). It also illustrates that, once the union of X is given, the probability of X will not be affected by the probability of (A). This means that, once all the neighbouring nodes for X are known, knowing the state of (A) provides no additional information about the state of X. It is this kind of statistical neighbourhood for X that is called a Markov blanket (Kirchhoff et al., 2018).

The concept of the MB of a node or a set of nodes is central to the algorithms used in this thesis and presented in Section 2.4.

2.3. QUANTITATIVE COMPONENT OF A BAYESIAN NETWORK

2.3.1. Basics of probability calculus

The probability calculus allows us to represent the independencies which other systems require, but also allows us to represent any dependencies which we may need (Korb and Nicholson, 2004). Furthermore, the language of probabilities consists of statements (propositions) about probabilities of events (Kjærulff and Madsen, 2005). In general, and citing two common examples, an event can be considered as an outcome of a particular observation of a value of a variable (or set or variables), or a result of an experiment such as the water test mentioned previously.

We briefly introduce the formal language of probability through the use of Venn diagrams (see

Figure 2.9). Considering a universe of elements U, where $X \subseteq U$, the chance that an element sampled randomly from U belongs to X defines the probability of the latter, and is denoted by P (X). This probability can informally be understood as the relative area occupied by X in U.

Supposing now that $U = X \cup Y \cup \overline{X \cup Y}$, then the probability that a random element from U belongs to $X \cup Y$ is defined as: $P(X \cup Y) = P(X) + P(Y) - P(X \cap Y)$. Furthermore, if X and Y are disjoint (i.e. $X \cap Y = \emptyset$), then $P(X \cup Y) = P(X) + P(Y)$.

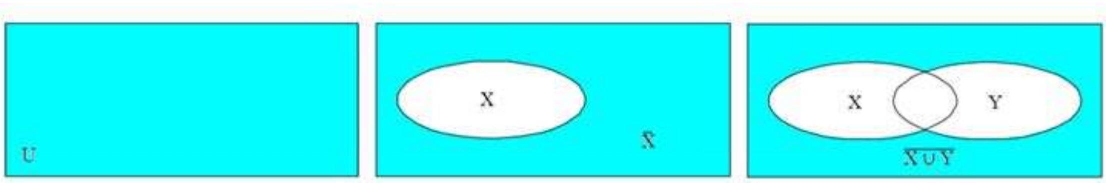


Figure 2.9. The space event U (left), P (X) (centre), and P (X ∪ Y) (right).

2.3.2. Conditional probability

The concept of conditional probability is crucial for the useful application of the probability calculus.

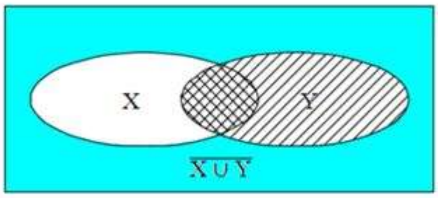


Figure 2.10. Conditional probability: $P(X \mid Y) = P(X \cap Y) / P(Y)$.

If we consider Figure 2.10 and assume that we know that a random element from U belongs to Y, the probability that it belongs at the same time to X is then obtained as the ratio $P(X \cap Y) / P(Y)$. Here, the notation $P(X \mid Y)$ is used to denote this ratio and is read as "the conditional probability of X given Y". Thus, we have:

$$P(X \mid Y) = \frac{P(X \cap Y)}{P(Y)} = \frac{P(X, Y)}{P(Y)}, \text{ or}$$

$$P(X, Y) = P(X \mid Y)\, P(Y)$$

This last equation is called the factorization of the joint distribution for the elements X and Y.

2.3.3. Conditional Probability Tables

A conditional probability table (CPT) quantifies the interlinkages between connected nodes, which is done by specifying a conditional probability distribution for each node. It should be highlighted that CPTs apply only for the case of discrete variables.

In order to construct a CPT, and in first instance, for each node it is needed to look at all the possible combinations of states of those parent nodes. Each such combination is called an instantiation of the parent set. For each distinct instantiation of parent node values, it is needed to specify the probability that the child will take each of its states.

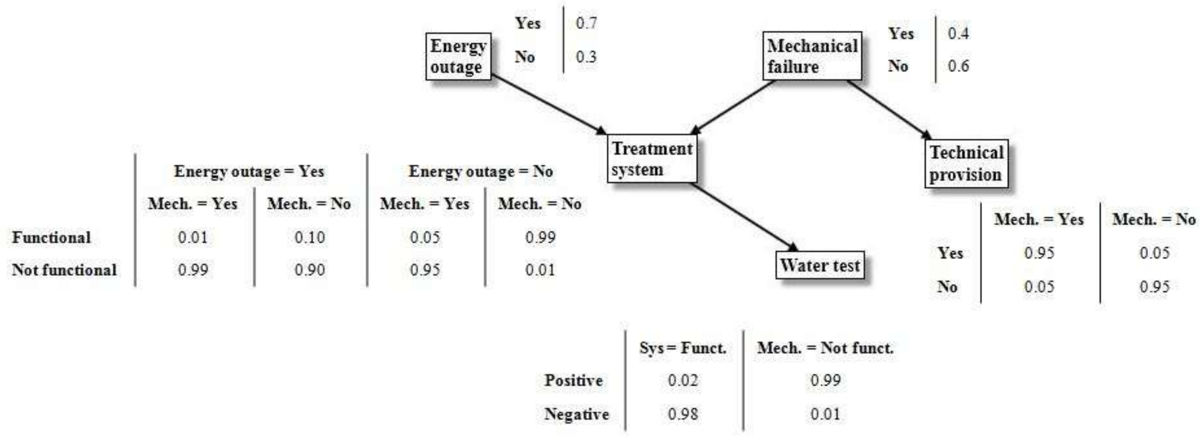


Figure 2.11. Conditional probability tables (CPTs) for each node.

For example, consider the Treatment system node of Figure 2.11. Its parents are Energy outage and Mechanical failure and take the possible joint values {<Yes, Yes>, <Yes, No>, <No, Yes>, <No, No>}. The CPT specifies in order the probability of Treatment system functionality for each of these cases to be: <0.01, 0.10, 0.05, 0.99>. Since these are probabilities, and must sum to one over all possible states of Treatment system node, the probability of non functionality is already implicitly given as one minus the above probabilities in each case. Thus, the probability of treatment system non functionality in the four possible parent instantiations is <0.99, 0.90, 0.95, 0.01>.

Input nodes also have an associated CPT, containing only the so–called prior probabilities. In this example, the prior for an energy outage is given as 0.7, indicating that 70% of the times there is a storm, the electrical infrastructure suffers from an energy outage.

2.3.4. Axioms of Bayesian probability calculus

The following three axioms provide the basis for Bayesian probability calculus, and summarize the considerations introduced above (Kjærulff and Madsen, 2005):

– **Axiom 1**: For any event a, $0 \leq P(a) \leq 1$, the $P(a) = 1$ if and only if event *a* occurs with certainty.

– **Axiom 2**: For any two mutually exclusive events, *a* and *b*, the probability that either *a* or *b* occur is:

$$P\ (a\ \text{or}\ b) = P\ (a) + P\ (b)$$

In general, if events $a_1,\ldots,a_n$ are pairwise exclusive, then:

$$P\left(\bigcup_{i}^{n} a_i\right) = P\ (a_1) + \ldots + P\ (a_n) = \sum_{i}^{n} P\ (a_i)$$

– **Axiom 3**: For any two events, *a* and *b*, the probability that both *a* and *b* occur is:

$$P\ (a\ \text{and}\ b) \equiv P\ (a, b) = P\ (b \mid a)\ P\ (a) = P\ (a \mid b)\ P\ (b)$$

Here, P (a, b) is called the joint probability of the events a and b.

In words, Axiom 1 simply says that a probability is a non–negative real number less than or equal to 1, and that it takes the value 1 if and only if the associated event has happened for sure. Axiom 2 states that if two events cannot occur at the same time, then the probability that either one of them occurs is equal to the sum of the probabilities of their individual occurrences. Finally, Axiom 3 says that the probability that two events (*a* and *b*) occur at the same time can be computed as the product of the probability of event *a* (*b*) occurring conditional on the fact that event *b* (*a*) has already occurred and the probability of event *b* (*a*) occurring.

2.3.5. Rule of Total Probability

Bayesian Networks are defined over a (finite) set of nodes, each of which represents a finite set of exhaustive and mutually exclusive states (or events). Thus, (conditional) probability distributions for variables (i.e. over exhaustive sets of mutually exclusive events) play a central role in BNs (Kjærulff and Madsen, 2005).

If X is a (random) variable (or node) with domain dom (X) = $\{x_1,\ldots, x_n\}$, then P (X) denotes a probability distribution (i.e., a vector of probabilities summing to 1), where:

$$P\ (X) = [P\ (X = x_1),\ldots, P\ (X = x_n)] = [P\ (x_1),\ldots, P\ (x_n)]$$

On the other hand, if the probability distribution for a different variable Y is given conditional on a variable (or set of variables) X, then the notation P (Y | X) is used, as introduced in previous Section. This means that, for each possible value (state), $x \in$ dom (X), we have a probability distribution P (Y | X = x) = P (Y | x).

Let P (X, Y) now be a joint probability distribution for two variables X and Y with dom (X) = $\{x_1,\ldots, x_m\}$ and dom (Y) = $\{y_1,\ldots, y_n\}$. Considering the fact that dom (X) and dom (Y) are exhaustive sets of mutually exclusive states of X and Y, respectively, Proposition 2 introduced above gives the rule of total probability:

$$\forall i: P\left(x_i, y_1\right) + \ldots + P\left(x_i, y_n\right) = \sum_{j=1}^{n} P\,(x_i, y_j)$$

Using this equation, we can calculate P (X) from P (X, Y):

$$P\,(X) = \left(\sum_{j=1}^{n} P\left(x_1, y_j\right), \ldots, \sum_{j=1}^{n} P\left(x_m, y_j\right)\right) = \sum_{j=1}^{n} P\left(X, y_j\right) = \sum_{Y} P\,(X, Y)$$

2.3.6. Baye's Rule

Generalizing Axiom 3 to arbitrary (random) variables X and Y, we obtain the so–called fundamental rule of probability calculus:

$$P\,(X, Y) = P\,(X \mid Y)\,P\,(Y) = P\,(Y \mid X)\,P\,(X)$$

From this equation, Bayes' rule follows immediately:

$$P\,(Y \mid X) = \frac{P\,(X \mid Y)\,P\,(Y)}{P\,(X)}$$

Using Axiom 3 and the rule of total probability, the equation above can be rewritten as follows:

$$P\,(Y \mid X) = \frac{P\,(X \mid Y)\,P\,(Y)}{P\,(X \mid Y{=}y_1)\,P\,(Y{=}y_1) + \ldots + P\,(X \mid Y{=}y_n)\,P\,(Y{=}y_n)}$$

That is, the denominator in Bayes' rule formula can be derived from the numerator in the same formula. However, the denominator P (X) hardly enters into consideration because it is merely a normalizing constant P (X) = P (X | Y) P (Y) + P (X | -Y) P (-Y), which can be computed by requiring that P (Y | X) and P (Y | -X) sum to unity. Thus, Bayes' rule is often written as follows:

$$P\ (Y \mid X) \propto P\ (X \mid Y)\ P\ (Y) \text{ or in general: posterior} \propto \text{likelihood x prior}$$

The usual Bayesian interpretation asserts that the probability of a variable Y conditioned upon some evidence X is equal to its likelihood P (X | Y) times its probability prior to any evidence P (Y), normalized by dividing by P (X) (so that the conditional probabilities of all variable states sum to 1). Here, the prior distribution, P (Y), expresses the initial belief about the variable Y, and the posterior distribution, P (Y | X), expresses the updated belief about Y in light of the observation X. Bayes' rule tells how to obtain the posterior distribution by multiplying the prior P (Y) by the ratio P (X | Y) / P (X), where P (X) is a constant for each state of Y.

2.3.7. The Chain Rule

A useful generalization of the equation P (X, Y) = P (X | Y) P (Y) is the so–called chain rule formula. It states that if we have a probability distribution, P (X), over a set of variables X = $\{X_1,\dots,X_n\}$, then the probability of the joint event $(X_1,\dots, X_n)$ can be written as a product of n conditional probabilities:

$$P\ (X) = P\ (X_1 \mid X_2,..,X_n)\ P\ (X_2,\dots, X_n)$$

$$P\ (X) = P\ (X_1 \mid X_2,..,X_n)\ P\ (X_2 \mid X_3,..,X_n) \cdots P\ (X_{n-1} \mid P_n)\ P\ (X_n)$$

$$P(X) = \prod_{i=1}^{n} P\ (X_i \mid X_{i+1},\dots,X_n)$$

Here, it is important to remark that the order in which the variables are selected has an important impact. Thus, there are n factorial different factorizations of P (X), and to each factorization corresponds a unique DAG. However, all of these DAGs are equivalent in terms of dependence and independence properties (Kjærulff and Madsen, 2005).

Recalling the Markov property, the structure of a BN implies that the value of a particular node is conditional only on the values of its parent nodes. This reduces previous equation to:

$$P\ (X) = \prod_{i=1}^{n} P\ (X_i \mid \text{Parents}\ (X_i))$$

2.3.8. Inference in Bayesian Networks

Bayesian Networks, like other statistical models, can be used to answer questions about the nature of the data that go beyond the mere description of the behavior of the observed sample (Scutari and Denis, 2015). The techniques used to obtain those answers are known in general as inference. The basic task for any probabilistic inference system is to compute the posterior probability distribution for a query node (or set of query nodes), given the evidences related to other nodes. This task is called probabilistic inference. Inference in BNs is very flexible, as evidence can be entered about any node while beliefs in any other nodes are updated (Korb and Nicholson, 2004).

For example, we can consider X_i as a node in which we are interested (our objective node), and Parents (X_i) = X_e as a set of nodes whose states can be known. Then, the posterior distribution of X_i given X_e can be obtained by computing the probability of each possible state of X_i given each possible configuration of X_e. This probability distribution can be obtained from the joint distribution introduced immediately above. In fact, there is no need to compute the joint distribution, since there are efficient algorithms that allow the calculation of $P(X_i \mid X_e)$ taking advantage of the factorization of the joint distribution imposed by the network structure (Aguilera et al., 2011).

Probabilistic inference, however, can be done once the qualitative component of the BN is built (i.e. the DAG). As reflected in the introductory Chapter, we use so–called structure learning algorithms (SLAs) to obtain the network structure. Following, we introduce the details related to these.

2.4. STRUCTURE LEARNING ALGORITHMS

2.4.1. Principle for structure learning

As introduced previously, the DAG of a BN defines a factorization of the joint probability distribution of a set of variables $X = \{X_1,\ldots,X_n\}$, into a set of local probability distributions, one for each variable. The form of this factorization is given by the Markov property (see Section 2.2.3) of the BN, which states that every variable considered, X_i, directly depends only on its parents, Parents (X_i). Here, we provide again the associated expression but expanded to continuous variables:

$$P(X) = \prod_{i=1}^{n} P(X_i \mid \text{Parents}(X_i)) \qquad \text{(discrete variables)}$$

$$f(X) = \prod_{i=1}^{n} f(X_i \mid \text{Parents}(X_i)) \qquad \text{(continuous variables)}$$

The correspondence between conditional independence (of the variables) and graphical separation (of the associated nodes of the graph) is extended to an arbitrary triplet of disjoint subsets of X by Pearl (1988) with the d–separation criterion (see Section 2.2.5). Therefore model selection algorithms first try to learn the graphical structure of the BN (hence the name of structure learning algorithms) and then estimate the parameters (i.e. the conditional probability tables, CPT) of the local distribution functions conditional on the learned structure (Scutari, 2010). This two–step approach has the advantage that it considers one local distribution function at a time, and it does not require to model the overall joint distribution function explicitly.

2.4.2. Existing algorithms for structure learning

Structure learning algorithms (SLA) are automatic approaches that provide the optimum structure of the network, spurred on by data. These can be grouped in two main categories: constraint–based and score–based algorithms:

– **Constraint–based algorithms:** These algorithms learn the network structure by analyzing the probabilistic relationships entailed by the Markov property of the BN (see Section 2.2.3) with conditional independence (C–Ind) tests. Then, a graph which satisfies the corresponding d–separation statements (see Section 2.2.5) is constructed (Scutari, 2010).

– **Score–based algorithms:** These algorithms assign a score to each candidate BN and then try to maximize it with a heuristic search algorithm (Scutari, 2010).

In this thesis, we focus on the use of constraint–based SLA, which are applied to a large database (Chapters III) and to a small database (Chapter IV). Two are the main reasons for this. First, the use of conditional independence tests reduces the subjectivity of the links among the nodes of the network, if compared to the use of heuristic methods in the case of score–based algorithms. Second, and despite the large amount of data needed to guarantee the reliability of the C–Ind tests, a recent study points out that constraint–based algorithms are more accurate than score–based algorithms for small sample sizes (Scutari et al., 2018).

As detailed by Scutari (2010), the constraint–based algorithms are all based on the inductive causation (IC) algorithm developed by Verma and Pearl in 1991. This algorithm provides a theoretical framework for learning the structure of the BN model from the available data. The process to do this can be summarized in three steps:

1. Network *skeleton* (see Section 2.2.1) **learning**. To do this, and since an exhaustive search is computationally unfeasible even for all but the simplest datasets, all learning algorithms use some kind of optimization such as restricting the search to the Markov Blanket of each node (see Section 2.2.6).

2. All links' direction setting. All the directions are set in relation to the links that are part of a *V–structure* (a triplet of nodes incident on a converging connection $X_j \rightarrow X_i \leftarrow X_k$).

3. DAG structure satisfaction. The directions of the other links are set as needed to satisfy the acyclicity constraint.

2.4.3. Applied software

Notably, a large amount of software (both free and commercial) is available for developing a BN model. Existing software employs the SLA introduced above, adding the possibility to apply a hybrid approach as well (Liu et al., 2017;Madsen et al., 2016). In this thesis, we use the free *R software* and its package *bnlearn*, developed by Scutari (2010).

bnlearn implements the following constraint–based learning algorithms, which are used and tested in the following chapters:

– **Grow–shrink (*gs*)**: Based on the grow–shrink Markov blanket, it represents the simplest Markov Blanket (MB) detection algorithm used in a SLA (Margaritis, 2003). This detection is based on pairwise independence tests and it consists of two phases, a growing and a shrinking one (hence its name). In the growing phase, variables which are dependent on a selected variable constitute an initial empty set of variables. In other words, as long as the MB property of the selected variable is violated, the variables are added to the empty set until there are no more such variables. In this process however, there may be some variables that were added that were really outside the MB. The shrinking phase identifies and removes these variables. In brief, the MB for all variables are identified as a first step, and then used to guide the construction of the Bayesian Network of the domain.

– **Incremental association (*iamb*)**: Based on the incremental association MB (IAMB) algorithm (Tsamardinos et al. 2003), which is based on a two–phase selection scheme (a forward selection followed by an attempt to remove false positives). This algorithm and the previous one follow the same two–phase structure. However, there is one important difference which relies on the order in which variables are selected to detect the MB. This implies the appearance of more false positives.

– **Interleaved incremental association (*inter.iamb*)**: Another variant of IAMB which uses forward stepwise selection (Tsamardinos et al. 2003) to avoid false positives in the Markov Blanket detection phase.

– **Fast incremental association (*fast.iamb*)**: A variant of IAMB which that employs speculation to recover the MB faster by reducing the number of conditional independence tests (Yaramakala and Margaritis 2005).

– **Max–min parents and children (*mmpc*)**: This algorithm learns the underlying skeleton of the BN, with no attempt to determine the direction of the links (Tsamardinos et al. 2006). Given a variable of interest and statistical data, this algorithm returns the set of parents and children associated to that variable. In other words, it provides a way to identify the existence of links to and from the variable of interest, without identifying the orientation of the links. Repeating this with each variable as the one of interest, all the links (in an un–oriented fashion) can be identified in the network (i.e. identifying the skeleton of the BN).

On the other hand, conditional independence tests focus on the presence of individual links. Since each links encodes a probabilistic dependence, conditional independence tests can be used to evaluate whether that probabilistic dependence is supported by the data (Scutari and Denis, 2015). In this sense, several conditional independence tests from information theory and classical statistics are available for use in coupled with the constraint–based SLA. Furthermore, the C–Ind tests must be chosen with respect to their data typology. As mentioned previously, in this thesis, we will use discrete and continuous variables. Thus, the C–Ind tests differ for each case.

For the case of discrete variables, several C–Ind tests are available. For computing time, this selection is reduced to **mutual information (*mi*)** and **Pearson's X^2(*x2*)** tests (see details in Scutari, 2010).

On the other hand, and for continuous variables, the selection is reduced as well to avoid intensive computing time. Specifically, we apply **to linear correlation (*cor*)**, **Fisher's Z (*zf*)**, and **mutual information (*mi-g*)** C–Ind tests (see details in Scutari, 2010).

Once the structure of the BN has been learned from the data (through the combination of SLA and C–Ind tests), the task of estimating and updating the parameters of the joint probability distribution is greatly simplified by the decomposition into local distributions (Scutari and Denis, 2015). Specifically, the parameters of these local distributions (i.e. conditional probabilities) are estimated (or learned) from the data available. The applied software and package offer the possibility to automate this task through the use of a specific function (*bn.fit*) and two different estimators: *maximum likelihood* (*mle*) and *Bayesian* (*bayes*) estimators (see details in Scutari and Denis, 2015).

2.5. KEY MESSAGES

From this Chapter, we highlight the following key messages:

– The qualitative component of a BN (i.e. DAG) is a compact representation of independencies and dependencies among a set of variables, allowing reasoning to proceed in any direction across the network of variables. Furthermore, it provides a powerful language for formulating, discussing and communicating qualitative interaction models.

– The quantitative component of a BN quantifies the strength of variable dependencies in terms of conditional probability distributions. Through the use of the Bayes' theorem, BNs automate the process of updating the probability distributions of variables whose states have not been observed, given some set of new evidences (i.e. probabilistic inference).

– The DAG and the conditional probability distributions of a Bayesian Network can be obtained automatically from a given dataset. This is done through the combination of structure learning algorithms and conditional independence tests, which apply the Marcov property, the Marcov Blanket detection and d–separation criterion. This approach makes the process computationally feasible.

CHAPTER III. COMBINING EXPERT KNOWLEDGE AND BAYESIAN NETWORK MODELLING

The water, sanitation and hygiene (WaSH) sector has witnessed the development of multiple tools for multidimensional monitoring and for supporting decision–making. Hierarchical and composite indicator (CI)–based conceptual frameworks provide one illustrative example. However, these approaches do not address the existing interrelationship of the indicators they comprise. In this line, Bayesian networks (BNs) are increasingly being exploited to assess WaSH issues and to support decision–making processes.

In this Chapter, we aim to evaluate the validity, reliability and feasibility of BNs in replicating an existing CI–based conceptual framework. We adopt a data–driven approach and propose a semi–automatic methodology. As a pilot study, we used the regional monitoring initiative Rural Water Supply and Sanitation Information System (SIASAR). Data from two different countries are processed and analyzed to calibrate and validate the model and the method. The major findings show: i) the model inference capacity improves when structure is provided to the networks (according to the CI–based framework); ii) key components that explain a pre–defined objective variable are reduced and quantified (implying important advantages in data updating); and iii) interlinkages among these components can be identified (which might enhance multi– and trans–disciplinary actions).We conclude that BNs accurately replicate the CI–based conceptual framework, with great potential for a wider application.

This Chapter is based on papers:

Requejo-Castro, D., Giné-Garriga, R., Flores-Baquero, Ó., Martínez, G., Rodríguez, A., Jiménez Fdez. de Palencia, A., and Pérez-Foguet, A. 2017. SIASAR: A country–led indicator framework for monitoring the rural water and sanitation sector in Latin America and the Caribbean. Water Pract. Technol. 12, 372–385. https://doi.org/10.2166/wpt.2017.041.

Requejo-Castro, D., Giné-Garriga, R., Pérez-Foguet, A. 2019. Bayesian Network modelling of hierarchical composite indicators. Sci. Total Environ. 668, 936–946. https://doi.org/10.1016/j.scitotenv.2019.02.282.

3.1. INTRODUCTION

Indicators play a key role in monitoring and evaluation, reporting, decision– and policy–making and public communication. An important feature of indicators is their capacity to summarize, focus and condense information about complex systems (Godfrey and Tood, 2001). However, a solely indicator cannot capture the complexity of the real world, and much efforts has been put into developing related approaches. For instance, composite indicators (CIs) have been widely used to evaluate the existing multi–dimensionality of the problems at hand (Nardo et al., 2005), enhancing multi– and cross–disciplinary approaches. Some of these CIs have been structured hierarchically (i.e. indicators, sub–indices and indices) based on conceptual frameworks defined by experts (see examples in Bandura, 2006; Singh et al., 2009) and for enhancing multi– and cross–disciplinary approaches. In the water, sanitation and hygiene (WaSH) sector, various approaches have been implemented to support decision–making from different perspectives; global monitoring (e.g. JMP and GLAAS), benchmarking of utilities performance (e.g. IBNET), and service sustainability assessment (e.g. WPDx and SIASAR). From a more academic perspective, CIs have been used to evaluate WaSH aspects from many disciplinary perspectives and conceptual frameworks: composites have tackled issues that are water–related (Bordalo et al., 2006; Cho et al., 2010; Cohen and Sullivan, 2010; Giné-Garriga and Pérez-Foguet, 2010, 2011; Sullivan et al., 2003), sanitation–related (Giné-Garriga et al., 2017; Giné-Garriga and Pérez-Foguet, 2018; WSP, 2015) or hygiene–related (Giné-Garriga and Pérez-Foguet, 2013; Webb et al., 2006). Additionally, more integrated approaches have addressed WaSH–related issues from a human rights perspective (Flores-Baquero et al., 2016a; Luh et al., 2013) as well as from a more sectorial focused one (Giné-Garriga and Pérez-Foguet, 2013; Godfrey et al., 2014; Requejo-Castro et al., 2017).

One major weakness is that CIs do not address the existing interrelationship of the indicators they comprise; thus, they do not describe the increasing interdependency of the real world. This drawback has been widely tackled by applying data–driven and the traditional "cause–effect" approach. Within the former, classical techniques such as Principal Component Analysis (PCA) and Factor Analysis (FA) have highlighted the statistical relationships between indicators in terms of a smaller number of components or factors, respectively (Nardo et al., 2005). These techniques are based on the variance of a given dataset. While PCA reduces the dimensionality of a dataset by finding correlated variables, FA determines the number of latent independent variables underlying the data. On the other hand, and mainly in the environmental field, the principle of causality has been introduced through two different approximations: causal chains and causal networks. Within the former, most of the publications apply the Pressure–State–Response framework (PSR; OCDE, 1993) and its transformations: Driving force–State–Response (DSR; UN, 1996) and Driving force–Pressure–State–Impact–Response (DPSIR; EEA, 1999). Here, the main idea is to identify factors (for instance, the progressive chain of events) from the driving force and related pressure indicators, which lead to changes, impacts and responses. Other authors have suggested that causal networks within the DPSIR framework are more appropriate than causal unidirectional chains for dealing with the complexity of real world connections (Lin et al., 2009; Niemeijer and De Groot, 2008). A few studies have applied techniques, such as the Analytic Network Process (Saaty, 2001) or PCA and FA, to quantify (in terms of weight) the linkages between indicators (Hou et al., 2014; Vacik et al., 2007; Wolfslehner and Vacik, 2011). Both the causal chain (mostly DPSIR framework and its derivatives) and causal networks approaches have been helpful for: i) conceptual framework development (Chandrakumar and McLaren, 2018; Ortiz-Lozano, 2012; Taft and Evers, 2016; Wolfslehner and Vacik, 2011); ii) scenario assessment (Chung and Lee, 2009; Ramos-Quintana et al., 2018; Scharin et al., 2016); and iii) structuring modelling exercises (García-Santos et al., 2018; Pirrone et al., 2005). The PSR conceptual framework has been also applied to address the linkages between water scarcity and poverty (Pérez-Foguet and Giné-Garriga, 2011).

Bayesian networks (BNs) are another step into this direction. They have been exponentially used to explore the interdependencies and cause–effect relationships, simulating complex problems that involve a large number of variables that are highly interlinked (Aguilera et al., 2011; Marcot, 2017). BNs thus present a complementary approach to tackling the above–mentioned drawbacks. Furthermore, BNs have been used to identify the key factors that influence aspects of interest (Li et al., 2019; Song et al., 2018), and to elucidate the network structure underlying the data–at–hand, through associated structure learning algorithms (SLA) (Alameddine et al., 2011; Garcia-Prats et al., 2018).

In this Chapter, we focus on the latter line of research. Although the use of empirical data to generate plausible BN model structures appears as an alternative, how to operate in a systematic way remains elusive. Considering that the combination of SLAs along with expert involvement might be most promising, our approach falls on replicating existing conceptual frameworks, which represent expert knowledge, through the use of SLA and available data. In particular, our aim is to expand and deepen the knowledge about the validity, reliability and accuracy of using BNs to replicate CI–based conceptual frameworks. To do this, we provide a systematic methodology for network construction to replicate the structure of CIs that are organized hierarchically. We adopt a data–driven approach, using one regional monitoring initiative as a pilot study: the RuralWater Supply and Sanitation Information System (SIASAR, for Sistema de Información de Agua y Saneamiento Rural). We opt for this pilot study due to i) its open–database availability for interested stakeholders, and ii) its complex hierarchical structure of indicators and CIs.

We structure this Chapter as follows. In Section 3.2, we present in detail the case study, highlighting the technical and organizational aspects involved. Next, in Section 3.3, we explain the propose methodology for CIs–based conceptual frameworks replication. In Section 3.4, we present and discuss the results focused on method validation and results implication in monitoring and planning purposes. Finally, we summarize the key messages extracted from the study in Section 3.5.

3.2. CASE STUDY: THE SIASAR INITIATIVE

In this Section, we describe the Rural Water and Sanitation Information System (SIASAR; Sistema de Información de Agua y Saneamiento Rural). SIASAR is a regional sector information system (IS) and a country–led monitoring initiative developed in Latin America and Caribbean (LAC) countries. SIASAR seeks to support decision–making of a variety of stakeholders involved in the sector (such as policy makers, national and local planners and sector practitioners). Among others, one aim of this initiative is to improve resource allocation by influencing targeting and prioritization; thus, it promotes evidence–based planning (Pena et al., 2014).

In particular, and following the background of this initiative, we present and analyze SIASAR from a two–fold perspective. First, we focus on major aspects related to the information cycle, including the issues of i) data collection, ii) data analysis, and iii) data use. Second, we highlight the existing participatory processes of the initiative. Both aspects represent the way in which expert knowledge is brought together into the scene and are essential to visualize the applicability of our proposal (i.e. BNs modelling). In addition to this, we provide a range of illustrative examples to foster a better understanding about SIASAR's scope and performance.

3.2.1. Background

The SIASAR initiative was initially launched in 2011 by the governments of Nicaragua, Honduras and Panama. Although these countries already had their own IS, these were out–of–date and overly focused on the water component, largely neglecting sanitation and hygiene issues. In this context, strategic partners such as the World Bank (through the former Water and Sanitation Program, currently known as Water Global Practice), the Inter–American Development Bank, the Spanish Agency for International Cooperation and the Swiss Agency for Development and Cooperation joined efforts to support these countries in the development of SIASAR. This IS focuses not only on service delivery but also integrates sustainability aspects as a core element. This last aspect was identified by and agreed upon by country experts as the main challenge to be addressed in the WaSH sector.

In 2012, the first version of the SIASAR conceptual model, questionnaires and Information and Communications Technology (ICT) tools became functional. This milestone allowed countries to first collect and process information and then to display it publicly through the SIASAR website and other dissemination mechanisms (e.g., automatic reports, dynamic maps and defined indicators). Since 2013, with a consolidated system and more than 5,000 registered communities, SIASAR has expanded, mainly through the natural framework of the Central American Forum and the Dominican Republic of Drinking Water and Sanitation (FOCARD–APS; Foro Centroamericano y República Dominicana de Agua Potable y Saneamiento). In 2014, the first Regional Agreement was signed, and SIASAR was adopted as the regionally approved and free affiliation IS for the FOCARD–APS countries as well as for those who wanted the convenience of using these instruments. Thus, Dominican Republic, Costa Rica and the Mexican state of Oaxaca joined the initiative in 2014, and Peru, the Brazilian state of Ceará, Bolivia, Paraguay and Colombia joined between 2015 and 2016. Today, SIASAR is in use in twelve countries, after the enrollment of Kyrgyzstan to the initiative in 2018.

Country members adopted a Regional Normative in 2014 (revised in 2016) that gives a clear institutional and operational body to the initiative. This progress is extremely important, as SIASAR is located in the water–related governmental structures of each country. Furthermore, costs of sector technicians as well as of ICT development required to operate the IS are carried by the countries themselves; however, this requires the design of coordinated and collaborative structures within and between countries. As a result, each member country has now implemented a well–structured institutional framework for information and related monitoring mechanisms that is common to all (i.e. covering political, advisory and support, operative and administrative, and executive levels). Specifically reflected in its Normative, each nation is committed to appointing a leader institution that has that goal of ensuring the development, implementation, promotion and financing of the IS (SIASAR, 2016). The creation of such structures, and the commitment of ensuring the sustainability of the IS through its institutionalization, implementation and capacity building are the minimal requirements for joining the initiative. In parallel, these groups are coordinated by one SIASAR country, which assumes a one–year leadership of group organization and economic management, and transfers it after this period. Similarly, national teams have the support of external advisory groups, which are mutually agreed upon.

It is important to stress that this entire initiative, from the organizational to the functional levels, has been created ad hoc by the SIASAR community itself. It is not dependent on any organization or international structure. SIASAR has designed its own coordination and work space and has provided budget and distributed costs among country members. This level of self–management achieved by these countries is one of the strengths that allows SIASAR to be considered a successful case of a collaborative and effective network among teams from 12 countries.

3.2.2. Data collection

Public investment in the WaSH sector of LAC countries has been traditionally biased toward the construction of new infrastructure, and little attention has been paid to other factors that compound sustainable water and sanitation service delivery (Lockwood et al., 2010). Understanding those factors is critical for addressing sustainability gaps and for improving policy development, sector planning, priority setting, budget allocation, project design and technical assistance provision. This core idea led countries to design a set of survey instruments to analyze the quality and sustainability of services from different perspectives: i) the community; ii) the water system; iii) the service provider; and

iv) the technical assistance provider (see Table 3.1). In parallel, the alignment of SIASAR with international monitoring standards (e.g. indicators related to use of water and sanitation infrastructure, as those proposed by the JMP) was taken into account. Briefly, one specific questionnaire was elaborated to collect data from each information source, as shown in the following table.

Table 3.1. Relevant data associated to each questionnaire of SIASAR.

Community	Location and georeference; population; water coverage (at household level); sanitation and hygiene infrastructure and use (at household level); water, sanitation and hygiene software (at education and health centres); community associated water systems and service providers; ongoing projects
Water System	Location and georeference; service type; water intakes; system infrastructure status (catchment, conduction, treatment, storage, distribution); water quality
Service Provision	Type of provider; organization; gender equity; legal status; tariff; revenues and expenses; accountability; operation and maintenance
Technical Assistance Provision	Type of provider; jurisdiction; human, economic and logistic resources; community coverage, frequency and type of support

For data collection processes, the SIASAR community paid attention to three key stages. The first stage involves those preliminary tasks needed to ensure successful field work. From these activities, special focus is given to: i) previous contacts with local institutions and sector practitioners in a given area, as this aspect favours field planning, initiative dissemination and generation of synergies; and ii) survey team training given by the SIASAR–responsible entity in each country.

The second stage represents one of the salient aspects of SIASAR, as it combines data collection from households, the water systems and the service provider. This is especially relevant as widely used household surveys (e.g., Multiple Indicator Cluster Surveys of UNICEF, and the Census of Population and Housing) are not sufficient to monitor many relevant questions related to the WaSH sector (Giné-Garriga et al., 2013). A separate questionnaire was therefore developed to assess these different information sources. Data are then collected through different mechanisms: a closed–question survey, direct observation and water quality testing. For a given geographical area, the methodology consists of visiting all communities in the area. In each community, all existing water systems are inspected, members of the organizations in charge of providing the service are interviewed and a tour around the community (including schools and health centers (SHC)) takes place. Associated technical assistance providers are identified as well; it should be pointed out that these actors generally have a different scale of intervention. Finally, sanitation and hygiene information is obtained through household visits and direct observation. The selected sample of households is defined according to each country's resources and/or community participation degree. Additionally, the use of ICT–based devices are noteworthy, as these facilitate the survey teams' ability to collect, store and transmit related data.

Finally, the third stage integrates the validation process, which is crucial for ensuring data quality. Validation is carried out through: i) an instant check facilitated by the survey device (internal programming and detection of logical errors) and an agreement with the interviewed players; and ii) a final verification executed by municipal or national authorities. Once the information is validated, data are published on the public website. As can be seen in Table 3.2, the majority of the SIASAR countries have already collected a significant amount of data. The case of Nicaragua is noteworthy, as it carried out a baseline of all rural communities, systems and service providers. This milestone was officially certificated by its government. Furthermore, and as expected during any data collection process, Nicaragua has also finished updating this baseline.

Table 3.2. Validated monitoring results at SIASAR by country (updated on December 2020).

Country	Communities	Water Systems	Service Providers
Bolivia (2016)	1,079	1,207	939
Colombia (2016)	5,298	2,728	2,536
Costa Rica (2015)	80	5	8
Dominican Republic (2013)	2,353	664	473
Honduras (2011)	4,523	3,276	3,278
Kyrgyzstan (2018)	1,715	1,166	905
Nicaragua (2011)	4,862	5,442	2,558
Panama (2011)	1,388	638	684
Paraguay (2016)	49	5	1
Peru (2015)	9,910	10,070	10,070
State of Ceará (2016)	90	53	23
State of Oaxaca (2015)	132	128	126
TOTAL	**26,956**	**25,382**	**21,601**

In brackets, year of joining SIASAR initiative.

Undoubtedly, the SIASAR initiative has grown over the past few years. This growth brings the challenge of constantly reviewing survey instruments, with the aim of integrating each country’s realities and of ensuring comparability. Under a principle of simplicity – use as little information as necessary, but not less –, each country’s particularities are analyzed, discussed and finally harmonized and approved by all countries. Additionally, SIASAR visualizes the need of alignment and collaboration with other international monitoring systems. In this sense, a thorough revision of survey instruments is currently taking place, in order to tailor them to post–2015 key monitoring elements.

3.2.3. Data analysis

One salient aspect of SIASAR is the manner that collected data are organized and analyzed (Pérez-Foguet and Flores-Baquero, 2015). Six aggregated dimensions are defined to assess water and sanitation services from different and complementary points of view. The aim of this structure is to keep different aspects in focus that characterize an increasing decentralized WaSH sector, as in practice, institutional roles and responsibilities of sectorial issues are assumed by different stakeholders (Giné-Garriga and Pérez-Foguet 2013a, 2013b). This characteristic is common to most of the SIASAR countries. The dimensions mentioned have been proposed to measure: i) the water service level (WSL); ii) the community sanitation situation and various hygiene issues at the household level (SHL); iii) the condition of water system infrastructure (WSI); iv) the service provider performance; v) the technical assistance provider performance; and vi) the WaSH situation in public institutions (SHC). Additionally, at a higher level, the cited dimensions are aggregated into two partial indices: i) water, sanitation and hygiene service level (WSHL), and ii) water services sustainability index (WSSI). These partial indices aim to keep the focus on aspects related to quality and sustainability of services identified by all member countries. Finally, a last level is represented by an aggregated water and sanitation service performance (WSP) index. These last indices provide a means of initiating discussion and stimulating public interest. All presented elements are listed in Table 3.3.

Table 3.3. General Index, Partial Indices, Dimensions and Components of SIASAR conceptual model.

Water and Sanitation service Performance index (WSP)	
Water, Sanitation and Hygiene service Level (WSHL)	**Water Services Sustainability Index (WSSI)**
Water Service Level (WSL)	**Water System Infrastructure (WSI)**
Accessibility (ACC) Continuity (CON) Seasonality (SEA) Quality (QUA)	System Autonomy (AUT) Production Infrastructure (INF) Water Catchment Protection (PRO) Treatment system (TRE)
Sanitation and Hygiene Service Level (SHL)	**Service Provision (SEP)**
Sanitation Service Level (SSL) Personal Hygiene (PER) Household Hygiene (WAT) Community Hygiene (COM)	Organizational Management (ORG) Operation & Maintenance Management (OPM) Economic Management (ECO) Environmental Management (ENV)
Schools and Health Centres (SHC)	**Technical Assistance Provision (TAP)**
Water Supply in Schools (SWA) Water Supply in Health Centres (HWA) Sanitation in Schools (SSH) Sanitation in Health Centres (HSH)	Information Systems (ICT) Institutional Capacity (INS) Community Coverage (COV) Intensity of Assistance (INT)

Each dimension comprises four components. In turn, each component is fed by a short list of single indicators, with a total of 109 indicators. In terms of method and technique, index construction relies on a simple step–by–step procedure: i) the selection and combination of key indicators into their corresponding subindices, using an equal and dimensionless numeric scale; ii) the determination of weights for each subindex and their aggregation to yield an overall index; and iii) the dissemination of index values by means of a grading system, classifying communities in four levels.

First, indicators are classified according to the previously described conceptual framework. As collected data are frequently represented on different scales (such as percentage of systems with adequate water treatment, distance–to–source in meters, service continuity in hours per day, and so forth), they have to be normalized prior to their analyses. A score between 0 and 1 is assigned for each parameter, whereby 1 represents the best performance and 0, the worst–case scenario. Components are then defined by simple and easy–to–use multi–attribute utility functions. For instance, there are criteria whose values are associated with linear variations (e.g. water coverage). An additional indicator, such as the distance to the water source, can also be considered to evaluate the overall value of the component accessibility (see example in Table 3.4). A second example takes into account several criteria to assess the component OPM of the service provider: i) a different punctuation is given according to the residual chlorine measurement obtained; ii) a combination of different OPM aspects are assessed and rated; and iii) a final value of the utility function is provided by a linear mean of both criteria (Table 3.4).

Table 3.4 Examples of utility functions associated to the components of Accessibility (top) and Operation & maintenance management (bottom).

Accessibility (ACC)				
Effective coverage	Coverage = 0	Coverage * Accessibility factor ACC fact. = 1 (if average dist. ≤ 100 m) ACC fact. = 2/3 (if average dist. > 100 m)		Coverage = 1 Average dist. < 100 m
Criteria	**0**	**Linear variation**		**1**
		0.33	**0.66**	
Chlorine basic operation (residual chlorine)	Cl ≤ 0.1 mg/l	0.1 mg/l < Cl ≤ 0.3 mg/l	Cl > 1 mg/l	0.3 < Cl ≤ 1 mg/l
General assessment of OPM	Neither corrective nor preventive maintenance is provided	Corrective AND/ OR preventive maintenance is provided	Corrective AND/ OR preventive maintenance is provided, AND OPM costs are registered	Corrective AND preventive maintenance is provided, AND OPM costs are registered, AND a plumber is present at the organization
Operation & maintenance management (OPM)				

Next, different components of each dimension are aggregated into a single value. Two major issues need to be addressed: i) the choice of weights should reflect the relative importance of each component, and ii) the aggregation function should be consistent with the theoretical framework (Nardo et al., 2005; Giné-Garriga and Pérez-Foguet, 2010; Flores-Baquero et al., 2016a). For weight assignment, two approaches were compared: i) equal weights, and ii) weights according to expert opinion (analytical hierarchical process). Several experts from all member countries were involved in this process. Based on comparative analysis, equal weights are assigned to all components. Similarly, partial indices are calculated by using an equal weighted grouping of all dimensions, and a general index (the WSP index) is created by giving both partial indices the same relative importance. For the aggregation method, two different alternatives were tested: i) linear (compensatory), and ii) geometric (partial compensatory). According to the analysis carried out, partial compensatory methods (geometric) might favor the appearance of null values, hampering the duty of discrimination among results. Thus, all dimensions are constructed by allowing the compensation of their components (additive aggregation). However, due to the first compensation, posterior aggregations for partial and general indices are geometric.

Finally, in order to foster prioritization and decision–making, the achieved results were made more understandable for final users and stakeholders by linking components, dimensions and index values to a defined set of categories (A, B, C or D, whereby A represents the best result and D, the worst). This representation can be done in several ways, and two alternatives were tested here: i) equal intervals, and ii) different intervals. The results of the two tested methods differed significantly from each other. Overall, however, the different interval method was the preferred method: despite being less simple conceptually, the fact that it requires a higher overall score in order to move up to a better category sets a higher service threshold, which can be seen as a positive aspect. Thus, the different interval method is the classification adopted for visualizing results. Specifically, the intervals are defined as follows: A, [1–0.9], with both limits included; B (0.9–0.7]; C (0.7–0.4]; and D (0.4–0].

The involvement of the member countries in conceptual framework design has been indispensable. First, preference levels (punctuation) of a component’s utility functions were agreed by common consent at the sectorial level. The same procedure was carried out to define an aggregation methodology, while the assignment of weights was based on a wider consultation (as mentioned previously). There is no doubt about the need to preserve the consensus among countries in relation to the SIASAR concept and its monitoring framework. However, it is also necessary to validate the conceptual model against real data. The validation showed that the model is sufficiently flexible to evolve and to be adapted to future requirements. This principle of flexibility allowed different versions of the conceptual model to be developed. As a result, and in terms of calibration, survey tools as well as the definition of the different components have been improved. The aim was to favor i) the refinement of the preference levels, and ii) the duty of discrimination.

3.2.4. Data use

The ultimate goal of sound sector–related data is to facilitate its use and to improve decision–making. To do this, two elements are necessary (Grosh, 1997): i) the data must be analyzed to produce outcomes that are relevant to the policy question, and ii) the analysis must be disseminated and transmitted to policy makers. Assuring that data are easily accessible and are presented in a user–friendly format will stimulate their use. Otherwise, decision–making will be carried out without considering the information.

When using SIASAR data, the most remarkable aspects to take into account are i) the existence of a common monitoring architecture, ii) the possibility to compare WaSH issues at different scales, and iii) the development of a regional sector–related community in which knowledge exchange and good practices transcend beyond national borders. As a starting point, the SIASAR community designed a distinctive, easy–to–use and meaningful dissemination method of results, which aims to address sustainability aspects, that is applied to all SIASAR elements (indices, dimensions and components). According to the agreed upon intervals (discussed in the previous section), a specific meaning was defined to facilitate interpretation. The SIASAR grading system is represented graphically in Figure 3.1, using the WSI as an illustrative example. The "A" grade represents the desirable situation of a completely functional system. Over time, the system is likely to experience different technical issues due to its use. If these deficiencies can be addressed by the community, service provider, etc., then the functionality is classified with a "B" grade. This ranking status commonly reflects the fact that, in a short–term period, actions could be taken that would allow the initial functionality to be recovered. When no measures are taken on the short–term, deficiencies become more pronounced, and external support would then required for recovery. This aspect represents the main difference between the "B" and "C" grades. Finally, a "D" grade highlights the absence of a system or the ability to recover it. This last point might be a consequence of not taking actions when issues were initially detected. In this last scenario, community, service provider, etc., need external financial and technical support to recover the full functionality of the system.

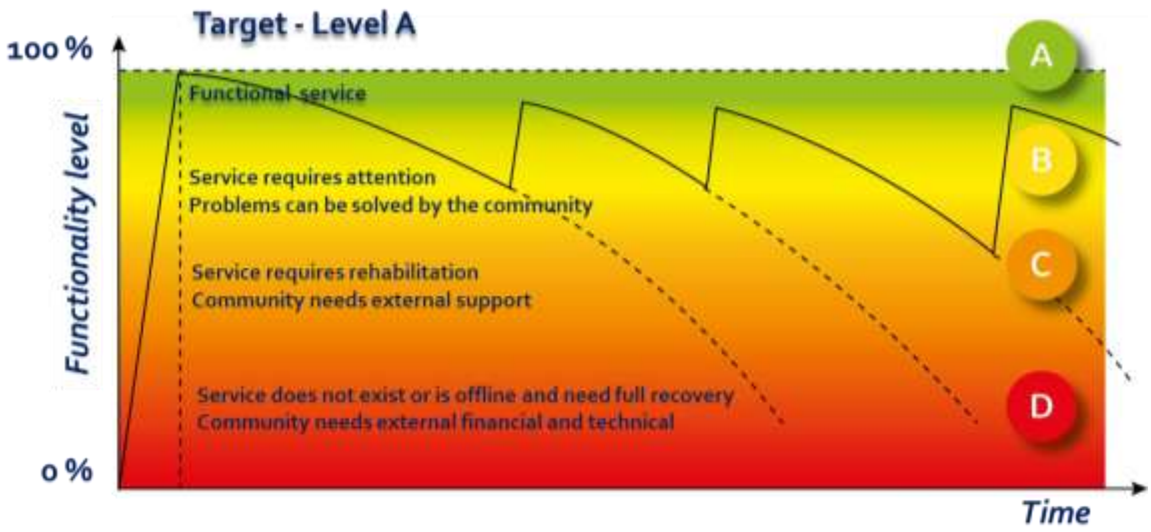


Figure 3.1. SIASAR distinctive classification methodology A/B/C/D, where each value is associated to a specific meaning that has been defined and acquired by all country members. Source: SIASAR, 2016.

To exemplify results from the regional level and the visualization instruments employed, Figure 3.2 presents results of the sanitation and hygiene service level (SHL) dimension for four country members. As mentioned, this dimension provides a simultaneous point–of–view of the community sanitation situation and various hygiene issues at the household level. Note that a "D" classification is given to 45% and 48% of the communities in Nicaragua and Panama, respectively, but only to 17% and 23% of the communities in Honduras and Dominican Republic, respectively. In any case, sanitation and hygiene services are deficient and require priority attention. In addition to this, a high percentage of communities are qualified as "C", ranging from 32% in Panama to 48% in Honduras, which underscores the need of external support to improve the service. This first approach provides i) a direct visualization of the countries with the most need to those possible interested actors, and ii) the starting point of a more in–depth analysis. Nevertheless, these results must be analyzed carefully, as available data differ notably among these countries (see Table 3.2). For instance, the baseline of Nicaragua provides a more reliable image of the SHL situation, while the current Panama database might not be completely representative of the rural national condition. However, objective comparability is possible, as an equal set of indicators to assess SHL have been employed. It should be noted that same nature of analysis might be done at a general and partial index level, as well as a component plane. Additionally, and within the SIASAR community, countries that count with a more tangible management (such as Honduras and the Dominican Republic) share their experience to support and guide partner initiatives.

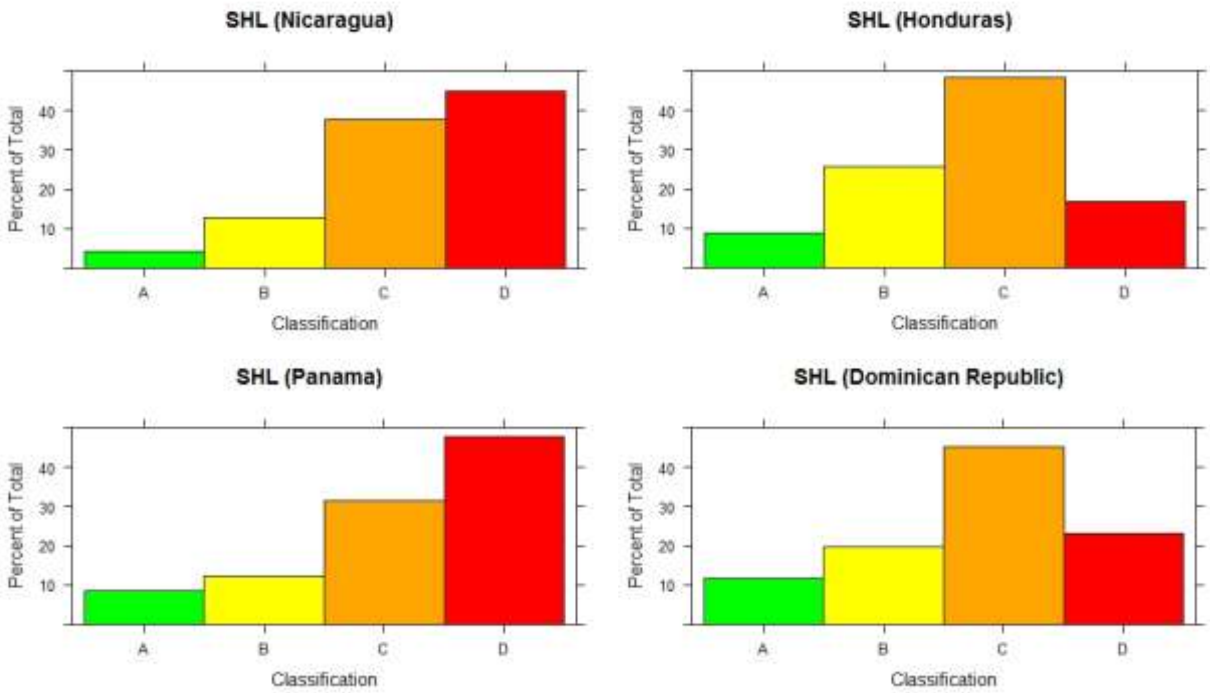


Figure 3.2. Results associated to the evaluation of "Sanitation and Hygiene service Level, SHL" dimension, obtained by the aggregation of its four different components (data available at http://doi.org/10.5281/zenodo.571351).

Beyond the aggregated indices, a model structure allows a narrower focus on specific components. Following a previous first approach and analysis, Figure 3.3 presents detailed information about the SHL dimension in Nicaragua. For this, maps are powerful instruments for displaying information and enable non–technical audiences to easily understand current sectorial situation. The model permits prioritization among the different components. In this case, hygiene–related aspects are visualized as the ones with the higher need to improvement. Specifically, these components deal with appropriate hand–washing practices (SHL.PER), with safe water storage

(SHL.WAT) and with the practice of open defecation and community cleanliness (SHL.COM). For these aspects, the eastern region of the country presents a clear deficiency. Additionally, combining this information with health data could provide a complete picture of the context. On the other hand, components related to improved sanitation infrastructure (SHL.SSL) associate lower service levels to the south–east area of the country, which should be considered in conjunction with the previous results. This first assessment might lead to establishing strategies to tackle sectorial needs. For the local decision–making level, the SIASAR platform also provides listed communities and rankings, thereby allowing the most vulnerable segments of the population to be precisely determined so that policy attention and public resources can be directed to them. Importantly, results are easily obtained by different administrative scales, allowing decision–makers to better identify needs and target future investments more effectively.

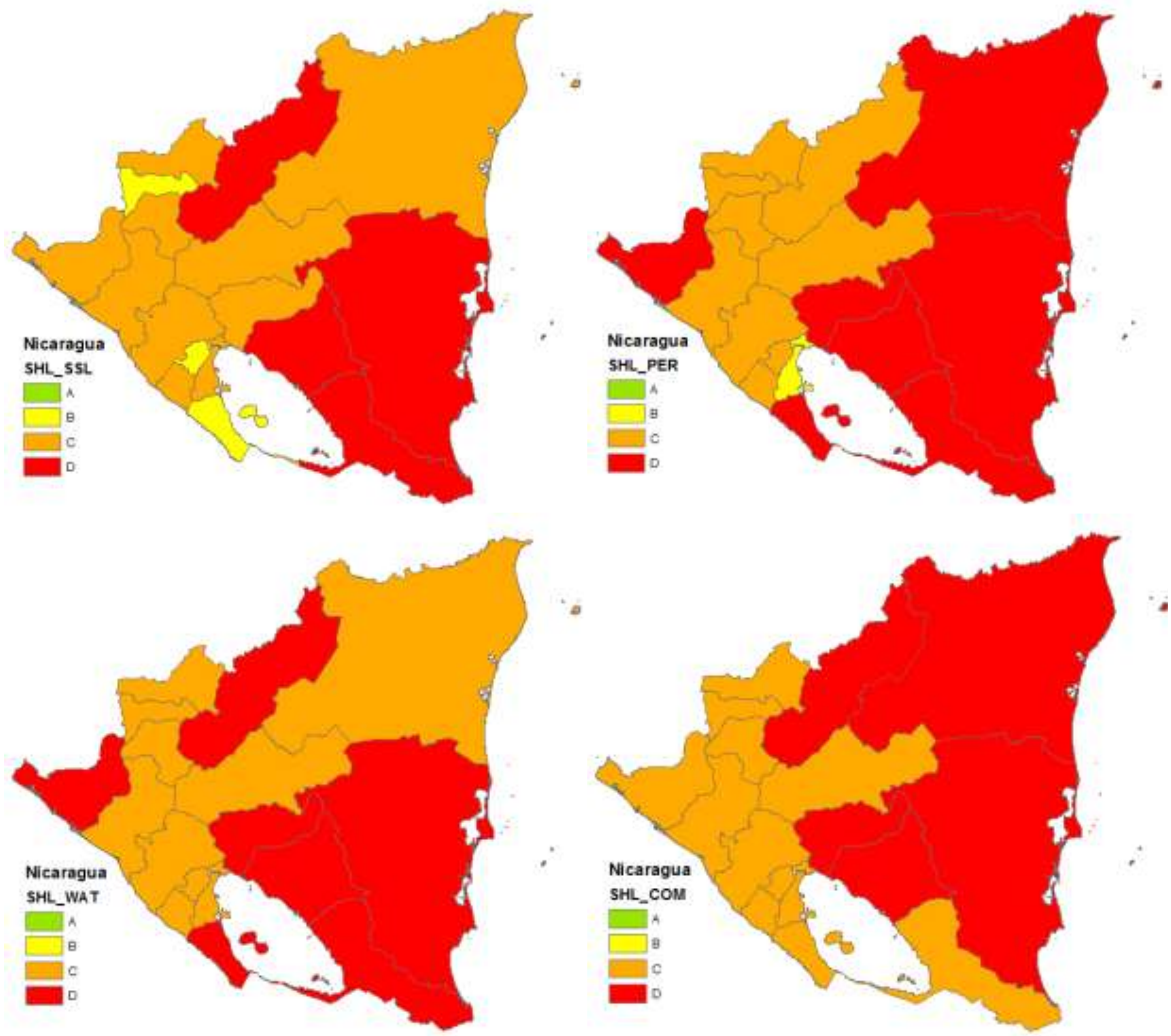


Figure 3.3. Results represented by the four components of "Sanitation and Hygiene service Level, SHL". Aggregation to shown administrative units considers population size. Upper–left: "Sanitation Service Level, SHL.SSL"; Upper–right: "Personal Hygiene, SHL.PER"; Bottom–left: Household Hygiene, SHL.WAT"; Bottom–right: "Community Hygiene, SHL.COM".

To promote data use, SIASAR has designed and developed a battery of harmonized reports. They provide a comprehensive assessment of key issues reflected in the conceptual model. As the aim is to guarantee the usefulness of these tools, reports have been tested in field with key stakeholders, paying attention to the local level. The following examples show the practical use of SIASAR as a decision–making tool. In Nicaragua, during the period 2013–2016, 64 rural municipal plans for water supply and sanitation were developed using data from the system, supporting the prioritization of the most vulnerable communities to receive investments and technical assistance. Since 2014 in Honduras, sectorial profiles of 28 municipalities have been developed based on SIASAR information that target technical assistance activities and inform the development of Municipal Development Plans. This is especially relevant as these plans are an instrument by which Honduran municipalities formally request the transfer of national funds for local investments. In Panama, SIASAR data were used in 2016 to better target investments and technical assistance in indigenous communities. In Dominican Republic, 33 water systems were rehabilitated during 2016 based on information collected through SIASAR.

3.2.5. Final considerations

In this Chapter, we exploit the conceptual framework of SIASAR. As described, it comprises six aggregated dimensions and three additional indices. Nevertheless, at the time of this research, data was only available for four of the six dimensions. Thus, we consider a simplification of the conceptual model (Table 3.5). Similarly, each dimension comprises four components, which are fed by a short list of single indicators (see Annexes Table A1). In addition, the different composites are constructed by aggregating the components arithmetically in the case of the four dimensions (or geometrically for the partial and general indices; see Annexes Table A2).

Table 3.5. SIASAR simplified conceptual model.

Water and Sanitation service Performance index (WSP)	
Water, Sanitation and Hygiene service Level (WSHL)	**Water Services Sustainability Index (WSSI)**
Water Service Level (WSL)	**Water System Infrastructure (WSI)**
Accessibility (ACC) Continuity (CON) Seasonality (SEA) Quality (QUA)	System Autonomy (AUT) Production Infrastructure (INF) Water Catchment Protection (PRO) Treatment system (TRE)
Sanitation and Hygiene Service Level (SHL)	**Service Provision (SEP)**
Sanitation Service Level (SSL) Personal Hygiene (PER) Household Hygiene (WAT) Community Hygiene (COM)	Organizational Management (ORG) Operation & Maintenance Management (OPM) Economic Management (ECO) Environmental Management (ENV)

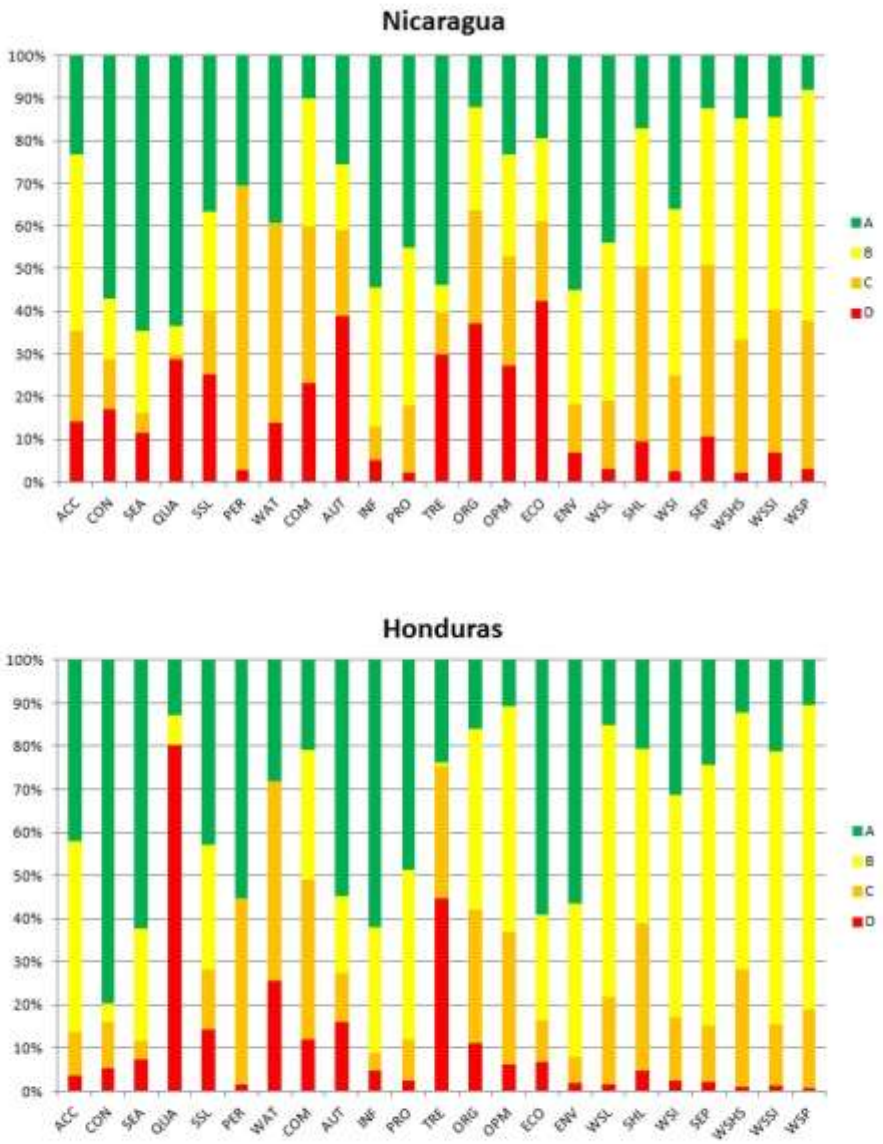


Figure 3.4. Components, dimensions, partial indices and general index A–B–C–D distributions. ACC, accessibility; CON, continuity; SEA, seasonality; QUA, quality; SSL, sanitation service level; PER, personal hygiene; WAT, household hygiene; COM, community hygiene; AUT, system autonomy; INF, production infrastructure; PRO, water catchment protection; TRE, treatment system; ORG, organizational management; OPM, operation & maintenance management; ECO, economic management; ENV, environmental management; WSL, water service level; SHL, sanitation and hygiene service level; WSI, water system infrastructure; SEP, service provision; WSHL, WaSH service level; WSSI, water service sustainability index; WSP, water and sanitation service performance index.

We process and analyze data from two different countries, namely Nicaragua and Honduras. For Nicaragua, we analyzed a baseline of all rural communities, water systems and service providers; after data pre–processing, we used a total number of 3,495 communities, with values associated to all components detailed in the simplified conceptual model. For Honduras, we found that 3608 communities fulfilled these requirements (both datasets are available at https://doi.org/10.5281/zenodo.804010). The distribution of the primary data according to the intervals or states is shown in Figure 3.4. In general, all components possess values associated with each state, with the exception of PER and WAT, for which values belong to the A, C or D states (due to the utility function structures). Specifically, for Nicaragua, the average distribution of A, B, C and D states are 38.3, 23.0, 21.3 and 20.3, respectively (Annexes Table A3). However, important differences are found when focusing on individual states. For instance, 64.7% of the rural communities are evaluated as A for SEA, while just 10.1% are evaluated as A for COM (Figure 3.4). Additionally, it is possible to identify components that are in a more precarious situation (i.e. the ones related to hygiene and service provider performance). For Honduras, the average distribution for the states A, B, C and D is 42.2, 27.3, 18.7 and 15.2, respectively. In this case, there are wider differences within the states, such as D, for which there is a maximum of 80.2 and a minimum of 1.5. Here, in contrast the Nicaragua, the components QUA and TRE require more attention. Overall, these two countries represent two different realities and specificities within the same sector, thus making them suitable for the purpose of this work.

3.3. METHODS

This Section proposes a step–by step methodology to replicate the SIASAR hierarchical CI–based framework (see Table 3.3) by exploiting the flexibility of BNs. First, however, we present the main novelty of this work in terms of method, and then we introduce the main assumptions of the approach adopted.

3.3.1. Initial settings

Two main approaches can be taken when developing a BN model: manual or automatic (Aguilera et al., 2013). A manual approach includes expert opinion and complementary literature as part of the process of defining which variables are dependent on each other, and to which extent.
An automatic approach uses structure learning algorithms (SLA) to provide the optimum structure of the network, spurred on by data. This data–driven approach can reduce the subjectivity of the decisions to be made when defining the structure of the network and can also help to minimize the need for expert elicitation, which is a time–consuming process (Alameddine et al., 2011). To the best of our knowledge, no previous studies in the WaSH sector have proposed a data–driven approach when applying BNs modelling. In model construction, three key assumptions have been made: i) the method should be applicable to large set of databases; ii) a limited number of states has been used for each variable. Specifically, we employed the A–B–C–D grading system that characterized the presented pilot study; and iii) variables are only allowed to connect others at the same or the next hierarchical level (Figure 3.2).

3.3.2. Model generation

Once the initial settings have been introduced, the proposed methodology for BN model generation comprises four main stages (see Figure 3.5): model proposal (A), model calibration (B), model validation (C) and method validation (D). Each stage integrates different steps which are specified as follows:

– **Step 0. Conceptual model selection and data split.**

The first step is to select an appropriate conceptual framework to test the proposed methodology. We suggest those that possess at least three levels of variables (e.g. indicators, partial indices and a general index). Then, we propose randomly splitting the data into two parts: one for training the model, and the other for testing. This process, which is directly related to model evaluation, helps to ensure that the final result is feasible and defensible (Chen and Pollino, 2012). In this case, we opted for assigning 70% of the dataset to training, and 30%, to testing. The training dataset is used for the stages A and B of the methodology.

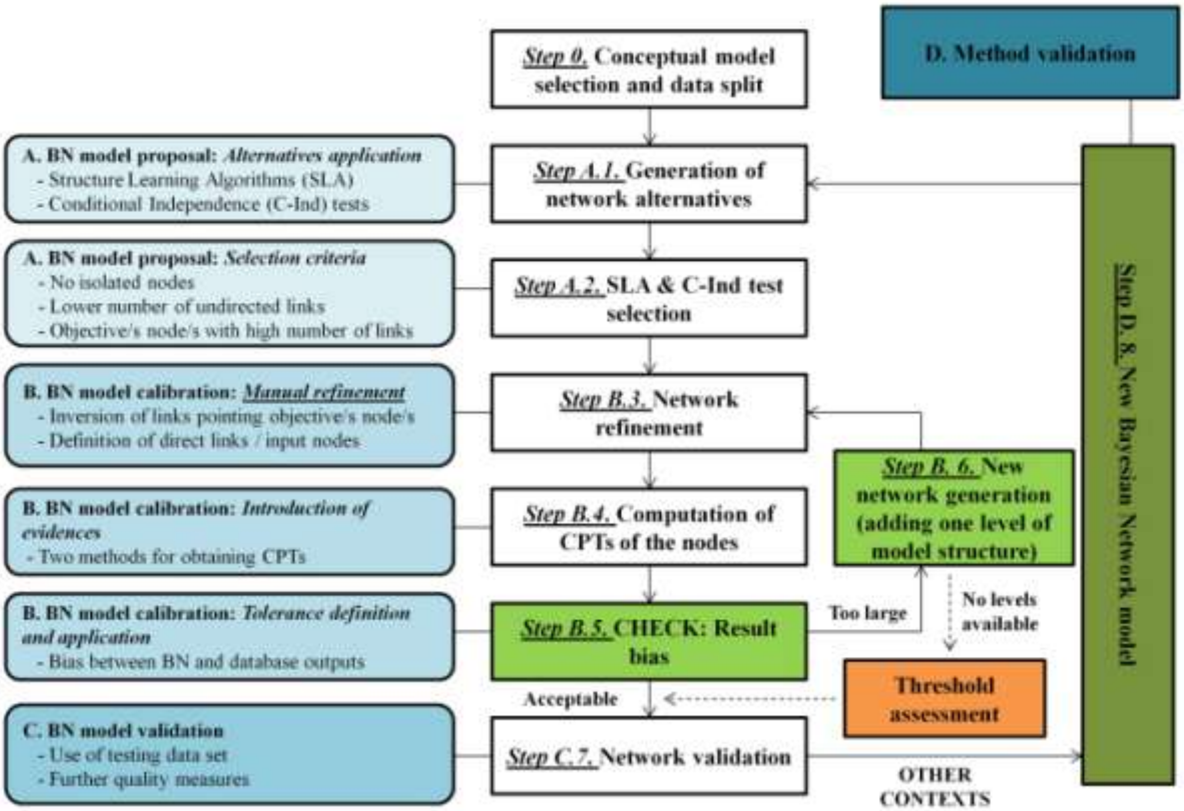


Figure 3.5. Step–by–step methodology for BN model generation and validation.

– Step A.1: Network alternatives generation.

The bnlearn (version 4.1) package implements the following constraint–based learning algorithms (Scutari, 2010): grow–shrink (gs), incremental association (iamb), fast incremental association (fast.iamb), interleaved incremental association (inter.iamb) and max–min parent and children (mmpc) (see Section 2.4.3). Additionally, the C–Ind tests must be chosen with respect to their data typology. In this case, all values are discrete. For computing time, the C–Ind test selection is reduced to mutual information (mi) and Pearson's X^2 (x2) tests. After applying the combination of both SLA and C–Ind tests to the database, ten primary networks were obtained.

– Step A.2: Structure learning algorithm (SLA) + conditional independence (C–Ind) test selection.

Alameddine et al. (2011) used constraint–based algorithms to learn the structure of the network from data but also suggested comparing different potential networks by evaluating a model's ability to either incorporate the relevant endpoint (understood as the answer of interest) or to identify variable links. In order to select the final primary network (i.e. the SLA and C–Ind tests in tandem), we propose several joint criteria for making the final selection; specifically, it should: i) not leave a considerable number of nodes isolated; ii) present a lower number of undirected links; and iii) identify a higher number of links associated with the objective node(s) – for instance, the node WSP (from the general index) can be considered as the objective node, according to the hierarchical structure of the presented conceptual model.

– Step B.3. Network refinement.

Once the primary network has been selected, a further manual refinement is required (in contrast to the previous process, which can be carried out automatically). This process, as the first part of the BN model calibration, comprises several actions (see Section 2.2.1 for nomenclature):

i) Inversion of links associated with the objective node. It might occur that the link between the objective node and any other node goes from the former to the latter. Considering the structure of the conceptual framework at hand, this must be solved by reversing this direction;

ii) Definition of direct links. BNs can only be fully operative (e.g. able to simulate scenarios) in the absence of undirected links. If this is not the case, a complete directed acyclic graph (DAG) cannot be obtained. Therefore, we recommend providing this direction, as supported by expert consultation;

iii) Definition of input nodes. We propose three alternatives for the final selection of the network input nodes: i) a data–driven approach, in which inputs nodes are selected by providing the minimum manipulation to the network (using input nodes proposed by SLA and the C–Ind test); ii) an interquartile range (IQR) approach, with input nodes as well as intermediate ones (e.g., those between the input and objective nodes) represented by those variables with highest IQR (see Annexes Table A4); and iii) a smart variable approach, in which input nodes are selected according to their facility for data collection in field. No matter which are chosen, this manipulation must be done carefully, and some decisions must be taken in order to avoid closed loops. At this point, four different functional networks are obtained for further analysis.

– **Step B.4. Computation of CPTs of the nodes.**

CPTs of the nodes represent the probability of each possible state in a child node, given each possible event in the parent node(s). In this study, node states are represented by an A–B–C–D grading system (inherited from the selected conceptual model). Thus, every node is associated with a probability distribution according to these states. To simplify the nomenclature, we refer to model results as inferred distributions, and the ones provided by the available data, as IS (information system) distributions.

Once networks are functional, a direct use (i.e. forward direction from input nodes to objective node, see Section 2.2.2) is carried out. This application is known as predictive inference (Carriger et al., 2016). For this, evidence is introduced to compare inferred and IS distributions. Specifically, IS distributions (obtained from Nicaragua database) were assigned to the corresponding input nodes. Inferred distributions at the WSP node were then compared with the IS distributions provided by the data.

This procedure was carried out for all of the different networks. We also suggest testing the two methods available to compute the CPTs of any node of interest, namely the maximum likelihood estimates (mle) and the Bayesian setting (bayes) (Scutari and Denis, 2015).

– **Step B.5. Result bias check.**

The last step regarding the calibration process is to assess each network's inferred results. A priori, a threshold bias between 0% and 5% is established. If one, two or all networks provide results within the threshold, the network that provides a lower bias (e.g., with a lower difference between inferred and IS distributions) should be selected. If the results are similar, the minimum mean bias should be used to carry out the final network selection. If either of these two situations is the case, the procedure should jump to Step C.7 (BN model validation). However, if the resulting bias is larger than the established threshold, an iterative intermediate step should be carried before model validation, as detailed in the following Step B.6.

– **Step B.6. New network generation.**

If the obtained bias is not acceptable, we propose that the network is provided with structure, which is related to the conceptual model selected; in other words, the structure represents the expert knowledge contribution during model development. For instance, the previous steps could be carried out by setting a first scenario using the sixteen components of the conceptual model and the general index. If the bias is too large, a second scenario should be simulated introducing the two partial indices as new nodes (WSHL and WSSI), as well as the sixteen components and general index, and the bias should be re–checked. If the bias is still large, the loop involving Steps B.3–B.5 should be repeated (which would add a new level of model structure) until an acceptable bias is achieved. If the bias is still too large but it is not possible to add a new level of structure to the network, the suitability of the established threshold and the subsequent trade–offs should be assessed.

– **Step C.7. Network validation.**

Different actions are suggested for validating the selected network:

i) Check using testing dataset. Similar to Step B.4, evidence is introduced to compare inferred distributions with IS distributions. Based on the network obtained, the dataset kept for testing can be used, and result biases can then be checked. Optionally, the same procedure might be done using the complete dataset prior to splitting.

ii) Assessment of further quality measures. Apart from evaluating the bias obtained with respect to the objective node, we recommend that the inferred distributions associated with those nodes, which provide structure to the model, should also be assessed. They should then be compared to the associated real distributions.

– **Step D.8. Method validation.**

Last but not least, a final step is included in this study with the aim to validate the proposed methodology. This step might not be possible when dealing with other conceptual frameworks, as additional data from another context may be required. In such a case, we recommend focusing on the results obtained in previous steps. In this study, it was possible to access data from another country, which is similar in terms of methods and results, to validate the methodology. Although it is unlikely that one model fits all country members, a preliminary check should be carried out using the model previously obtained (e.g., from the first country considered), prior to recalculating from scratch for the second country. In case the resulting bias is too large, Steps A.1–C.7 should be applied. For this case, we carried out this process using the database from Honduras.

3.4. RESULTS AND DISCUSSION

3.4.1. Testing the proposed methodology

We applied the proposed methodology to two WaSH–related country databases – Nicaragua and Honduras. Initially, and according to the step–by–step proposal, different SLA and C–Ind tests were applied to the database of Nicaragua. A first scenario ("16 + 1") considers those sixteen components as well as the general index (WSP) of the selected conceptual model. Fromthe ten different primary networks obtained in first instance, six networks provided a structure containing a high amount of isolated nodes. Thus, only the remaining four networks were considered suitable for selection (see Figure 3.6). Considered the overall criteria proposed, the tandem "fast.iamb" SLA and "mi" C–Ind test conforms the selected primary network. Specifically, this tandem presents i) no isolated nodes, ii) three undirected links, and iii) 13 direct links pointing to the objective node.

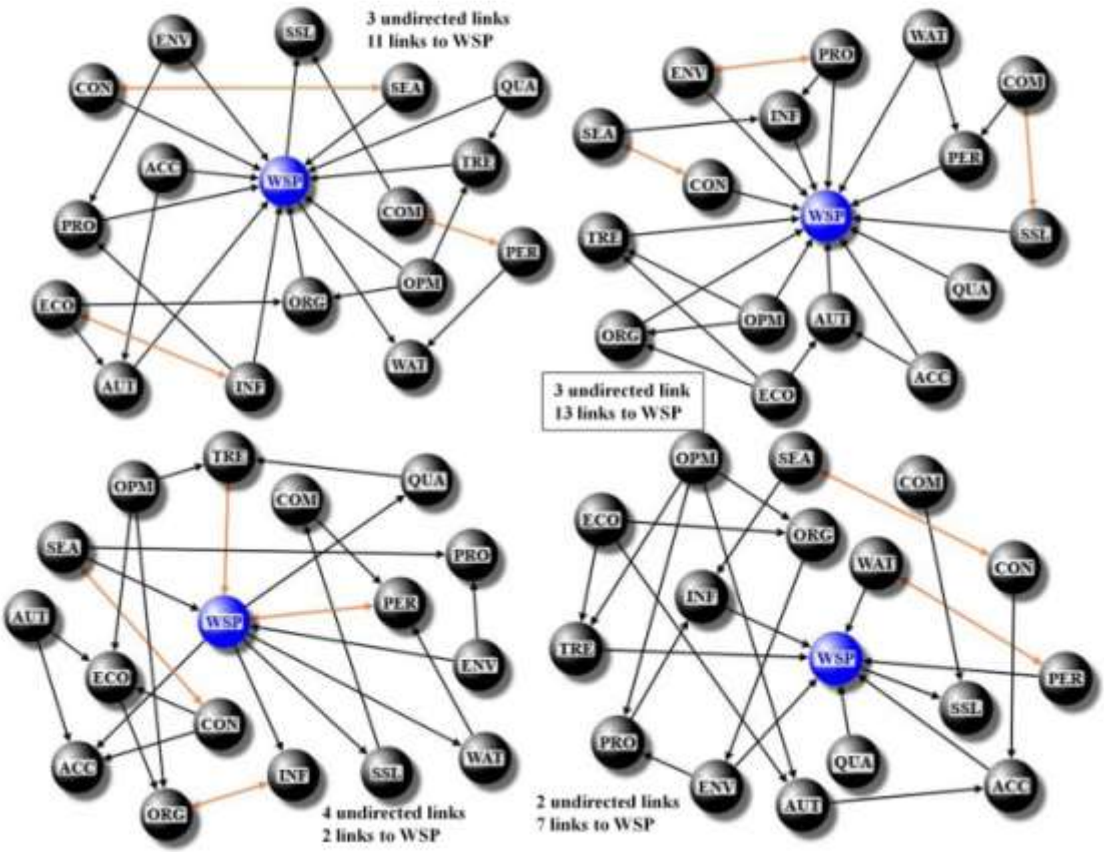


Figure 3.6. Primary networks resulting from the application of different structure learning algorithms and C–Ind tests. Top–left: fast.iamb (x2); top–right: fast.iamb (mi); bottom–left: inter.iamb (x2); bottom right: inter.iamb (mi). In black, input nodes. In blue, objective node. The final selection is highlighted.

The first step in model calibration requires a manual refinement of the selected primary network, by appropriately defining links associated to the objective node, converting undirected links into direct ones and establishing input nodes following the four proposed alternatives (Figure 3.5). For the Nicaragua case, four different networks were obtained (see Figure 3.7). CPTs for nodes were computed, and evidence (e.g., IS distributions, elicited from data) was assigned to input nodes. Finally, the inferred distributions associated with the WSP node were compared to the IS ones provided by Nicaragua dataset. In this first scenario (16+1), no acceptable biases were obtained (see Annexes Table A5). Therefore, expert knowledge (in terms of provision of structure according to the selected conceptual model) was provided to the candidate networks. Specifically, this second scenario was tested by integrating the WSHL and WSSI nodes, which represent the partial indices of the conceptual framework. In this case, acceptable biases were obtained for those networks, using "lowest IQR" and "smart" as inputs nodes. However, after using the test dataset to validate the networks, the biases obtained were not acceptable (see Annexes Table A5).

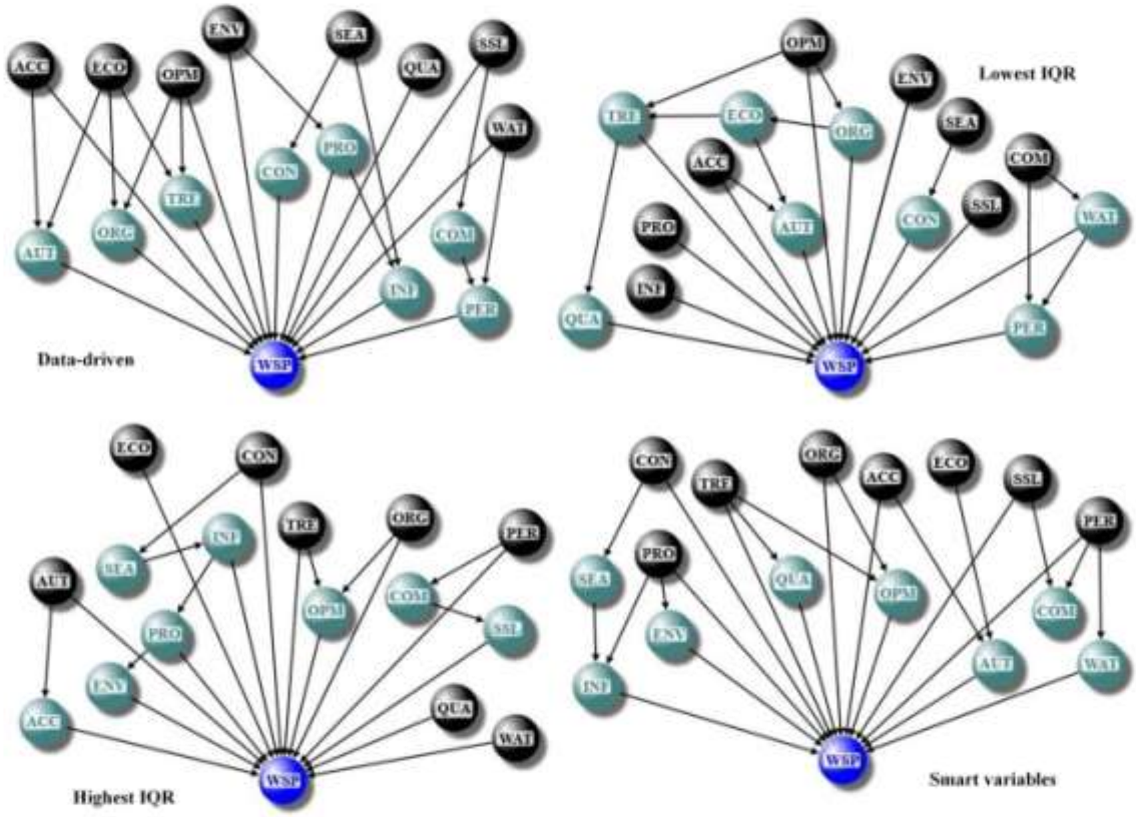


Figure 3.7. Candidate networks obtained from the tandem "fast.iamb" SLA and "mi" C–Ind test and assigning different inputs nodes according to the proposed approaches. In black, input nodes. In blue, WSP objective node.

As a consequence, a third scenario was set out by including those nodes representing the four dimensions of the conceptual model (e.g., WSL, SHL, WSI and SEP), resulting in four different networks (see Figure 3.8). After evidence was assigned to the input nodes, and bias results were checked, the network in which the input nodes were represented by those ones with the lowest IQR were found to provide slightly better results and were therefore selected. A validation process was then carried out using the testing dataset. Additionally, the unsplit dataset (all data) was used as well for the validation process (see Annexes Table A5), and further quality measures were checked.

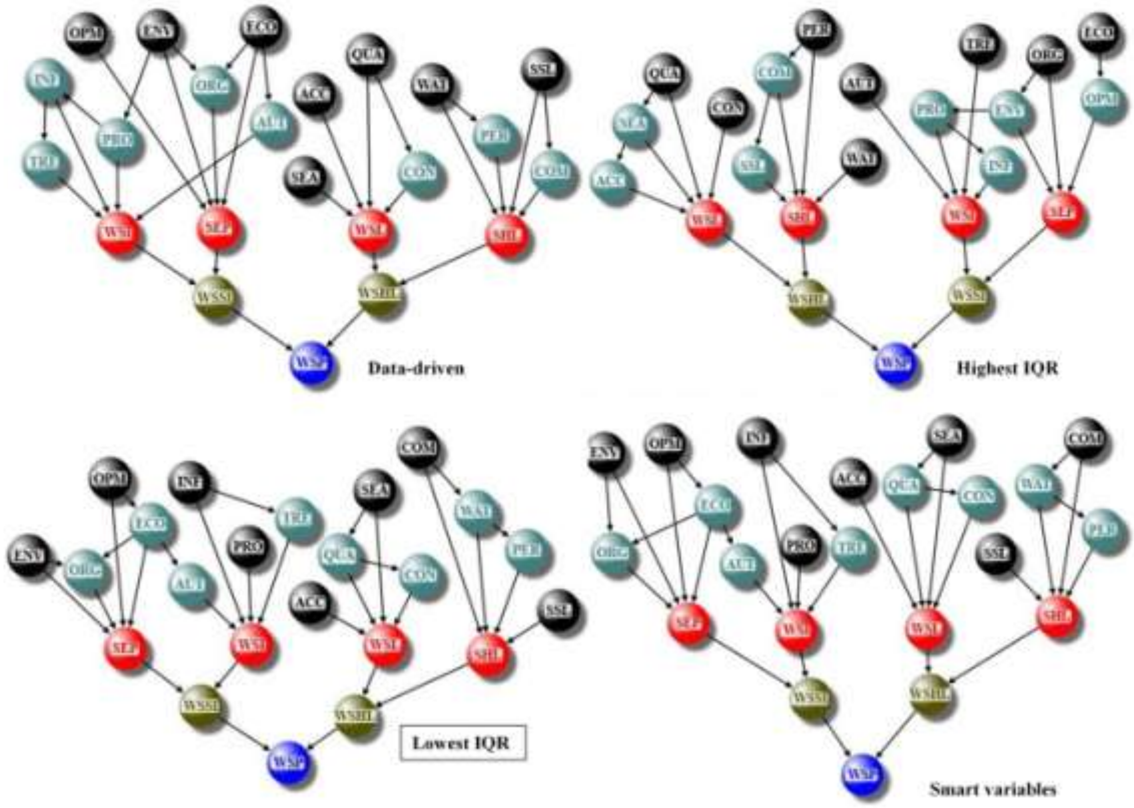


Figure 3.8. Full structure (expert knowledge) provision to networks after the iterative process proposed in the methodology. In black, input nodes. In red, nodes representing SIASAR conceptual model dimensions. In dark green, nodes representing SIASAR partial indices. In blue, WSP objective node. The final selection is highlighted (see Annexes Table A5 as well).

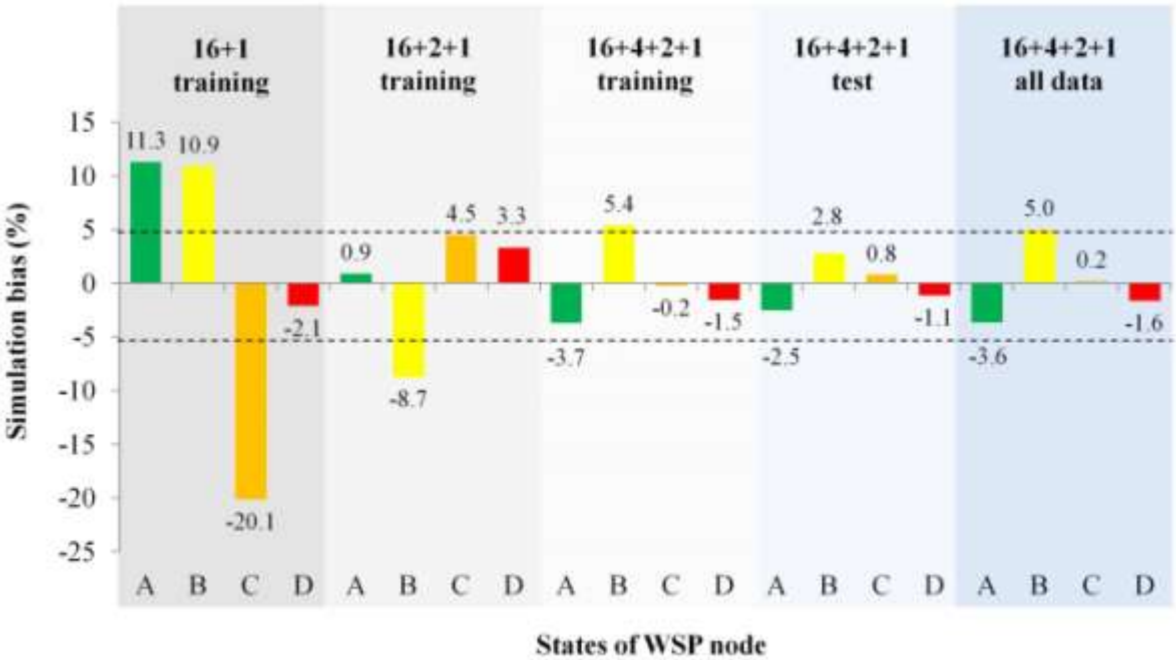


Figure 3.9. Resulting biases over WSP IS distribution associated to the stages of calibration and validation and for the case of Nicaragua. SLA + C–Ind test: fast.iamb (mi). Input nodes: lowest IQR. Results are obtained by subtracting the values provided by the database from those provided by the model (i.e. $WSP_{model} - WSP_{database}$).

Figure 3.9 summarizes the step–by–step procedure described above, with a focus on the selected network (fast.iamb + mi, lowest IQR as input nodes). It is evident that the biases are reduced and fall within the threshold established (up to 5%) once network structure is provided. Specifically, when the training dataset is used, this network infers a lower number of communities classified as A (3.7%), while overestimating the communities classified as B (5.4%). On the other hand, those communities in state C are estimated with an insignificant bias. As a negative aspect, the model assigns a state B to 1.5% of the communities (52 locations out of 3495) that were classified as D. However, once the testing and unsplit (all) datasets are applied, these biases are even lower. Furthermore, when focusing on the other variables of the network (i.e. dimensions and partial indices), the results provided by the model do not excess the threshold established (Table 3.6). As a consequence, the final network is positively validated.

Table 3.6. Further quality measures to validate the network. Result biases are presented regarding the dimensions, partial indices and general index of the conceptual model, based on the full (unsplit) dataset from Nicaragua.

Nodes	A	B	C	D
Water & san. service performance index (WSP)	–3.6	5.0	0.2	–1.6
WaSH service level (WSHL)	–2.4	4.7	–1.6	–0.7
Water service sustainability index (WSSI)	–4.4	4.2	1.6	–1.4
Water service level (WSL)	–0.8	2.3	–0.9	–0.6
Sanitation and hygiene service level (SHL)	–3.2	3.3	4.0	–4.1
Water system infrastructure (WSI)	–4.0	5.5*	–0.6	–0.9
Service provision (SEP)	–0.1	–1.6	2.9	–1.2

Values are express as percentages, taking as a reference the IS distributions of each node.
* Errors higher than 5% threshold established.

In summary, this example makes it evident that biases can be reduced by structure provision. This is a major finding in terms of results. The introduction of intermediate variables makes conditional probability tables (CPTs) smaller and tractable (Marcot, 2017). This is coherent with the process carried out, as the computational time is also reduced when providing structure to the network. However, we found out that introducing intermediate or summary variables (i.e. dimensions and partial indices) improves model inference capacity as well.

In order to validate the proposed methodology, the final network obtained for Nicaragua was first applied to the context of Honduras. In doing so, network input nodes were populated with the IS distributions associated with the context of the latter. Then, WSP inferred distributions were compared to the IS ones. In this case, results had biases that were too large (e.g. up to 7% in WSP, and up to 36% in WSI; see Annexes Table A6). Nonetheless, the proposed step–by–step methodology was fully applied from the initial stage in order to check its validation. Similar to the previous BN model, “fast.iamb (mi)” was the final selection of SLA and C–Ind test. In addition to this, lower biases were obtained as well when providing full structure (expert knowledge), but in this case, using a “smart variables" approach (see Annexes Table A7).

The final results (in terms of errors) reveal that, in six cases, the biases reached values of up to 9.1% (Table 3.7). Even if the desired goodness of the model was not fully achieved, the overall results are positive enough to not be discarded (with 79% of the values inferred below the established threshold). However, we propose two measures to tackle this situation. First, the initial threshold of 5% might be redefined according to the problem at hand and then assessed to determine whether or not it is too strict. Second, and in order to counteract this systematic error, we propose a simple action of providing new evidence (IS) distributions (e.g., newA–B–C–D) to the network input nodes. Considering the IS distributions as "x" and the inferred values as "y", the difference "x – y" (bias) is obtained (as shown in Table 3.7). When new evidence is provided, new inferred values "z" are obtained. In this way, a correction of the results should follow the operation "z – (x – y)". The validation of this methodology based on the examples provided here strongly indicated that this methodology can be used for network construction regardless of the context at hand.

Table 3.7. Result biases regarding the dimensions, partial indices and general index of the conceptual model. The full dataset of Honduras was used in this case.

Nodes	A	B	C	D
Water & san. service performance index (WSP)	–3.6	6.3*	–2.3	–0.4
WaSH service level (WSHL)	–1.8	3.9	–1.8	–0.3
Water service sustainability index (WSSI)	–5.1*	7.9*	–2.0	–0.8
Water service level (WSL)	–0.7	1.6	–0.8	–0.1
Sanitation and hygiene service level (SHL)	–2.6	5.1*	–0.8	–1.7
Water system infrastructure (WSI)	–1.1	1.5	0.5	–0.9
Service provision (SEP)	–5.9*	9.1*	–1.9	–1.3

Values are express as percentages, taking as a reference the IS distributions of each node.
* Errors higher than 5% threshold established.

3.4.2. The network for Nicaragua

The graphical result obtained using the proposed methodology highlights the reduction in the number of input variables that explain the general index WSP (Figure 3.10). Thus, the BN model identifies, as key components, variables related to water accessibility (ACC), seasonality (SEA), sanitation service level (SSL), community hygiene (COM), water system infrastructure (INF), water catchment protection (PRO) and the service provider's operation and maintenance (OPM) and environmental (ENV) management. This aspect is especially relevant for data updating purposes, as the questionnaires that feed the conceptual model collect an important amount of information. Here, two datasets can be differentiated: 1) those that are collected only once and are not considered in the conceptual model (e.g., name of the community, administrative scales and geospatial coordinates of water system elements, among others); and 2) those that are integrated into the conceptual model.

Specifically, this model is fed with a set of 43 questions. For Nicaragua, the 8 input nodes obtained would just require 22 questions (51%) to infer the values of the CIs and aggregated indices. As a consequence, important savings in terms of time (and thus, of economic resources) are achieved.

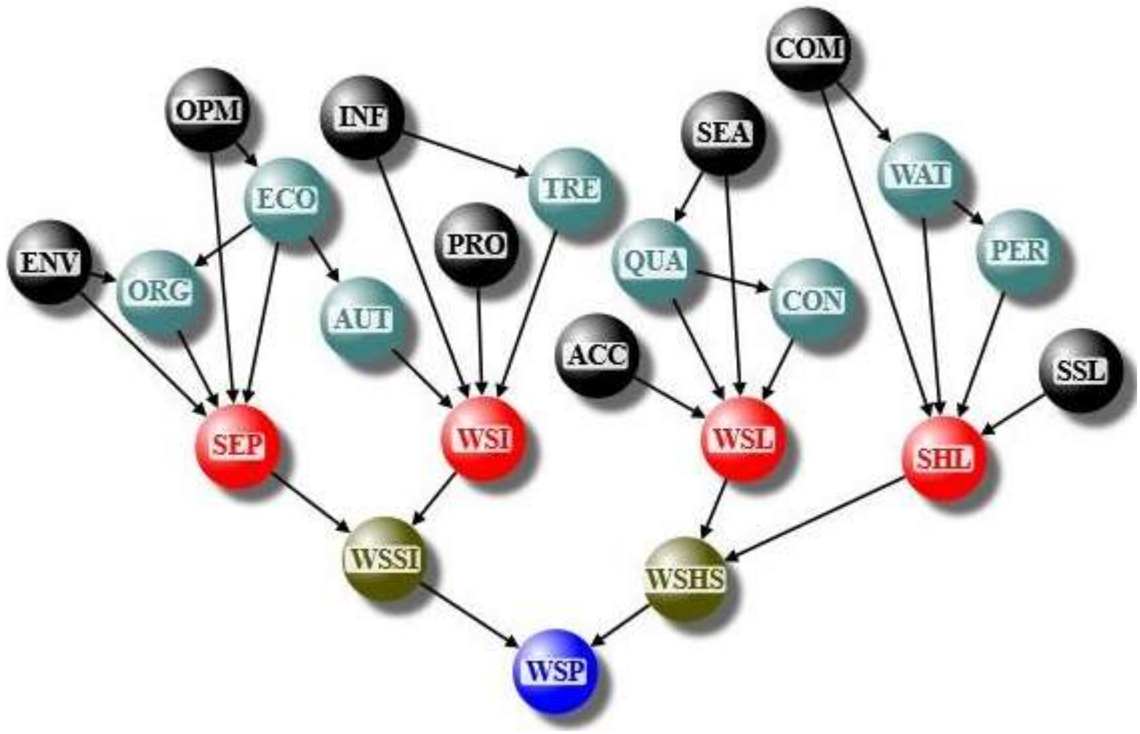


Figure 3.10. Final network for the case of Nicaragua (the software NodeXL was used to depict the results). In black, input nodes; in grey, intermediate nodes (in terms of components); in red, nodes representing conceptual model dimensions; in dark green, nodes representing partial indices; and in blue, the WSP objective node. See Figure 3.4 for abbreviations.

We also would like to point out that, with the BNs approach, links can be identified between the different components at hand, which is an advantage over a CI–based approach. Of note, these links represent dependencies rather than cause–effect linkages. Further, it is possible to identify intra–components relationships. Here, the model identifies coherent dependencies among hygiene–related components (i.e. COM, WAT and PER). Equally coherent are links between water seasonality (SEA) and water quality (QUA), as well as between QUA and service continuity (CON), which have been already documented. The former argues the possibility of accessing higher–risk water sources via changes in the type of primary water source used by households during the dry season (Pearson et al., 2016). The latter points out that providing water intermittently can compromise water quality in the distribution system (Kumpel and Nelson, 2016). Going deeper into the Nicaragua database (i.e. by checking specific contingency tables), one can observe that those communities without seasonality problems (i.e. that are qualified as A), also have no water quality issues (43% of the rural communities). The same statement can be made for communities evaluated as A for QUA and CON (38% of the rural communities). In addition to this, the model identifies a dependency between the status of the production infrastructure (INF) and the treatment system (TRE). The service provider performance appears to have four components that are interconnected. However, the model only identifies in this case one inter–component relationship (i.e., the link between the service provider's economic management (ECO) and system autonomy (AUT)). From the Nicaragua database, one can observe a higher correlation when ECO and AUT are evaluated as D (20% of the rural communities). AUT is evaluated as the capacity of the storage system (Pérez-Foguet and Flores-Baquero, 2015), and it seems logical that a lack of economic resources is negatively related to construction of appropriate storage infrastructures. A sensitivity analysis was carried out to identify the key contributors on water and sanitation performance index (WSP) for rural communities among the input nodes. For this, we applied an inverse use of the network (see Section 2.2.2), as recently tested by Li et al. (2019). Also known as diagnostic inference (Carriger et al., 2016), the model is run in a backward direction (from objective to input nodes). Specifically, Figure 3.11 shows the results of predicted changes of all input variables when assuming hard evidence for a sustainable WaSH service provision (i.e. WSP = A). The sensitivity analysis suggests that operation and maintenance management (OPM) and community hygiene (COM) are the two most important components affecting WSP index. These are followed by sanitation service level (SSL), water system infrastructure (INF) and seasonality (SEA). Those components related to environmental management (ENV), water catchment protection (PRO) and water accessibility (ACC) appeared to have the least impact. If the aim is to achieve sustainable services and to support those communities more in need, large efforts might be oriented to those communities that have been graded as D for OPM (16%), SSL (12%), COM (11%) and SEA (7%).

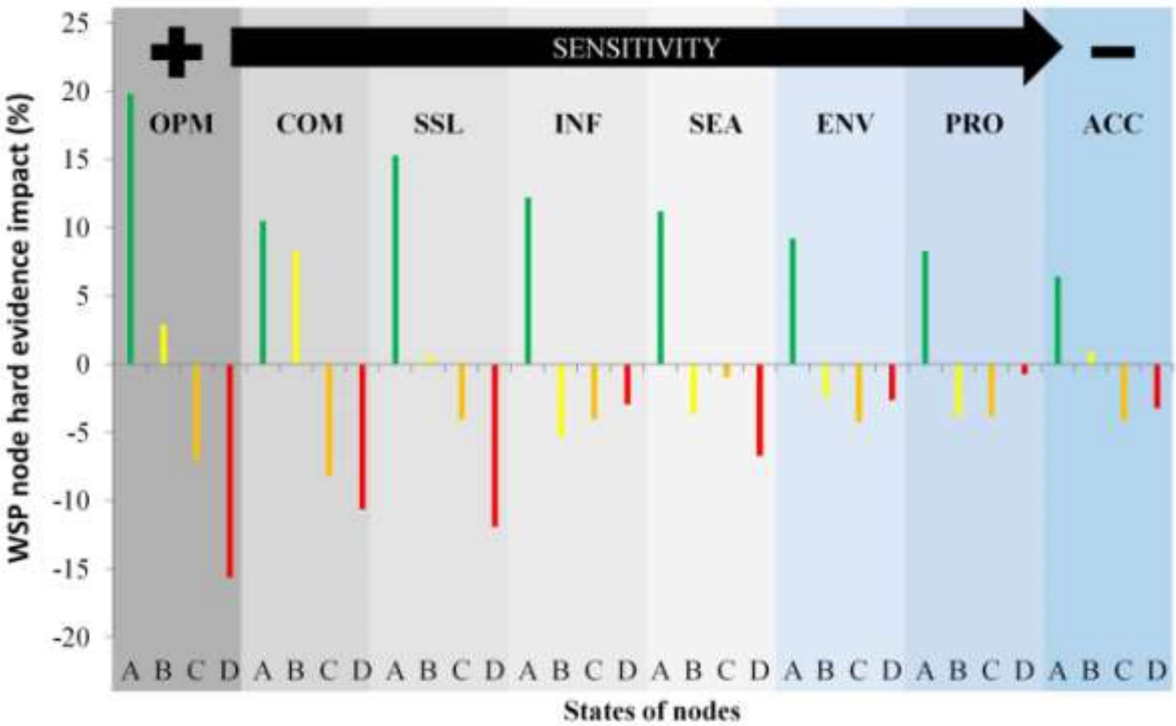


Figure 3.11. Nicaragua sensitivity analysis results and predicated impacts on inputs states with the objective node of WSP set at A=100%. See Figure 3.4 for abbreviations.

3.4.3. The network for Honduras

The network obtained for the case of Honduras is depicted in Figure 3.12. Similar to that for Nicaragua, the number of components explaining the WSP node is reduced by half. Although similar key variables are identified by the BN model (i.e. for ACC, SSL and PRO), the results present many more differences. For instance, the key explanatory components rely on continuity (CON), personal hygiene (PER), water system treatment (TRE) and service provider's organizational (ORG) and economical (ECO) management. However, a higher number of inter–component relationships are identified.

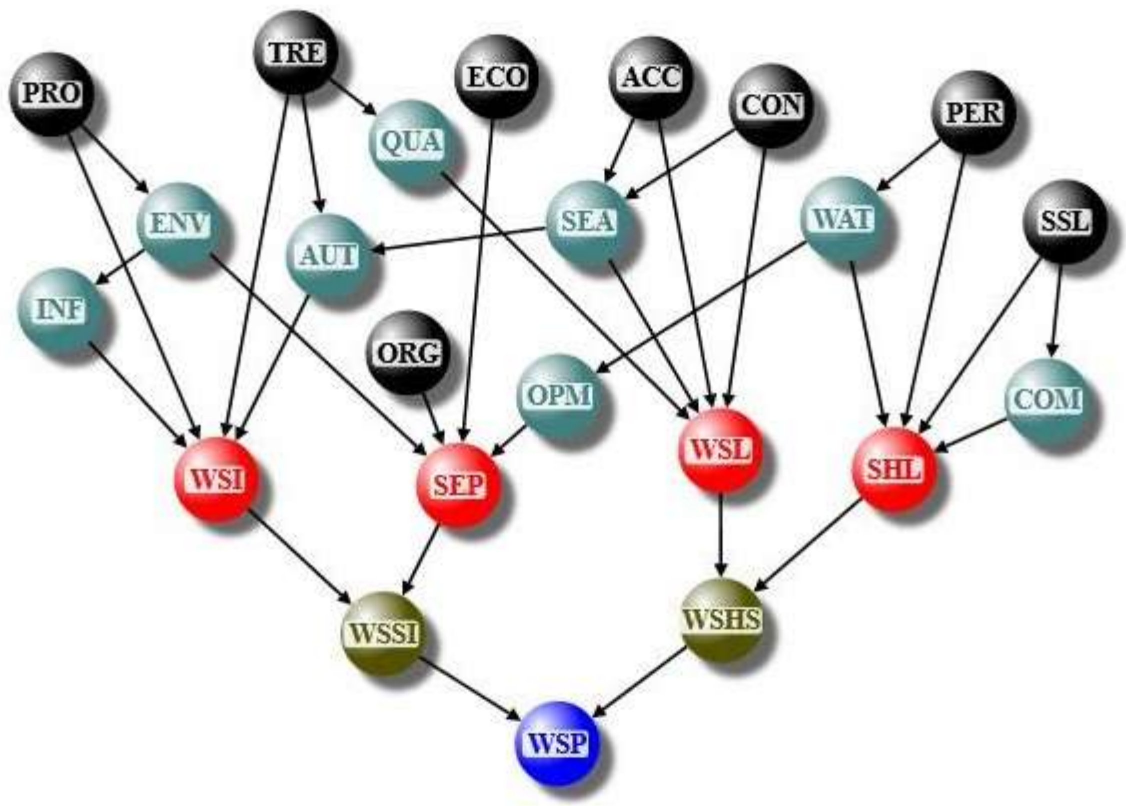


Figure 3.12. The final network for Honduras. In black, input nodes; in grey, intermediate nodes in terms of components; in red, conceptual model dimensions; in dark green, partial indices; and in blue, the WSP general index. See Figure 3.4 for abbreviations.

We would like to highlight the fact that the input nodes of this network are so–called "smart" variables. In this case, the time savings from data updated would be even greater as compared to Nicaragua. Remarkably, it would not be necessary to visit the different elements of the water system, which normally is a time–consuming task, especially in disperse rural areas.

Further, it is important to highlight the existing differences when the model identifies links among components. However, we recall that this research is data–driven by nature. In this case, we find that the results obtained are coherent. For example (and focusing on inter–component relationships), the nodes system treatment (TRE) and water quality (QUA) are logical connections. Similarly, water catchment protection (PRO) is associated with the environmental management (ENV) of the service provider. The model also identifies a dependency between seasonality (SEA) and system autonomy (AUT). Contingency tables from the Honduras database shows that in 37% of the rural communities are graded A for these two components. Similarly, in 43% of the communities, the best qualification is achieved simultaneously for service provider's ENV and the status of the production infrastructure (INF). Surprisingly, the model identifies a link between household hygiene (WAT) and operation and maintenance management (OPM). As far as intra–component linkages, coherent results are found in relation to those dependencies between sanitation service level (SSL) and community hygiene (COM), as well as seasonality (SEA) with both accessibility (ACC) and continuity (CON). In contrast, the model does not identify any dependency between the components associated to the service provider performance.

Similarly as for Nicaragua, we performed a sensitivity analysis following the same procedure described previously (see Figure 3.13). The analysis suggests that treatment system (TRE) and personal hygiene (PER) are the two most influencing components in the WSP index, followed by water catchment protection (PRO), sanitation service level (SSL) and continuity (CON) and lastly, economic (ECO) and organizational (ORG) management and accessibility (ACC).

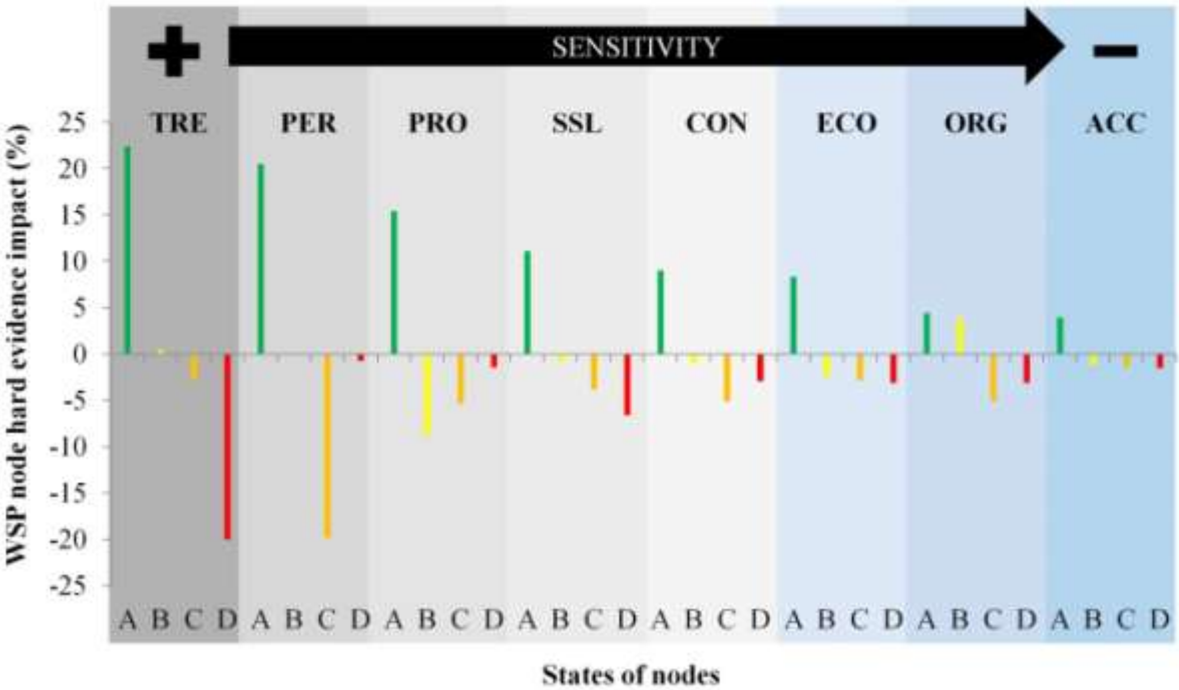


Figure 3.13. Honduras sensitivity analysis results and predicated impacts on inputs states with the objective node of WSP set at A=100%. See Figure 3.4 for abbreviations.

3.5. KEY MESSAGES

In this Chapter, we have proposed a step–by–step methodology to reproduce CI–based conceptual frameworks that integrate a hierarchical structure. For this, we have exploited the flexibility of BNs. Using a regional information system as a pilot study, we were able to successfully calibrate and validate the methodology. As a result, we have developed a semi–automatic procedure (with manual decisions in one step of the method), which relies basically on a data–driven approach.

Some key messages can be highlighted from this Chapter:

– The results obtained here reveal how expert knowledge (in terms of network structure) improves model inference capacity. The biases achieved for the case of Nicaragua do not reach the established threshold of 5%. Similarly, positive results were obtained for the case of Honduras. However, in six out of 28 cases (12%), the biases reached values of up to 9.1%. Nonetheless, even though the desired goodness of the model was not fully achieved, the overall results can be considered positive enough as to not discard it.

– The two models obtained allowed us to identify the key variables that explain the objective one (in this case, the general index of the selected conceptual framework). This fact is especially important when considering the existing difficulties of the sector in updating the required data. As a consequence, important savings (both in terms of time and economic resources) can be made. In addition to this, the flexibility of BNs permitted us to quantify, for each context, the key contributors to the water and sanitation performance index for rural communities.

– BNs are also able to identify the interdependencies of variables at hand. This fact makes this approach more suitable than the use of CIs. In this sense, using BNs might enhance multi– and trans–disciplinary actions.

CHAPTER IV. EXPLORING INTERLINKAGES BETWEEN SDG 6 AND THE 2030 AGENDA THROUGH A DATA–DRIVEN BAYESIAN NETWORKS APPROACH

The Sustainable Development Goals (SDGs) are presented as integrated and indivisible. Therefore, for supporting decision–making, conventional indicator-based frameworks need to be combined with approaches that capture and describe the links and interdependencies between the Goals and their targets.

In this Chapter, we propose a data–driven Bayesian Networks (BNs) approach to identify and interpret SDGs interlinkages. We focus our analysis on the interlinkages of SDG 6, related to water and sanitation, across the whole 2030 Agenda, using SDG global available data. To analyze and validate the BN results, we first demonstrate the robustness of the BNs approach in identifying indicator relationships (i.e. consistent results throughout different country sample sizes). Second, we show the coherency of the results by comparing them with an exhaustive study developed by UN–Water. As an added value, our data–driven approach identifies further interlinkages, which are contrasted against the existing literature. We conclude that the approach adopted is useful to accommodate a thorough analysis and interpretation of the complexities and interdependencies of the SDGs.

This Chapter is based on paper:

Requejo-Castro, D., Giné-Garriga, R., Pérez-Foguet, A., 2020. Data-driven Bayesian Network modelling to explore the relationships between SDG 6 and the 2030 Agenda. Sci. Total Environ. 710, 136014. https://doi.org/10.1016/j.scitotenv.2019.136014.

4.1. INTRODUCTION

On 25 September 2015, the 2030 Agenda resolution announced 17 Sustainable Development Goals (SDGs) and underscored their integrated and indivisible nature (United Nations General Assembly, 2015). The SDGs seek to address the three dimensions of sustainable development (SD) – environmental, social and economic–and their institutional/governance aspects (Costanza et al., 2016). Lack of integration across these dimensions in development strategies, policies and implementation has long been perceived as amajor weakness in previous attempts towards SD, such as in the Millennium Development Goals (MDGs) (Le Blanc, 2015; Liu et al., 2018; Obersteiner et al., 2016). In the SDG era, more holistic and integrated approaches are needed to elucidate the interdependencies among the different targets and goals, as well as to facilitate their effective implementation.

Indicator frameworks are a useful tool for policy making, benchmarking and public communication (Nardo et al., 2005; Singh et al., 2009) and will represent the backbone of monitoring progress towards the SDGs at all levels (i.e. local, national, regional and global). Their assessment will require quality, accessible, timely and reliable disaggregated data from all countries (United Nations General Assmebly, 2015). This, in turn, will require much greater efforts and investments in building national statistical capacities and strengthening statistical quality and standards. However, this challenge comes with a huge opportunity within the so–called “data revolution” (UN–IEAG, 2014). To date, data collection and harmonization has been assigned to at least one lead technical or specialist agency (SDSN, 2015), some of which are already elaborating data baselines and reports and present a starting point for SDG achievement. This step forward has promoted an emerging catalogue of publications (reviewed elsewhere; Allen et al., 2018), which include indicator–based assessments. An illustrative example is the development of an unofficial SDG Index (Sachs et al., 2018) as a tool to provide indicative country–level estimates and trends, covering 111 and 88 indicators for the OEDC and the 193 UN member countries, respectively. Countries are ranked according to the index values, and indicators that require priority attention are identified for each country. Despite the likely usefulness of this approach, indicator–based assessments can fall short on explaining how multiple and interacting forces have led to specific outcomes (Schmalzbauer and Visbeck, 2016). Such assessments, therefore, need to be complemented with analyses that enable interlinkages among targets and indicators to be assessed (Allen et al., 2018; Le Blanc, 2015).

Several contributions have addressed SDGs interlinkages to a certain extent. From a more conceptual and qualitative perspective, SDGs have been read as a network of targets connecting the different goal areas (Le Blanc, 2015), or analyzed and presented as a list of relationships (ICSU–ISSC, 2015). They have been also organized through a grading system of interactions (Nilsson et al., 2018), with specific focus on one SDG (Bangert et al., 2017; Coopman et al., 2016; Hall et al., 2018; Herrera, 2019; Singh et al., 2018; UN–ESCAP, 2016), or on a “nexus approach” (e.g. water–energy–food nexus) (Fader et al., 2018; Pahl-Wostl, 2017; Rasul, 2016) with the aim to understand connections, synergies and trade–offs (Liu et al., 2018). On the other hand, from a quantitative point of view, SDGs relationships have been assessed to support planning and decision–making for their implementation by applying sophisticated modelling approaches to evaluate reduced and different sets of Goals (Collste et al., 2017; Gao and Bryan, 2017;Mainali et al., 2018), to assess the (in)consistency of the SDG framework (Spaiser et al., 2017), to simulate and evaluate the interactions among multiple SDG policy options over one specific Goal (Obersteiner et al., 2016) and to introduce stakeholder's knowledge (Kanter et al., 2016; Khalili et al., 2017).

In parallel, Bayesian networks (BNs) have gained popularity among practitioners (Aguilera et al., 2011; Marcot, 2017; Marcot and Penman, 2019) for exploring the interdependencies and cause–effect relationships, simulating complex problems that involve a large number of variables that are highly interlinked. The flexibility of BNs is commonly exploited in scenario simulation and analysis (e.g. Bromley et al., 2005; Dang et al., 2019; Eldridge et al., 2019; Gonzalez-Redin et al., 2019; Molina et al., 2009). BNs have also been used to identify the key factors that influence aspects of interest (Li et al., 2019; Song et al., 2018), to replicate hierarchical composite indicators (Requejo-Castro et al., 2019) and to elucidate the network structure underlying data at hand, through associated structure learning algorithms (SLA) (Alameddine et al., 2011; Garcia-Prats et al., 2018).

In this Chapter, we propose a data–driven BNs approach to identify and interpret SDGs interlinkages. Specifically, we apply SLA to automatically capture those interlinkages spurred on by data. We selected SDG 6 on water and sanitation as a case study. We first developed a BN model and then used it carry out a comprehensive analysis of achieved results, after which we tested their robustness and validated them through an extensive literature review.

4.2. CASE STUDY: SDG 6 ON WATER AND SANITATION

We selected the dedicated goal on water and sanitation to explore its interlinkages across the 2030 Agenda. SDG 6 reads “to guarantee the availability of water and its sustainable management and sanitation for all” (United Nations General Assembly, 2015), and includes eight targets, six of which are based on outcomes, and two of which are based on the means of implementation. Specifically, Targets 6.1 and 6.2 relate to drinking–water, sanitation and hygiene; Target 6.3 expands the framework beyond the use of sanitation facilities to focus on wastewater and water quality; Targets 6.4 and 6.5 refer to water–use efficiency and water scarcity, and the implementation of Integrated Water Resources Management (IWRM), respectively; Target 6.6 focuses on healthy water–related ecosystems; and Targets 6.a and 6.b suggest the importance of international cooperation and local stakeholder participation to achieve previous targets.

Water and sanitation is at the very core of sustainable development (Mugagga and Nabaasa, 2016; Nhamo et al., 2018; United Nations, 2018a; UN–Water, 2016; WWAP, 2019). Available water and adequate sanitation for all and for different purposes are pillars of human health and well–being, thus contributing to the achievement of other development goals such as health, adequate nutrition, gender equality, education and poverty eradication (Bartram et al., 2005; Cairncross et al., 2010; Cohen and Sullivan, 2010; JMP, 2015; UN–Women, 2018). We sought to capture the bi–directionality of the interlinkages: incorporating water and sanitation in other Goals is necessary for the achievement of Goal 6, and implementing targets under Goal 6 enables the achievement of a number of other targets across the 2030 Agenda. We thus contribute to the existing applications of BN modelling to the SDG 6. The flexibility of BNs has been exploited to address the inherent complexity of individual SDG 6 targets, and the literature shows several studies on Target 6.1 (Cronk and Bartram, 2017, 2018; Fisher et al., 2015), Targets 6.1 and 6.2 (Dondeynaz et al., 2013; Giné-Garriga et al., 2018; Requejo-Castro et al., 2019) and Targets 6.4 and 6.5 (Mohajerani et al., 2017;Molina et al., 2009, 2010, 2013). To the best of our knowledge, however, BNs have not been applied to explore the relationships between targets of different goals.

We take as a reference point the UN–Water Analytical Brief entitled "Water and sanitation interlinkages across the 2030 Agenda for Sustainable Development" (UN–Water, 2016). This report captures the complex nature of the SDGs and gives a qualitative snapshot as far as the relationships between the SDG 6 and the 2030 Agenda, providing an overview of the target–level linkages and their interdependencies (UN–Water, 2016). This report allows comparing the results obtained in our study and validating the proposed data–driven approach.

4.3. METHODS

In this Section, we first introduce in detail the criteria and steps followed for data selection and pre–process. Specifically, we focus on the process of selecting the final set of indicators for the BN analysis (as well as a complete definition of these indicators), the assumptions made to deal with missing data, and the normalization process for correct data management. Second, we briefly detail the initial settings considered. Third, we describe the steps followed to carry out the BN analysis.

4.3.1. Data selection and data pre–process

Indicator selection

Globally available data for SDGs are provided by the different specialist agencies and published online by the United Nations Statistic Division (UNSD)[2]. In their website, latest official available data for all indicators are published and regularly updated at both the regional and country levels. In this study, a first screening of eligible indicators was conducted based on the study developed by UN–Water (2016), which analyses the relationships between targets of Goal 6 and rest

[2] Data available at https://unstats.un.org/sdgs/indicators/database.

of the Goals targets included in the 2030 Agenda. It comprises 107 outcome-based targets (excluding those related to the means of implementation, such as all the targets included in SDG 17) and 169 indicators, and provides a summary table of all these linkages, identifying as well whether the link represents synergy (positive impact) or conflict (negative impact). The report shows, for instance, the water and sanitation links with those targets related to the reduction of poverty (i.e. SDG Targets 1.1, 1.2, and 1.4). In contrast, none of the SDG 6 targets are linked to SDG Target 11.5, which deals with reduction deaths and the number of people affected by natural disasters. In order to work with a manageable number of variables, we selected those SDG targets showing a high number of synergies and/or conflicts (i.e. 3 or more linkages with SDG 6 targets). However, we have also considered Target 4.2, related to the access to quality in early childhood development, with only two identified linkages with SDG 6, to represent Goal 4. Thus, all SDGs are represented in this study with one or more targets.

In total, we analyzed 52 SDG targets and 80 associated indicators. However, global data were only available for 28 out of these 51 (55%) targets and 44 (55%) different indicators (UNSD, 2018). Although we did not consider any indicators related to the means of implementation, we included SDG Target 6.a due to its relevance for the study. Table 4.1 presents the final list of indicators, their definition, the custodian agency in charge of data reporting, and the number of countries with available information. For each indicator, we also specify how we dealt with missing data and data normalization (see next sub–Section).

Table 4.1. SDG indicators employed in the data–driven Bayesian network analysis. Source: UNSD, 2018.

SDG	Indicator (units)	Year(s)*	Source(s)	Countries with information
1	1.1.1. Poverty line of USD1.90 per day (% population)	2003–2016	WB & ILO	155 [a, 1]
	1.2.1. Poverty line below the national threshold (% population)	2000–2017	WB	133 [b, 1]
2	2.1.1. Prevalence of undernourishment (% population)	2015	FAO	167 [a, c, 1]
3	3.1.1. Maternal mortality ratio (number per 100,000 live births)	2015	WHO	180 [a, 1]
	3.2.1. Under–five mortality rate (number per 1,000 live births)	2016	UNICEF	187[1]
	3.3.5. People requiring interventions against neglected tropical diseases, NTD (number)	2016	WHO	185 [b, 1]
	3.8.1. Universal health coverage (UHC) service coverage index (0 – 100)	2015	WHO	181
	3.9.1. Age-standardized mortality rate attributed to household air pollution (deaths per 100,000 people)	2016	WHO	145 [a, b, 1]
	3.9.2. Mortality rate attributed to unsafe water, unsafe sanitation and lack of hygiene (deaths per 100,000 people)	2016	WHO	181[1]
4	4.2.2. Participation rate in organized learning (% children)	2000–2017	UNESCO–UIS	152 [a]

5	5.5.1. Proportion of seats held by women in national parliaments (% women)	2018	UN–Women & IPU	186 [a]
	5.5.2. Proportion of women in managerial positions (% women)	2000–2016	ILO	149 [b]
6	6.1.1. Proportion of population using AT LEAST BASIC drinking water services (% population)	2015	JMP	187
	6.2.1. Proportion of population using AT LEAST BASIC sanitation services (% population)	2015	JMP	187
	6.4.1. Water–use efficiency (USD/m^3)	2014	FAO	165 [b]
	6.4.2. Freshwater withdrawal as a proportion of available freshwater resources (%)	2014–2015	FAO	179 [a, 1]
	6.5.1. Integrated Water Resource Management implementation (%)	2017	UNEP	153 [a]
	6.6.1. Water body extent (permanent) (% of total land area)	2016	UNEP	188
	6.a.1. Total official flows for water supply and sanitation, by recipient (billions USD)	2016	WHO & OECD	130 [a, b]
7	7.1.1. Proportion of population with access to electricity (%)	2016	WB	189
	7.1.2. Proportion of population with primary reliance on clean fuels and technology (%)	2016	WHO	183 [a]
	7.2.1. Renewable energy share in the total final energy consumption (%)	2016	IEA & UN–DESA	189
	7.3.1. Energy intensity level of primary energy (Megajoules per constant 2011 purchasing power parity GDP)	2015	IEA & UN–DESA	183 [a, 1]
8	8.1.1. Growth rate of real GDP per capita (%)	2016	UN–DESA	189
	8.2.1. Annual growth rate of real GDP per employee (%)	2017	ILO	178 [a]
	8.5.2. Unemployment rate, 15 years old and over, both sexes (% population)	2000–2017	ILO	174 [a, 1]
9	9.1.2. Passenger volume, by air transport (tonne kilometres)	2016	ICAO	178 [b]
	9.4.1. Emissions of carbon dioxide (millions metric tons)	2015	IEA & UNIDO	137 [b, 1]
10	10.1.1. Growth rates of household expenditure or income per capita among the bottom 40 per cent of the population (%)	2009–2016	WB	94 [b]
11	11.1.1. Urban population living in slums (%)	2000–2014	UN–Habitat	92 [a, b, c, 1]
	11.6.1. Municipal Solid Waste collection coverage, by cities (%)	2001–2017	UN–Habitat & UN–DESA	98 [b]
	11.6.2. Annual mean levels of fine particulate matter ($PM_{2.5}$) in cities (μg/m^3)	2016	WHO	186[1]
12	12.2.1. Material footprint per capita – raw material – (tonnes)	2017	UNEP	166 [a, 1]
	12.2.2. Domestic material consumption per capita – raw material – (tonnes)	2017	UNEP	140 [a, 1]
	12.4.1. Compliance with the Stockholm Convention on hazardous waste and other chemicals (%)	2015	UNEP	171[a, b]

13	13.1.1. People affected by disaster (number)	1990–2017	UNDRR	112 [b, 1]
14	14.5.1. Average proportion of Marine KBAs covered by protected areas (%)	2018	UNEP–WCMC	137 [a, b, c]
15	15.1.1. Forest area as a proportion of total land area (%)	2015	FAO	188
	15.1.2.1. Average proportion of Freshwater KBAs covered by protected areas (%)	2018	UNEP–WCMC	133 [a, b]
	15.1.2.2. Average proportion of Terrestrial KBAs covered by protected areas (%)	2018	UNEP–WCMC	185 [a]
	15.2.1. Forest area net change rate (%)	2015	FAO	187 [a]
	15.4.1. Average proportion of Mountain KBAs covered by protected areas (%)	2018	UNEP–WCMC	146 [a]
	15.4.2. Mountain Green Cover Index (%)	2017	FAO	161 [a]
16	16.5.2. Bribery incidence (% of firms experiencing at least one bribe payment request)	2006–2017	WB & UNODC	138 [a, 1]

* By the time of this study, and for each indicator–country pair, the more recent data were used. When data were obtained from different years, the time period is specified.

Missing data and data gaps were addressed by applying: a) regional data, b) HDI group–related information, c) literature review. Missing data treatment was required as well for indicators with more than 179 countries in order to reach the final list of countries with information associated with all indicators considered.

[1]: Indicators transformed from the scale "less is better" to "more is better".

The final set of 44 indicators was assessed, to a different extent, in 189 countries. The full dataset of 189 countries and available data for all 44 indicators were extracted from the UNSD database. These countries were classified according to their Human Development Index (HDI) (UNDP, 2018), as this classification shows the unbiased nature of samples in terms of country development context and also helps us to deal with missing data. A representative number of countries from each HDI group was included (Table 4.2). However, only 7 countries have available data for the 44 indicators considered, and more than 50% of the selected countries do not have data for five or more indicators. To increase the final sample of countries, a set of assumptions was made for missing data treatment in the first three groups (referred to the number of indicators with no data available). A total number of 179 countries were finally included in the analysis.

Table 4.2. Number of countries considered in the study according to their HDI. Sources: UNDP, 2018; UNSD, 2018.

Human Development Index (HDI) group	**Number of countries**				
		Indicators with no data available (out of 44)			
		≤ 5	**≤ 10**	**≤ 15**	**≥ 15**
Very high	59	19	27	10	3
High	53	30	11	8	4
Medium	39	25	10	1	3
Low	38	18	15	5	0
Total	**189**	**92**	**63**	**24**	**10**

Imputation of missing data

As BNs are only fully functional if no data is missing, the following assumptions were made to deal with missing data:

– SDG regional data (when available) were used to fill information gaps at the country level. This assumption applied to 55% (24 out of 44) of the indicators considered (the number of countries using regional data for each indicator varied between indicators).

– When regional data were not available, information gaps were replaced considering the country's HDI group (UNDP, 2018) in two different manners. For some indicators, VH HDI countries obtained the highest score (e.g., for SDG 1.1.1, 0% of population below the international poverty line of USD1.90 per day; for SDG 6.a.1, 0 billion USD were received as official flows for water supply and sanitation). For other indicators, average values were assigned to replace missing data according to HDI group (i.e. very high, high, medium, or low). In total, this was applied to 35% of the indicators in this study (the information gaps varied from one indicator to another).

– Values from the literature were also considered when available. For example, a value of 1.2% prevalence of undernourishment rate (SDG indicator 2.1.1) was assumed for VH and H HDI countries with missing data (SDSN, 2016); and 6% of European urban dwellers living in extremely precarious conditions (UN–Habitat, 2015), which we computed it as proportion of urban population living in slums (SDG indicator 11.1.1). Considerations from existing literature were applied to 10% of the indicators considered.

Normalization

Prior to the BN analysis, indicators were normalized between 0 and 100, with 0 denoting the worst performance and 100 describing the optimum. To do this, those indicators expressed in percentage were kept invariable. On the other hand, the rest of indicators were normalized using a "min–max" technique. This method normalizes indicators to have an identical range by subtracting the minimum value and dividing by the range of the indicator values (Nardo et al., 2005). No max–min thresholds were fixed, and maximum and minimum values were defined according to the best and worst performance of the indicators, applying logarithms when values were either considerably lower or higher than the rest. Finally, a last transformation was required for several indicators according to a "more is better" scale (see Table 4.1). For instance, SDG indicator 9.4.1 (CO_2 emissions), which represents a "less is better" goal, was assessed by calculating the complementary value. In contrast, similar examples to SDG indicator 7.1.1 (proportion of population with access to electricity), a "more is better" indicator that is presented as a percentage, were kept constant according to a fixed scale.

4.3.2. Initial settings

We apply again the free R software and its package bnlearn (version 4.4), which implements the following constraint–based learning algorithms (see Section 2.4.3): grow–shrink (gs), incremental association (iamb), fast incremental association (fast.iamb), interleaved incremental association (inter.iamb) and max–min parent and children (mmpc). We consider that all indicators follow a normal distribution (see Annexes Figure A1). The C–Ind tests are chosen with respect to this data typology. To avoid intensive computing time, C–Ind test selection is reduced to linear correlation (cor), Fisher's Z (zf), and mutual information (mi-g) tests. By applying the combination of both SLA and C–Ind tests to the database, 16 candidate networks are obtained.

Scutari et al. (2017) suggest selecting a single BN model from the data and drawing the conclusions from this model, treating it as a "fixed" quantity. However, this model is not "fixed" and carries its own uncertainty from the selection procedure used to learn it from the data. To reduce this source of uncertainty, we applied the bootstrap technique (re–sampling), used most to determine confidence intervals (Henderson, 2005), to test the stabilities and strength of links among variables, and to obtain the direction of these links (Chao et al., 2018; Scutari et al., 2017).

4.3.3. Data–driven Bayesian Network model generation and analysis settings

To facilitate similar studies in the future (i.e., with a focus on different SDGs), we have provided a step–by–step methodology for this data–driven BN analysis. For validation purposes, we recommend identifying relevant reference studies in the literature. Here, we use the UN–Water Analytical Brief (UN–Water, 2016), which allows us to compare achieved results and to validate the proposed approach.

Analysis development is divided in two complementary stages (Figure 4.1). In the first stage, a BN model is developed that allows the identification and assessment of the interlinkages between selected targets and indicators. In the second stage, the robustness of the achieved results is assessed (i.e. the consistency of the interlinkages obtained through the data–driven approach). The step–by–step procedure to construct the BN model (i.e. first stage) from the dataset is as follows:

– **A1. SLA + C–Ind test tandem selection.** In this initial stage, we applied three selection criteria to identify the most suitable BN network: i) identify a higher number of links associated with the objective nodes (i.e. SDG 6 associated indicators); ii) present a higher number of directed links; and iii) leave a lower number of nodes isolated.

– **A2. Isolated nodes removal.** As these nodes do not contribute to the analysis, they were removed.

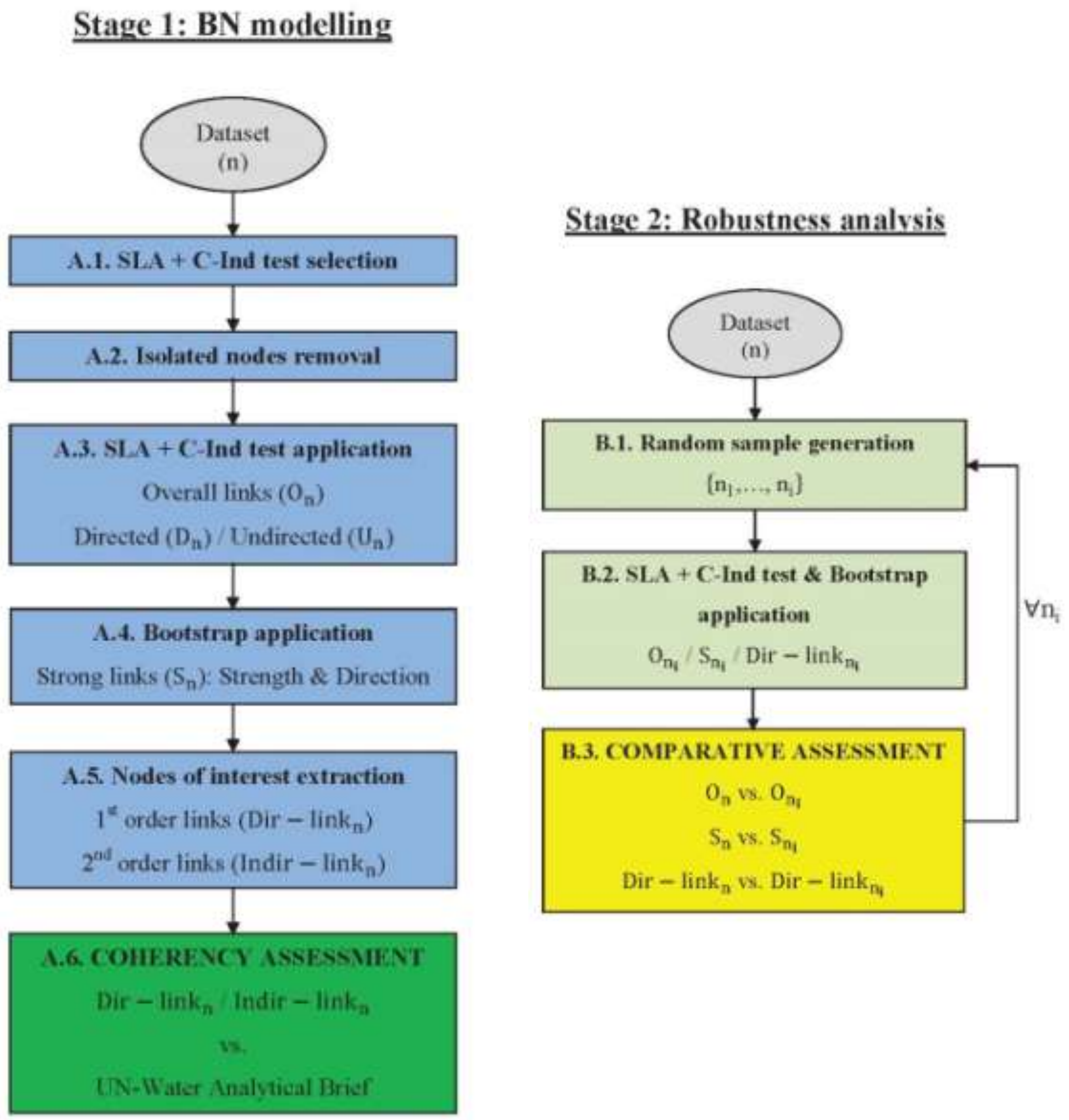


Figure 4.1. Process followed to carry out the BN analysis.

– **A.3. SLA + C–Ind test tandem application.** The overall interlinkages (O_n) identified by the model are obtained. They are differentiated between directed links (D_n), which imply one–way directions, and undirected links (U_n), which imply two–ways directions.

– **A.4. Bootstrap technique application.** To bootstrap, the so–called strong links (S_n) were identified. To do this, data were re–sampled 500 times, and the selected tandem SLA + C–Ind test is performed separately on each of the resulting samples, thus collecting 500 networks. The frequency of the links with which each appears in those networks was then computed (known as arc strength), and the resulting links that have a frequency above a certain threshold were selected (in this case, a value of 0.80 over 1). Specifically, three steps were followed: i) compute 100 bootstrapped networks to get a reference list of relationships, ii) select links that are repeated more than 60% from 100 new bootstrapped networks in comparison to the previous list, and iii) obtain the directions of the strong links (i.e. cause–effect direction).

– A.5. Nodes of interest extraction. As our focus was on those indicators related to SDG 6, the "first–order" or "direct" links (Dir–link$_n$) that associate these indicators with the neighbouring ones were extracted from O$_n$. Moreover, the "second–order" links (Indir–link$_n$) that represent indirect relationships through the above mentioned neighbour indicators, were analyzed.

– A.6. Coherency assessment. The interlinkages obtained in the previous step were then contrasted against those ones selected from the literature or based on expert opinion. Our comparative analysis focused on the UN–Water Analytical Brief (2016), complemented by an extensive literature review.

For the second stage of this analysis, the following steps were carried out:

– **B.1. Random samples generation (n$_i$)** from the initial number of 179 countries, using the sample sizes of 175, 160, 145, 130, 115, 100, and 85 countries. For each sample size, 100 different networks were generated.

– **B.2. SLA + C–Ind test and bootstrap application.** For each network associated to each sample size, the selected SLA + C–Ind test tandem (Step A.1) and the bootstrap technique were used. The overall relationships (O_{n_i}), the strong links (S_{n_i}), and the "first–order" (Dir–link$_{n_i}$) linkages were then determined.

– **B.3. Comparative assessment.** The relationships obtained were compared to the ones identified from the overall sample size. This comparison was complemented with further quality analysis in terms of results coherence.

4.4. RESULTS AND DISCUSSION

The overarching objectives of this section are: i) to identify the different interlinkages of interest from the overall dataset; ii) to test the robustness of the above results by comparing these results against the ones obtained from the different sample sizes; and iii) to assess in–depth the results with respect to the interlinkages between the SDG 6 and the 2030 Agenda.

4.4.1. Identifying interlinkages of interest

The tandem SLA + C–Ind test produced 16 candidate networks. The tandem incremental association (iamb) algorithm and mutual information (mi-g) test showed the best performance — according to the 3 criteria described — and was thus selected for analysis (Step A.1). Specifically, it identified 23 links associated to SDG 6 indicators, and 61 directed links (out of 65). Two nodes with no relationships within the network (6.6.1 and 15.2.1 indicators) were removed (Step A.2). Finally, the overall interlinkages (O_n) among SDG indicators and the strong links (S_n) and their direction were determined by bootstrap application (Steps A.3 and A.4) (Figure 4.2).

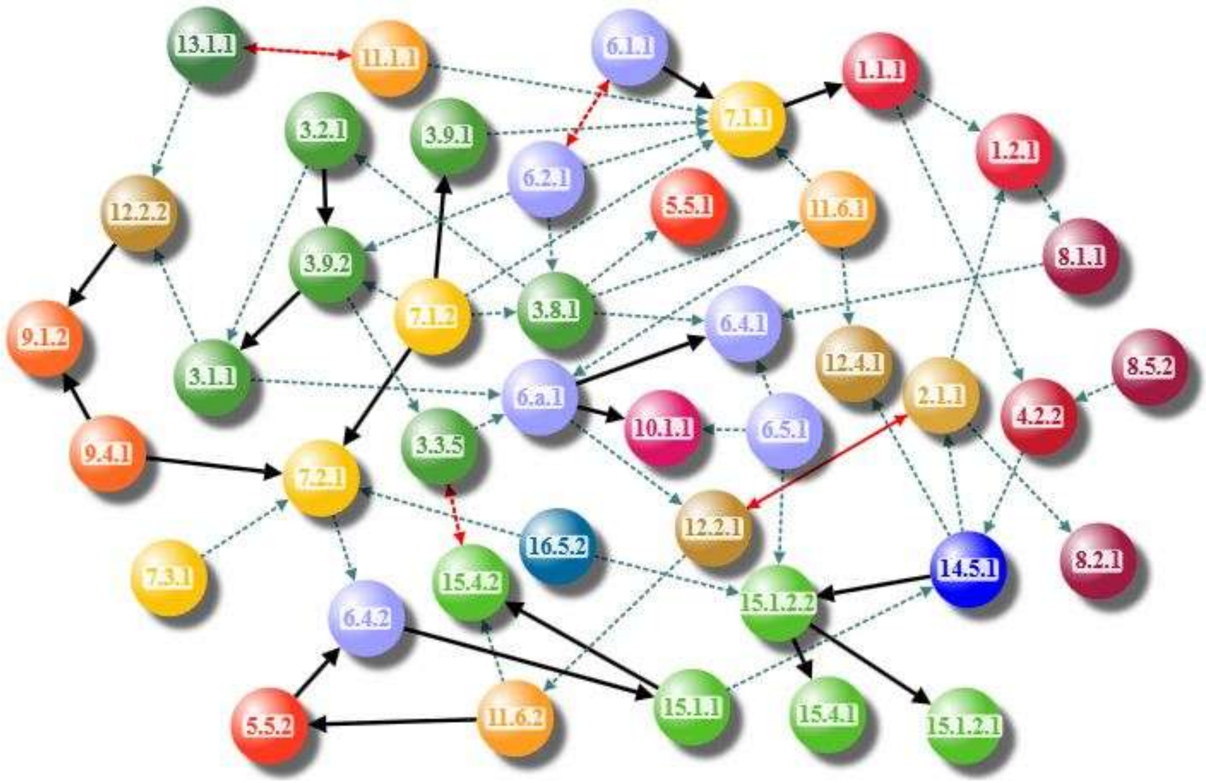


Figure 4.2. Reference network showing the interlinkages between the SDG indicators considered. Corresponding definitions to these indicators are given in Table 4.1. This network was obtained through the tandem SLA (iamb) and C–Ind test (mi-g). Three different elements are shown; strong links, S_n (black solid arrows), directed links, D_n (grey dot arrows) and undirected links, U_n (bi–directional red dot arrows).

4.4.2. Testing the data–driven approach robustness

To demonstrate the robustness of the results (Figure 4.2), we generated different random samples (Step B.1). For each sample size, and for each of the 100 networks generated, SDG indicators links (O_n) were identified together with the strong links (S_n) and their direction (Step B.2). Notably, the overall link repetitiveness decreased when the sample size of countries was reduced (Step B.3) (Figure 4.3). This decrease appears slightly more pronounced for the samples of n=175 and n=160 countries. When reducing the sample size to 115 countries (65% of the total), the repetitiveness mean value still reached 71.8%. Maximum and minimum values present unequal fluctuations, but those related to 90th and 10th percentiles showed a trend similar to the repetitiveness mean value.

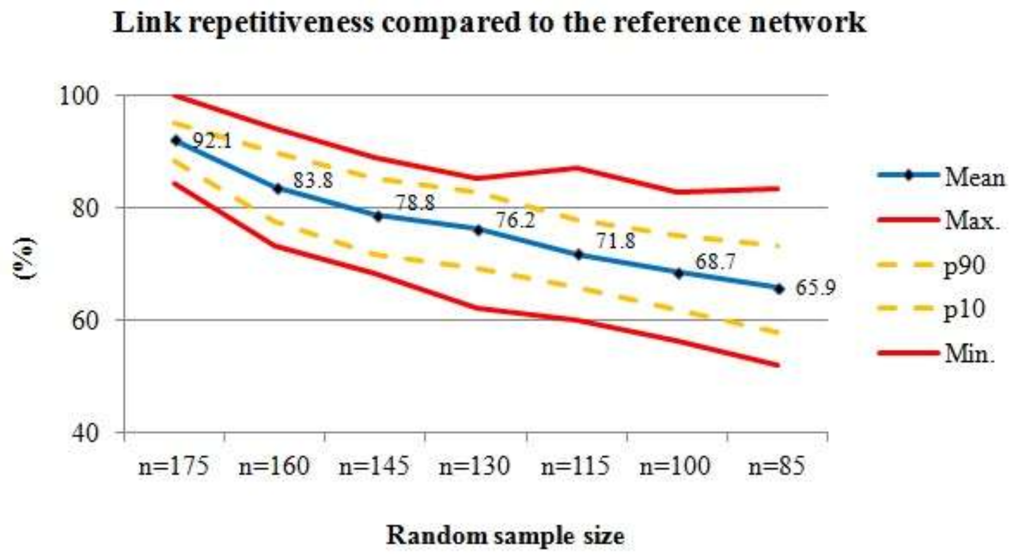


Figure 4.3. Overall link repetitiveness for the different random samples of countries in comparison to the reference network (179 countries and 42 SDG indicators).

The same decreasing tendency was observed for interlinkages identified as strong ones (Step B.3). For instance, when country sample was reduced to 72% (n=130), approximately half of the strong links (55%, 10 out of 18) were identified in at least 70% of the bootstrapped networks. This ratio increases to 62%, 74% or 100% for the samples of n=145, 160 or 175, respectively (see Annexes Table A8). Two trends can be observed: i) strong links with high repetitiveness even when the sample size of countries is reduced drastically; and ii) strong links with low repetitiveness when sample size is reduced (see Annexes Table A8). The performance of the model is positively evaluated up to the sample size of 130 countries.

Complementary to this, we carried out an in–depth analysis of the direction (i.e. cause–effect direction) of these strong links. For this, the strong links were firstly disaggregated, with all considered as undirected although they are not (see Figure 4.2). For instance, the obtained link from 3.9.2 to 3.1.1 is considered to be true for 3.1.1 to 3.9.2 as well. The direction of a link is obtained through the bootstrap technique, which assigns a value between 0.5 and 1, whereby 0.5 is related to an undirected link and 1.0 assures the direction of the link. Here, 72% (13 out of 18) of the strong links were identified to be in one specific direction throughout the different sample sizes (see Annexes Table A9). However, most links present values closer to 0.5, which should be taken carefully into consideration before stating a clear cause–effect of the links (see Annexes Table A10).

A further complementary assessment was carried out considering the "first–order" or direct (Dir–link$_n$) relationships associated with SDG 6 indicators (Step B.3) (see Table 4.3). In this case, only their frequency is taking into account but not their strength or direction. For n=130, 12 out of 27 (44%)

links were identified in more than 70% of the bootstrap networks (Table 4.3). This value increased to 60% and 67% for sample sizes n=145 and 160, respectively (see full details in Annexes Table A11). Again, two trends are observed: i) links that present a high repetitiveness while reducing the sample size (most of which coincide with the links identified as strong); and ii) relationships whose repetitiveness is reduced rapidly when decreased numbers of countries are in the sample.

Extending this assessment in terms of quality measures, we analysed the impact of the approach for missing data treatment in model results (Step B.3). We carried out the process described in Section 3 but considering only those countries with 10 or less SDG indicators presenting missing data (see Table 4.2). Thus, 155 countries were used for a second BN model construction. Table 4.3 shows that 78% (21 out of 27) of the links related to SDG 6 indicators were identified in the new model. In addition, 86% (6 out of 7) of the strong links are shown. This confirms that the approach used to fill information gaps has little impact on the results achieved.

Table 4.3. Links identified in relation to SDG 6 indicators, for different country samples.

SDG 6–related links identified			Repetitiveness (%)			
			n=175	**n=160**	**n=145**	**n=130**
3.9.2 (mortality rate due to unsafe WaSH)	**3.1.1**	**Maternal mortality ratio***	100	100	100	86
	3.2.1	**Infant mortality rate***	100	100	100	100
	3.3.5	People requiring interventions against NTD*	100	99	94	89
	6.2.1	Population using AT LEAST BASIC sanitation services*	100	98	84	86
	7.2.1	Renewable energy share in total final energy consumption	85	51	42	28
6.1.1 (basic drinking water)	6.2.1	Population using AT LEAST BASIC sanitation services*	99	87	70	68
	7.1.1	**Population with access to electricity***	100	100	100	96
6.2.1 (basic sanitation)	3.8.1	Universal health coverage (UHC)*	84	80	74	63
	3.9.2	Mortality rate attributed to unsafe WaSH*	100	98	84	86
	6.1.1	Population using AT LEAST BASIC drinking water services*	99	87	70	68
	7.1.2	Population with primary reliance on clean fuels and tech*	94	64	60	59
6.4.1 (water–use efficiency)	3.8.1	Universal health coverage (UHC)	63	49	27	30
	6.5.1	Degree of IWRM implementation*	89	62	52	38
	6.a.1	Total official development assistance (ODA)*	100	100	100	99
	8.1.1	Annual growth rate of real GDP per capita	97	78	62	59
6.4.2 (freshwater withdrawal)	**5.5.2**	**Proportion of women in managerial positions***	100	100	99	97
	7.2.1	Renewable energy share in the total final energy consumption	62	49	56	51
	15.1.1	**Forest area as a proportion of total land area**	100	100	97	94

6.5.1 (IWRM)	6.4.1	Water–use efficiency*	62	52	38	38
	10.1.1	Growth rates of household expenditure (bottom 40% pop.)*	63	46	30	27
	15.1.2.2	Average proportion of KBAs covered by protected areas*	83	69	62	53
6.a.1 (ODA for water and sanitation)	3.1.1	Maternal mortality ratio*	83	67	63	52
	3.3.5	People requiring interventions against NTD*	66	71	60	58
	6.4.1	**Water–use efficiency****	100	100	99	95
	10.1.1	**Growth rates of household expenditure (bottom 40% pop.)****	98	93	88	78
	11.6.1	Municipal Solid Waste collection coverage	47	35	36	32
	12.2.1	Material footprint per capita (raw material)*	98	94	82	82

In bold, strong links.
* Links identified in the second BN model (155 countries).
** Links identified in the second BN model but not as strong links.

We analyzed in more depth the coherency of the results obtained by constructing the contingency tables associated with the links presented in Table 4.3 (see also Annexes Table A12). To do this, we discretize the continuous values of the indicators in 5 different intervals. As an example, the relationship between the proportion of a population using at least basic drinking water services (6.1.1) and the proportion of population with access to electricity (7.1.1) was considered. This link, identified as strong one, shows a positive correlation according to the values of the diagonal of the table. In other words, an improvement in one of these indicators might generate a similar impact in the other one. This is consistent with the fact that access to drinking water services requires energy for the extraction, treatment, and distribution of water. Reciprocally, water is required to produce all forms of energy to some degree (United Nations, 2018a; UN–Water, 2016; WWAP, 2014).

Summarizing the results presented in this subsection, we demonstrated that the applied data–driven approach provides robust results up to certain sample size (i.e., n=130, which represents approximately 70% of the overall countries considered). Moreover, the strategy used for missing data treatment does not significantly affect the final results and might be considered as an appropriate approach for other studies. The applied data–driven techniques (SLA + C–Ind test and bootstrapping) allowed us to identify different kind of links (i.e. strong or not). However, these techniques fall short in identifying specifically the direction (i.e. cause–effect) of the links.

4.4.3. Assessing the SDG 6 interlinkages across the 2030 Agenda

To assess the results achieved with the aim to validate the proposed data–driven approach, we first compare the results obtained from the data with those presented in the UN–Water Analytical Brief (2016). We do not consider the direction of the links identified within this assessment but rather focus on dependencies between the indicators employed. In addition to this, and for each SDG 6 target, we explore both the “first–order” (Dir–link$_n$) and “second–order” (Indir–link$_n$) interlinkages identified (Step A.5) to evaluate their coherency with the main findings from an extensive literature review.

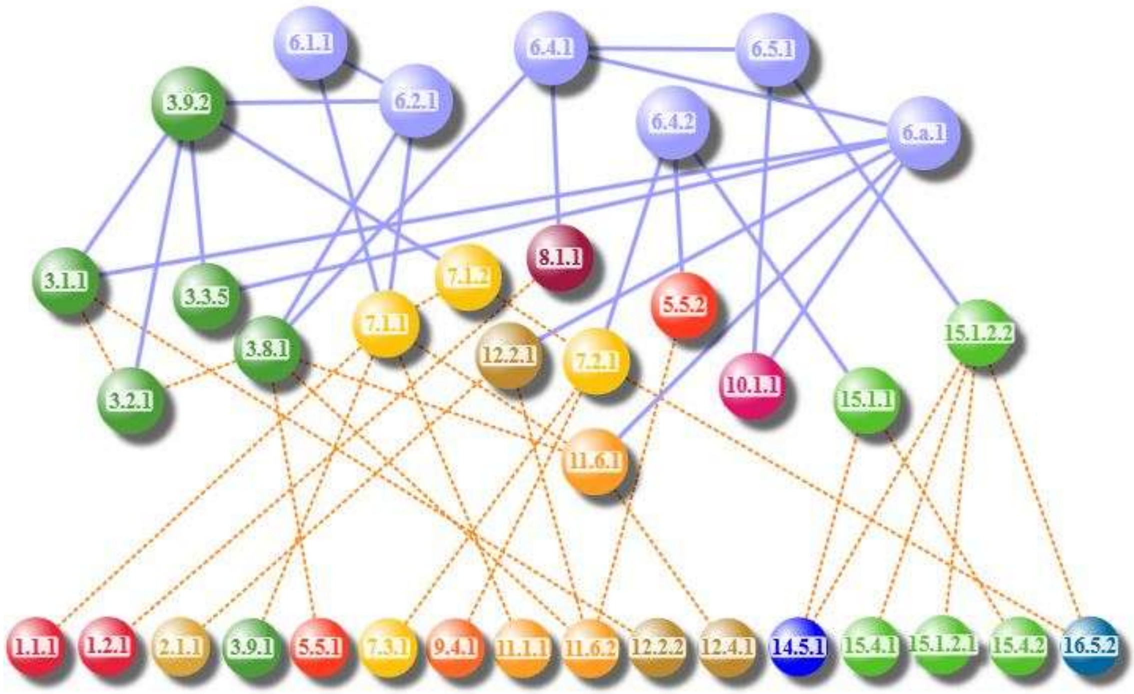


Figure 4.4. SDG 6 related interlinkages identified. "First–order" (Dir–link$_n$) linkages are represented by solid blue lines. "Second–order" (Indir–link$_n$) relationships are indicated by dotted orange lines.

The UN–Water Analytical Brief argues how Goal 6 impregnates the social, environmental and economic dimensions of sustainable development, identifying relationships with all SDGs. From the results depicted in Figure 4.4, it is observed that "first–order" (direct) interlinkages are identified in relation to Goals on health (SDG 3), gender (5), energy (7), economic growth (8), inequality (10), sustainable cities and communities (11), sustainable consumption and production (12) and terrestrial ecosystems (15). When considering "second–order" (indirect) links, identified interdependencies also includes the goals on poverty (1), food (2), infrastructure and industry (9), oceans (14), and peace and security (16). Specifically, 37 out of 42 indicators (88%) are connected as a result of the generated BN model. Indicators related to the participation rate in organized learning (4.2.2), economic growth per employee (8.2.1), unemployment rate (8.5.2), passenger volume by air transport (9.1.2), and people affected by a disaster (13.1.1) fall out of the direct and indirect relationships considered (not shown in Figure 4.4). These results including those targets i) identified in both the UN–Water Analytical Brief (2016) and the BN model (considering direct and indirect links), ii) identified within the Analytical Brief but not by the BN model, iii) identified by BN the model but not within the Analytical Brief, and iv) with no information available (Table 4.4).

Table 4.4. Summary of interlinkages (direct and indirect) associated with SDG 6 in comparison to those identified in the UN–Water Analytical Brief (2016).

Indicators	**Links identified (data–driven approach)**		**UN–Water Analytical Brief (2016) (Synergies & Conflicts)**	
	“First order” (direct)	**“Second order” (indirect)**	**Data available**	**Insufficient or no data available**
Access to at least basic drinking water services (SDG 6.1.1)	**2 direct links:** Access to at least basic sanitation services (1.4.1 & 6.1.2); Access to electricity (7.1.1)	**7 indirect links:** International poverty line (1.1.1); Essential health (3.8.1); Mortality due to air pollution (3.9.1); Mortality due to unsafe WaSH (3.9.2); Clean fuels and technology (7.1.2); Population in slums (11.1.1); Solid waste collection (11.6.1)	**Links in Analytical Brief but not in network:** Hunger (T2.1); Childhood development (T4.2); Economic growth (T8.1); Economic productivity (T8.2); Full employment (T8.5); Resilient infrastructure (T9.1); Sustain income growth (T10.1); Resilience to climate–related hazards and natural disasters (T13.1); Terrestrial and inland freshwater, forest and mountain ecosystems (T15.1, T15.2 & T15.4); Corruption and bribery (T16.5) **Links in network but not in Analytical Brief:** Universal electricity (T7.1)	Malnutrition (T2.2); Small–scale agricultural productivity (T2.3); Sustainable food production (T2.4); Education for sustainable development (4.7); Gender equality (T5.1, T5.2); Labour rights (T8.8); Sustainable tourism (T8.9); Inequalities (T10.2 & 10.3); Sustainable urbanization (T11.3); Marine pollution (T14.1); Desertification and loss of biodiversity (T15.3 & T15.5); Accountability (T16.6)
Access to at least basic sanitation services (SDG 6.2.1)	**4 direct links:** Essential health services (3.8.1); Mortality due to unsafe WaSH (3.9.2); Access to drinking water (1.4.1 & 6.1.1); Access to electricity (7.1.1)	**10 indirect links:** International poverty line (1.1.1); Maternal mortality ratio (3.1.1); Under-5 mortality rate (3.2.1); Interventions against NTD (3.3.5); Mortality due to air pollution (3.9.1); Women in governmental seats (5.5.1); Clean fuels and technology (7.1.2); Population in slums (11.1.1); Solid waste collection (11.6.1); Levels of PM (11.6.2)		
Water–Use Efficiency (SDG 6.4.1)	**4 direct links:** Essential health services (3.8.1); IWRM (6.5.1); ODA for water and sanitation (6.a.1); Growth rate (8.1.1)	**11 indirect links:** National poverty line (1.2.1); Maternal mortality ratio (3.1.1); Under-5 mortality rate (3.2.1); Interventions against NTD (3.3.5); Women in governmental seats (5.5.1); Access to sanitation (1.4.1 & 6.1.2); Household growth rates (10.1.1); Solid waste collection (11.6.1); Levels of PM (11.6.2); Material footprint (12.2.1); Terrestrial KBAs (15.1.2.2)	**Links in Analytical Brief but not in network:** Hunger (T2.1); Economic productivity (T8.2); Environmental degradation (T8.4); Resilient infrastructure (T9.1); Safe and affordable housing (T11.1); Waste management (T12.4); Climate–related hazards and natural disasters (T13.1); Forest area change (T15.2) **Links in network but not in Analytical Brief:** Maternal mortality (T3.1); Child mortality (T3.2); Water–borne diseases (T3.3); Universal health (T3.8); Women’s participation (T5.5); Marine ecosystems (T14.5)	Malnutrition (T2.2); Small scale agricultural productivity (T2.3); Sustainable food production (T2.4); Education for sustainable development (4.7); Sustainable tourism (T8.9); Sustainable industrialization (T9.2); Sustainable urbanization (T11.3); Green and public spaces (T11.7); Waste generation (T12.5); Desertification and loss of biodiversity (T15.3 & T15.5); Accountability (T16.6)
Freshwater withdrawal (SDG 6.4.2)	**3 direct links:** Women in managerial positions (5.5.2); Renewable energy (7.2.1); Forest area (15.1.1)	**7 indirect links:** Clean fuels and technology (7.1.2); Energy efficiency (7.3.1); CO_2 emissions (9.4.1); Levels of PM (11.6.2); Marine KBAs (14.5.1); Mountain Green Cover Index (15.4.2); Firms involved in bribery (16.5.2)		

Integrated Water Resource Management (SDG 6.5.1)	**3 direct links:** Water–use efficiency (6.4.1); Household growth rates (10.1.1); Terrestrial KBAs (15.1.2.2)	**7 indirect links:** Essential health services (3.8.1); ODA for water and sanitation (6.a.1); Growth rate (8.1.1); Marine KBAs (14.5.1); Freshwater KBAs (15.1.2.1); Mountain KBAs (15.4.1); Firms involved in bribery (16.5.2)	**Links in Analytical Brief but not in network:** Poverty (T1.1 & 1.2); Basic services (T1.4); Hunger (T2.1); Women's full and effective participation (T5.5); Universal electricity (T7.1); Renewable energy (T7.2); Energy efficiency (T7.3); Economic productivity (T8.2); Full employment (8.5); Resilient infrastructure (T9.1); Environmentally sound technology (T9.4); Safe and affordable housing (T11.1); Environmental impact of cities (T11.6); Sustainable management of natural resources (T12.2); Waste management (T12.4); Climate–related hazards and natural disasters (T13.1) **Links in network but not in Analytical Brief:** Household growth rates (10.1.1); Universal health (T3.8); Economic growth (T8.1); Marine ecosystems (T14.5)	Malnutrition (T2.2); Small–scale agricultural productivity (T2.3); Sustainable food production (T2.4); Education for sustainable development (4.7); Gender equality (T5.1, T5.2); Labour rights (T8.8); Sustainable tourism (T8.9); Inequalities (T10.2 & 10.3); Sustainable urbanization (T11.3); Green and public spaces (T11.7); Sustainable consumption and production (T12.1 &T12.3); Waste generation (T12.5); Marine pollution and ecosystems (T14.1 & T14.2); Desertification and loss of biodiversity (T15.3 & T15.5); Accountability (T16.6)

Synergies (plain text): Links which are likely to be mainly positive in that they may be mutually reinforcing or have positive interdependencies (UN–Water, 2016).

Potential conflict (underlined text): Links which usually still have positive aspects, but there exists a potential conflict in one or both directions (UN–Water, 2016).

SDG Targets 6.1 and 6.2 on access to drinking water and sanitation

Targets 6.1 and 6.2 refer specifically to the access to "at least basic" drinking water and sanitation services. Target 6.1 relates to improved drinking water sources where collection time is not more than 30 minutes for a round trip (including queuing), while Target 6.2 refers to improved facilities which are not shared with other households (JMP, 2017b).

Considering both "first–order" (direct) and "second–order" (indirect) interlinkages, the BN model identified, for the case of water, 30% (7 out of 23) of the target–level relationships noted in the UN–Water Analytical Brief. In contrast, this result increased to 48% (11 out of 23) for the sanitation–related indicator (see Table 4.4).

In Table 4.5, the coherency of the results is expanded and contrasted against the existing literature. Specifically, this comparison is carried out at 3 levels, of whether the link identified by the BN model is related to i) a direct relationship, ii) an indirect relationship, and iii) a missing relationship.

For direct relationships, there is a link between both SDG 6 indicators and the links with Goal 3 (health) and Goal 7 (energy). The latter is of particular relevance, as the UN–Water Analytical Brief does not refer to it specifically. However, water is required to produce energy, and vice versa (United Nations, 2018a; UN–Water, 2016; WWAP, 2014). In addition to this, energy is required to treat fecal sludge and wastewater. In turn, it is possible to produce energy from wastewater in the form of heat, biogas, and biofuels (United Nations, 2018a; UN–Water, 2016).

When considering indirect links, the spectrum of health and energy is expanded to the relationships between access to water and sanitation and Goal 1 (poverty), Goal 5 (gender), and Goal 11 (sustainable cities and communities). For instance, the results show a relationship with the population living below the international poverty line (1.1.1). As pointed out by Cohen and Sullivan (2010), there exists a mass of literature that examines the interlinkages between water and poverty from different points of view (e.g. economic assessment, physical accessibility, or a basic needs perspective). For instance, access to water (and sanitation) is a component of the Multidimensional Poverty Index formulated by the United Nations Development Programme (Alkire and Jahan, 2018). Additionally, and per definition, SDG 1 includes a target for universal access to basic services (Target 1.4). Another result points to the link with the proportion of seats held by women in national parliaments (5.5.1). The lack of adequate sanitation facilities might expose women and young girls to illness and safety risks, compromising their learning experience (UN–Women, 2018). Thus, it hinders the opportunities to reach professional positions of national responsibility.

From those relationships not identified by the BN model (see Table 4.4), we acknowledge the absence of the links related to the participation rate in pre–primary school (4.2.2) and the proportion of women in managerial positions (5.5.2), which might be treated together. Women and girls are responsible for water collection in 8 out of 10 households with water off–premises (UN–Women, 2018). In different world regions, it is likely that, if women and young girls reduce the time to collect water, they would have more time and opportunities to improve their lives through education, paid work, and better health (Fisher, 2008; ILO, 2019; UNDP, 2006a; Willetts et al., 2010). Moreover, it would give the opportunity to combat further problems that threaten poor women's well–being (Kevany and Huisingh, 2013). However, it cannot be assumed that increased water access reduces women's workload or strengthens women's empowerment (Ivens, 2008). This implies an unequal sharing of family and household responsibilities, which means that when public services such as education, childcare, water, and sanitation are cut back or become less affordable, it is usually women and young girls who fill gap, and the overall families do not enjoy these services (Desai and Alva, 1998; UN–Women, 2018). In addition to this, the BN model does not identify any relationship with Goal 8 (economic growth). Economic growth (8.1.1) and jobs rely on limited environmental resources such as water (ILO, 2018). Specifically, 78% of the jobs constituting the global workforce are water dependent (WWAP, 2016). Furthermore, the provision of WaSH services at home and in the workplace enables a robust economy by contributing to a healthy and productive population workforce (8.2.1) (WWAP, 2016). Investments in WaSH have paved a path to economic growth and unemployment rates (8.5.2) reduction and new business opportunities appear as a result of policies which address, for example, water (and sanitation) infrastructures (UN–EMG, 2011; WWAP, 2016).

Table 4.5. Literature review of the identified relationships (both direct and indirect) and the ones missing (in comparison to the UN–Water Analytical Brief) for SDG Targets 6.1 and 6.2.

	SDG 6 indicator	Interlinkages identified	Relationship assessment
1st ORDER (Direct)	6.1.1 6.2.1	6.1.1 – 6.2.1: Access to "at least basic" water and sanitation services	Water and sanitation have been jointly monitored together since 1930. A WaSH implementation approach has been in place since 1970 (Bartram et al., 2014; Herrera, 2019)
	6.2.1	3.8.1: Coverage of essential health services	The human right to essential health includes, among others, access to an adequate supply of basic sanitation (Backman et al., 2008)
	6.2.1	3.9.2: Mortality rate attributed to unsafe WaSH services	Intrinsically related per definition
	6.1.1 6.2.1	7.1.1: Access to electricity	Water as a source to produce energy, and vice versa (United Nations, 2018a; UN–Water, 2016; WWAP, 2014). Energy is required to treat fecal sludge and wastewater. Energy can be produced in the form of heat, biogas, and biofuels (United Nations, 2018a; UN–Water, 2016)
2nd ORDER (Indirect)	6.1.1 6.2.1	1.1.1: Population living below the international poverty line	Direct linkages between water and poverty from different points of view (e.g. economic assessment, physical accessibility, and basic needs perspective) (Cohen and Sullivan, 2010; Sullivan, 2002) Water and sanitation are components of the UNDP Multidimensional Poverty Index (Alkire and Foster, 2007; Alkire and Jahan, 2018; Alkire and Santos, 2014; Giné-Garriga and Pérez-Foguet, 2019) SDG 1 includes a target for universal access to basic services, such as water and sanitation (Target 1.4)
	6.2.1 6.2.1	3.1.1: Maternal mortality rate 3.2.1: Under–five mortality rate	Extensive literature dealing with the effects of WaSH on health (e.g. Bartram et al., 2005; Cairncross et al., 2010; Cheng et al., 2012; Esrey et al., 1991; Feachem, 1984)
	6.2.1	3.3.5: People requiring interventions against NTD	WaSH interventions can reduce the number of people requiring interventions against NTD (e.g. Fitzpatrick and Engels, 2015; Hotez et al., 2015; United Nations, 2018a; WHO, 2015a)
	6.1.1	3.8.1: Coverage of essential health services	The human right to health includes, as well, an adequate supply of safe water (Backman et al., 2008)
	6.1.1 6.2.1	3.9.1: Mortality rate attributed to household and ambient air pollution	Consequence of using solid fuels for domestic purposes, such as cooking, heating or treating water Countries presenting higher 3.9.1 rates coincide with countries presenting higher 3.9.2 rates (mortality due to unsafe WaSH) (WHO, 2018)
	6.2.1	5.5.1: Proportion of women in national parliaments	Lack of adequate sanitation facilities might expose women and young girls to illness and safety risks, compromising their learning experience and hindering the opportunities to develop a professional career (UN–Women, 2018)
	6.1.1 6.2.1	7.1.2: Primary reliance on clean fuels and technology	Lack of 7.1.2 access leads to high levels of household air pollution (United Nations, 2018b; World Bank, 2018). Potential link if it is considered the existing relationship between air pollution and unsafe WaSH
	6.1.1 6.2.1	11.1.1: Urban population living in slums	Access to water and sanitation helps in promoting better housing and slum upgrading (UN–Habitat, 2018)
	6.1.1 6.2.1	11.6.1: Urban solid waste collection	Existing connection with SDG 11 is established through Target 11.6 (reduction environmental impact of cities) (UN–Habitat, 2018)

MISSING	6.1.1 / 6.2.1	2.1.1: Prevalence of undernourishment	Caused by inadequate dietary intake and infectious diseases, such as diarrhoea. WaSH interventions are frequently implemented to reduce the latter (Dangour et al., 2013) "Zero hunger" is highly dependent on progress in ensuring availability and sustainable management of water and sanitation (ICSU–ISSC, 2017) Increasing literature applying nexus approaches, such as the water–energy–food nexus (Rasul, 2016; Pahl-Wostl, 2017)
	6.1.1	3.1.1: Maternal mortality rate 3.2.1: Under–five mortality rate	Extensive literature dealing with the effects of WaSH on health (e.g. Bartram et al., 2005; Cairncross et al., 2010; Cheng et al., 2012; Esrey et al., 1991; Feachem, 1984)
	6.1.1 / 6.2.1	4.2.2: Participation rate in organized learning 5.5.1: Proportion of women in national parliaments (only for 6.1.1) 5.5.2: Proportion of women in managerial positions	Women are responsible for water collection in 8 out of 10 households with water off–premises (UN–Women, 2018) Reducing the time to collect water would provide more time and opportunities for education, paid work, and better health (ILO, 2019; Fisher, 2008; UNDP, 2006a; Willetts et al., 2010) Opportunity to combat further problems that threaten poor women's well–being (Kevany and Huisingh, 2013) Increased water access might not reduce women's workload or strengthen women's empowerment (Ivens, 2008) Due to unequal sharing of household responsibilities, and availability and affordability of public services (e.g. education, water and sanitation), women and young girls usually fill the gap, and overall, families do not enjoy these services (Desai and Alva, 1998; UN–Women, 2018)
	6.1.1 / 6.2.1	8.1.1: Economic growth 8.2.1: Growth rate per employee 8.5.2: Unemployment rate	Based on limited environmental resources, such as water (ILO, 2018) 78% of the jobs constituting the global workforce are water dependent (WWAP, 2016) WaSH services enable a robust economy by contributing to a healthy and productive population workforce (WWAP, 2016) Investments in WaSH have paved a path to economic growth, unemployment rates reduction and new business opportunities (UN–EMG, 2011; WWAP, 2016)
	6.1.1 / 6.2.1	9.1.2: Air traffic	Growth in traffic at airports also brings growth in the direct jobs generated (ATAG, 2018) Peripheral regions air activity appears to boost regional development, while in core regions regional growth causes airport activity (Mukkala and Tervo, 2013) Relationship between air traffic and economic growth and employment links with the access to water
	6.1.1 / 6.2.1	9.4.1: CO_2 emissions	Global economic and population growth as the most important drivers. Contribution of economic growth has risen sharply comparing to population growth (IPCC, 2014)
	6.1.1 / 6.2.1	10.1.1: Growth rates inequalities	Inequalities in access to water and sanitation services between SDG regions, between countries within each region, within individual countries, between urban and rural areas, sub–national regions and wealth quintiles (JMP, 2017a)
	6.1.1 / 6.2.1	13.1.1: People affected by disasters	WaSH interventions can prevent outbreaks of waterborne diseases in both emergency settings and displaced population (Brown et al., 2012; Watson et al., 2007)
	6.1.1	15.1.1: Forest areas	Forests play a large role in regulating fluxes of atmospheric moisture and rainfall patterns over land through evapotranspiration and transpiration (Ellison et al., 2012; 2017)

		Natural forests transport water locally and globally (Ellison et al., 2017). These are suggested to be capable of “pumping” atmospheric moisture from the ocean to land in order to compensate the river runoff and ensuring maximum ecosystem productivity (Makarieva and Gorshkov, 2007) Land conversions from forests to agriculture or forest protection might imply trade–offs in both downstream and upstream communities (Ellison et al., 2017; Pramova et al., 2012; Sheil et al., 2016)
6.1.1 6.2.1	15.1.2.1: Freshwater KBAs 15.1.2.2: Terrestrial KBAs 15.4.1: Mountain KBAs	These provide a range of important ecosystem services, with drinking water a significant one (UNEP–WCMC and IUCN, 2016; UNEP–WCMC et al., 2018; United Nations, 2018b) Clear link between the treatment of fecal sludge and wastewater, and environment health (UN–Water, 2016)
6.1.1 6.2.1	16.5.2: Bribery practices	The water sector is not exempt of bribery practices, such as expediting new service connections after payment or favoritism in public procurement (Stålgren, 2006) These practices contribute to millions of people dying from illnesses caused by lack of access to sanitation (and clean water) (Stålgren, 2006)

SDG Target 6.4 on water–use efficiency and water stress

Target 6.4 includes two indicators that are strongly linked and offer complementary information. On the one hand, indicator 6.4.1 assesses to what extent a country's economic growth is dependent on the use of water resources, representing an economic indicator. On the other hand, indicator 6.4.2 is an environmental indicator, tracking the physical availability of freshwater resources (FAO, 2018).

In this case, the BN model identified 15 out of 20 (75%) of the target–level relationships extracted from the UN–Water Analytical Brief, taking into account both direct and indirect links. Similar to the case of access to water and sanitation, the links identified refer as well to Goals on poverty (1), health (3), gender (5), energy (7), and cities (11). However, in this case, the spectrum of the relationships obtained expands to Goals 12 (sustainable consumption and production), 14 (oceans), 15 (terrestrial ecosystems), and 16 (peace and security) (see Table 4.4).

A summary of the academic contributions to the direct, indirect, and missing interlinkages associated with the BN analysis is shown in Table 4.6. Focusing on the direct links identified, a relationship of water–use efficiency (6.4.1) and the degree of IWRM implementation (6.5.1) and the ODA for water supply and sanitation (6.a.1) can be observed. For 6.4.1, IWRM has been presented during the last decades as the framework to support the achievement of an efficient use of water (among other things) (GWP, 2000; UNEP, 2018). Target 6.a advocates expanding international cooperation and capacity–building in water–related activities and programs, such as water efficiency. In fact, a recent survey of 24 external support agencies show that more than 40% promote water use efficiency and sustainable withdrawals, and that 50% support the implementation of IWRM as a "very high" priority area (GLAAS, 2017). On the other hand, the results show a relationship between water–stress (6.4.2) and the renewable energy share in the total final energy consumption (7.2.1). Water is used for non–renewable energy generation (e.g. in the extractive industries for producing fuels or for cooling purposes in power plants), but also for renewable energy generation (e.g. as an input for energy crops or as driving force for hydroelectric turbines) (WWAP, 2014). However, the latter is also identified as a potential conflict, as hydropower and bio–energy might have significant impacts on land and water resources and ecosystems (UN–Water, 2016). In this study, the data used show that when the share of renewable energy increases, fewer countries show water stress (see Annexes Table A12). Another direct link that was identified is that one associated with the forest area as a proportion of total land area (15.1.1). Natural resources, such as land, have been acquired to satisfy immediate human needs, often at the expense of degrading the environment. Forests have been cleared for intensive agriculture and livestock, and for expanding urban settlements. Water demands associated with these practices, especially irrigation for agriculture, directly affect freshwater supplies and increase water scarcity levels (Foley et al., 2005; Mekonnen and Hoekstra, 2016; United Nations, 2018a). Similar to the previous relationship identified, the tendency of the data used in this study suggests that there is a positive correlation between high rates of forest coverage and low levels of water stress (see Annexes Table A12). In addition to these direct links associated to water–use efficiency (6.4.1) and water stress (6.4.2), we highlight those relationships identified by the BN model and not reflected within the Analytical Brief. For instance, a link between water–use efficiency (6.4.1) and the essential health service coverage (3.8.1), and indirectly to other health–related targets, can be observed (see Table 4.6). An increase in water–use efficiency makes more water available for drinking and other uses (UNEP, 2018). Access to improved water (and sanitation) represents a tracer indicator for universal health coverage achievement (WHO, 2015b) and is especially useful for monitoring the progressive realization of the right to health (Backman et al., 2008). In the case of water stress (6.4.2), it is observed a direct link with the proportion of women in managerial positions (5.5.2). Although this link has not been addressed within this specific focus, its interdependency has been largely analyzed. Several publications affirm that women's involvement in water management is a key aspect to improving effectiveness of programs and projects due to women's roles, concerns, and priorities in water–related issues (Ivens, 2008). This is believed to balance the access to the control over resources such as water (Panda, 2007; UNDP, 2006b) and to hasten the achievement of sustainability in the management of scarce water resources (GWA, 2003). The data employed in this study suggest that the higher the participation of women, the lower the water stress (see Annexes Table A12).

When paying attention to the indirect links, several relationships are provided by the BN model that are not reflected in the Analytical Brief. In particular, an indirect relationship between water–use efficiency (6.4.1) and maternal mortality (3.1.1), child mortality (3.2.1), and the number of people requiring interventions against neglected tropical diseases (3.3.5) can be observed. As mentioned previously, an increase in water–use efficiency makes more water available, which in turn positively affects health issues. In the case of water stress (6.4.2), a relationship with the marine Key Biodiversity Areas (KBAs) (14.5.1) can be observed. Much of the pollution affecting oceans and coastal zones comes from human activities, such agriculture or industry (United Nations, 2018a). In addition to this, population and economic growth are some of the major drivers that affect and will affect water resources (Ercin and Hoekstra, 2014; Vörösmarty et al., 2000). It has also been suggested that in this stress context, the protection of marine areas would rise.

Table 4.6. Literature review of the identified relationships (both direct and indirect) and the ones missing (in comparison to the UN–Water Analytical Brief) for SDG Target 6.4.

	SDG 6 indicator	Interlinkages identified	Relationship assessment
1st ORDER (direct)	6.4.1	3.8.1: Coverage of essential health services	An increase in 6.4.1 makes more water available for drinking and other uses (UNEP, 2018) Access to improved water (and sanitation) represents a tracer indicator for universal health coverage achievement (WHO, 2015b) Useful for monitoring the progressive realization of the human right to health (Backman et al., 2008)
	6.4.2	5.5.2: Proportion of women in managerial positions	Women's involvement improves programme and project effectiveness due to their roles, concerns and priorities in water–related issues (Ivens, 2008) It balances the access to the control over resources such as water (Panda, 2007; UNDP, 2006b) and accelerates the achievement of sustainability in scarce water resources management (GWA, 2003) Higher participation of women is correlated to lower levels of water stress (see Annexes Table A11)
	6.4.1	6.5.1: Degree of IWRM implementation	IWRM promotes the achievement of an efficient use of water (GWP, 2000; UNEP, 2018)
	6.4.1	6.a.1: ODA for water supply and sanitation	Support to water efficiency programmes included in Target 6.a definition More than 40% and 50% of surveyed agencies consider, respectively, water use efficiency and sustainable withdrawals and IWRM implementation as "very high" priority areas (GLAAS, 2017)
	6.4.2	7.2.1: Renewable energy share	Water is used for non–renewable energy generation (e.g. extractive industries or for power plants), but for renewable energy generation as well (e.g. input for energy crops or driving force for hydroelectric turbines) (WWAP, 2014) Potential conflict, as hydropower and bio–energy might have significant impacts on land and water resources and ecosystems (UN–Water, 2016) Tendency of lower levels of water stress when increasing 7.2.1 (see Annexes Table A11)
	6.4.1	8.1.1: Economic growth	An increase in 8.1.1 might enhance technological advancements that can improve efficiency in using water and, thus, reduce the exploitation of water resources (El Khanji, 2016; FAO, 2018)
	6.4.2	15.1.1: Forest area	Forests have been cleared for intensive agriculture and livestock, and for expanding urban settlements. Water demands associated with these practices, especially irrigation for agriculture, directly affect freshwater supplies and increase water scarcity levels (Foley et al., 2005; Mekonnen and Hoekstra, 2016; United Nations, 2018a) Positive correlation between high rates of forest coverage and low levels of water stress (see Annexes Table A11)

2nd ORDER (Indirect)	6.4.1	1.2.1: Population living below the national poverty line	Increasing water availability by using water more efficiently impacts positively on poverty alleviation. Potential conflict if development for poverty reduction and economic growth are not taken carefully to use water sustainably (UN–Water, 2016)
	6.4.1	6.2.1: Access to at least basic sanitation services 3.1.1: Maternal mortality rate 3.2.1: Under–five mortality rate 3.3.5: People requiring interventions against NTD 4.2.2: Participation rate in organized learning 5.5.1: Proportion of women in national parliaments	Higher levels of 6.4.1 increases water availability for different purposes (UNEP, 2018). This improves health of mothers and children, reduces the number of people requiring interventions against NTD, provides more learning opportunities for women, and reduces environmental impacts of cities
	6.4.2	7.1.2: Primary reliance on clean fuels and technology	The same people who lack access to improved water (and sanitation) are also likely to lack access to electricity and to rely on solid fuel for cooking (WHO, 2018; WWAP, 2014) With some exceptions, water stress is considered the symptom of water scarcity, which hinders the access of this resource (United Nations, 2018a)
	6.4.2	7.1.3: Energy efficiency	Water is required for energy production, and more efficient processes in this concern reduces water consumption and thus water stress (ICSU–ISSC, 2017; Ringler et al., 2013; United Nations, 2018a; UN–Water, 2016) Resource savings might be invested to increase production and thus hindering to achieve an overall decrease in demand (Unver et al., 2017; WWAP, 2014)
	6.4.2	9.4.1: CO_2 emissions	Energy generation contributes with the highest levels of CO_2 emissions (IPCC, 2014) and consumes large amounts of water (Li et al., 2012) Water sector as a greenhouse–gases emitter (Rothausen and Conway, 2011) Higher levels of water withdrawals are related to "medium" levels of emissions in relative terms (see Annexes Table A12) Different picture if so–called "virtual water" is considered within the analysis (Hoekstra and Hung, 2002; Longo and York, 2009)
	6.4.1	10.1.1: Growth rates inequalities	Increasing 6.4.1 implies an increase in drinking water availability. This impacts positively on people's health and the economy, thereby contributing to reducing inequalities
	6.4.1	11.6.1: Solid waste management 11.6.2: Levels of fine particulate matter (PM)	6.4.1 and 6.4.2 support waste reduction and improve its management, as well as progress on air quality levels (UN–Water, 2016) Effective waste management systems are crucial to access to safe WaSH services and to improve water resources quality and sustainability (UN–Habitat, 2018)

	6.4.2		Waste disposal cost rises in tandem with the investments and operating costs for reducing emissions to water (UN–Habitat, 2010) Anthropogenic sources of PM include, among others, solid–fuel combustion, and industrial and agricultural activities (Kim et al., 2015) These water consumer activities contribute to air pollution and hinder the sustainability of natural resources, as well as economic and social development (UN–Water, 2016; WWAP, 2016)
	6.4.1	12.1.1: Material footprint	Humans rely on raw materials to meet basic needs, such as access to water Water is used for material extraction processes, linking material and water footprints (United Nations, 2018a; Wiedmann et al., 2015) Resource efficiency means a small footprint per unit of product (Hoekstra and Wiedmann, 2014)
	6.4.2	14.5.1: Marine KBAs	Protected areas can work against improving rights and access to resources (Target 1.4) if they are established and enforced without engaging local stakeholders (Singh et al., 2018). This study does not point to the specific link with basic services Much of the pollution affecting oceans and coastal zones comes from human activities, such agriculture or industry (United Nations, 2018a) Population and economic growth are some of the major drivers that affect and will affect water resources (Ercin and Hoekstra, 2014; Vörösmarty et al., 2000). It might be suggested that in this stress context, the protection of marine areas would rise 10% of the countries suffer water stress while protecting a low percentage of marine areas (see Annexes Table A12)
	6.4.1	15.1.2.2: Terrestrial KBAs	Effort towards achieving water–use efficiency must incorporate, among others, the principle of conserving, protecting, and enhancing natural ecosystems (Unver et al., 2017)
	6.4.2	15.4.2: Mountain Green Cover Index	Mountains provide between 60% and 80% of the Earth's freshwater (FAO, 2015) Green coverage of mountain areas (i.e. forests, shrubs and trees) increases water availability and, thus, reduces potential water stress 53% of the countries (95 out of 179) show a positive correlation (see Annexes Table A12)
	6.4.2	16.5.2: Bribery practices	When water becomes scare, so does the competition for this resource. This creates more incentives to resort to corruption and to grab more than one's fair share (Transparency International, 2008) Data used do not suggest a clear relationship (see Annexes Table A12)
MISSING	6.4.1	2.1.1: Prevalence of undernourishment	Hunger and food security (secure access to sufficient amounts of safe and nutritious food for normal growth and development and an active and healthy life) are intrinsically related, and water plays an important role in this process (United Nations, 2018a) Regions with high levels of water stress show high prevalence of severe food insecurity, but the latter is present

6.4.2		in regions with low water stress as well (United Nations, 2018a) Agriculture plays a key role towards "zero hunger" and accounts for approximately 70% of water withdrawals Agricultural productivity, if not properly managed, jeopardizes the availability, sustainability, and quality of water for multiple purposes and users (ICSU–ISSC, 2017) Water–energy–food nexus has been extensively reviewed elsewhere (Albrecht et al., 2018)
6.4.1 6.4.2	8.2.1: Growth rate per employee 9.1.2: Air traffic 11.1.1: Urban population living in slums 13.1.1: People affected by disasters	Increasing water availability and access contributes to a healthy and productive population workforce, enables a robust economy and growth in activities such as airport activities, helps to promote slum upgrading (although increasing the potential overuse or pollution of water resources), and supports the prevention of waterborne disease outbreaks in both emergency circumstances and population displacements
6.4.1 6.4.2	12.4.1: Compliance with the Stockholm Convention	Sustainable and efficient use of water resources is mutually supportive to the safe management of chemicals and wastes throughout their life cycle (UN–Water, 2016)

SDG Target 6.5 on integrated water resources management

IWRM represents a process–oriented and aspirational target rather than an outcome as the previous ones. Its implementation supports balancing the environmental, social, and economic dimensions of sustainable development, and achieving all Goals across the 2030 Agenda (UNEP, 2018). Specifically, indicator 6.5.1 refers to the degree of IWRM implementation, which it is assessed through a self–assessed country questionnaire and organized into four main dimensions: enabling environment, institutions and participation, management of instruments, and financing (UNEP, 2018). Overall relationships related to the degree of IWRM implementation encompass 33% (7 out of 21) of the target–level links addressed in the UN–Water Analytical Brief (see Table 4.4). Even though IWRM is per definition wide in scope, the aggregated nature of this indicator means that it might mask further potential links. Those linkages identified are related to Goal 3 (health), Goal 8 (economic growth), Goal 10 (inequality), Goal 14 (oceans) Goal 15 (terrestrial ecosystems), and Goal 16 (peace and security) (see Table 4.7).

Unlike the UN–Water Analytical Brief, the BN model show a direct relationship between IWRM (6.5.1) and growth rates inequalities (10.1.1). It is acknowledged that water (and sanitation) is essential to reduce inequalities. IWRM concept calls to “leave no one behind”. This highlights overlapping aspects between IWRM and the human rights–based approach to water and sanitation (i.e. equality, equity, participation, and governance) (WWAP, 2019).

Notably, indirect links between IWRM and the coverage of essential health services (3.8.1) and economic growth (8.1.1) can also be observed, which are not reflected in the Analytical Brief. However, a recent report states the existence of a positive correlation with the Human Development Index (UNEP, 2018), where life expectancy (health) is one of its parameters (UNDP, 2018). Furthermore, it states that wealthier countries present higher degrees of IWRM implementation (UNEP, 2018). The BN analysis also shows a relationship between IWRM and marine KBAs (14.5.1). In general, KBAs provide a range of ecosystem services (e.g. drinking water) both up– and downstream. A key principle of IWRM is that water resources also need to be managed according to hydrological boundaries (UNEP, 2018).

SDG Target 6.a on international cooperation and capacity–building support

Unlike previous targets, Target 6.a focuses on the means of implementation to achieve SDG 6. Specifically, it assesses the amount of water– and sanitation–related official development assistance (ODA) that is part of a government–coordinated spending plan (6.a.1). As a comparison with the UN–Water Analytical Brief is not possible, only the direct links obtained from the BN model are considered to evaluate their coherency.

Interestingly, this indicator shows the highest number of direct links identified (see Table 4.8), which refer to Goal 3 (health), Goal 10 (inequality), Goal 11 (sustainable cities and communities), and Goal 12 (sustainable consumption and production). For instance, the BN model shows a link between the ODA (6.a.1) and both maternal mortality (3.1.1) and the number of people requiring interventions against neglected tropical diseases (3.3.5). In general, ODA for health has been much greater in countries with highest levels of maternal (and child) mortality (GLAAS, 2017; Pitt et al., 2010). In addition to this, from the data used in this study, the ODA for water and sanitation is greater in countries with higher rates of maternal mortality and with more interventions against neglected tropical diseases (see Annexes Table A12). However, some authors consider it necessary to increase the share of ODA for NTD control (Liese and Schubert, 2009). Another link identified by the BN model points out the relationship with the growth rate inequalities (10.1.1). A recent study states that ODA plays an important role in reducing gender inequalities and rural–urban disparities in social and human development (Ndikumana and Pickbourn, 2017).

Table 4.7. Literature review of the identified relationships (both direct and indirect) and the ones missing (in comparison to the UN–Water Analytical Brief) for SDG Target 6.5.

	Interlinkages identified	Relationship assessment
1st ORDER (Direct)	6.4.1: Water–use efficiency	IWRM promotes an efficient use of water (GWP, 2000; UNEP, 2018)
	10.1.1: Growth rates inequalities	Water (and sanitation) is essential to reduce inequalities IWRM concept calls to "leave no one behind". This highlights overlapping aspects between IWRM and the human rights–based approach to water and sanitation (i.e. equality, equity, participation, and governance) (WWAP, 2019)
	15.1.2.2: Terrestrial KBAs	Terrestrial ecosystems are important for rainwater infiltration, groundwater recharge, and river flow regimes. These influence water availability and quality, and they must be considered in the overall planning and management of the water resources (GWP, 2000)
2nd ORDER (Indirect)	3.8.1: Coverage of essential health services	Positive correlation with the Human Development Index (UNEP, 2018), which has life expectancy (health) as one of its parameters (UNDP, 2018)
	6.a.1: ODA for water supply and sanitation	ODA is mentioned within the financing dimension of IWRM as a potential and complementary source for its implementation (UNEP, 2018)
	8.1.1: Economic growth	Positive correlation with the HDI. Wealthier countries present higher degrees of IWRM implementation (UNEP, 2018)
	14.5.1: Marine KBAs 15.1.2.1: Freshwater KBAs 15.4.1: Mountain KBAs	These areas provide a range of ecosystem services (e.g. drinking water) both up– and downstream. A key principle of IWRM is that water resources also need to be managed according to hydrological boundaries (UNEP, 2018)
	16.5.2: Bribery practices	Countries with low perception of corruption count with a higher HDI and, in consequence, with higher levels of IWRM implementation (UNEP, 2018)
MISSING	3.1.1: Maternal mortality rate 3.2.1: Under–five mortality rate 3.3.5: People requiring interventions against NTD 3.9.1: Mortality rate attributed to household and ambient air pollution 3.9.2: Mortality rate attributed to unsafe WaSH services 4.2.2: Participation rate in organized learning	Countries likely to achieve the global Target 6.5 are predominantly the "high" and "very high" HDI countries (UNEP, 2018). There is a positive correlation with those indicators related to life expectancy, education, and standard of living
	5.5.1: Proportion of women in national parliaments 5.5.2: Proportion of women in managerial positions 13.1.1: People affected by disasters	The self–assessed country survey for the 6.5.1 indicator quantification (UNEP, 2018) integrates specific questions on women's participation at different levels and on the management instruments to reduce impacts of water–related disasters (partially related to 13.1.1)

1.1.1: Population living below the international poverty line 1.2.1: Population living below the national poverty line 8.2.1: Growth rate per employee 8.5.2: Unemployment rate	Water supply for different uses is a critical element of reducing poverty, creating good working conditions and making industrialization and consumption patterns sustainable with increased resource–use efficiency and environmentally sound processes Implementing the different SDG 6 targets provides operating mechanisms for IWRM implementation, as it promotes the coordination of different potential stakeholders and captures the impacts under those targets
2.1.1: Prevalence of undernourishment 7.1.1: Access to electricity 7.2.1: Renewable energy share 7.3.1: Energy efficiency	Coordinated efforts, such as the water–energy–food (WEF) nexus, have been documented as a complementary and catalyst approach to IWRM (United Nations, 2018a; UN–Water, 2016; WWAP, 2019) Defence of nexus approach over IWRM due to its multi–centric nature instead of water–centric one (Nhamo et al., 2018) IWRM challenged by suggestions supporting nexus approaches of interrelated development priorities (Woodhouse and Muller, 2017) WEF nexus analyses the links between achieving food, water and energy security and the impacts of these activities, aiming towards an efficient and fair balance of sector needs

Table 4.8. Literature review in relation to the direct relationships identified in relation to SGD Target 6.a.

Interlinkages identified	Relationship assessment
3.1.1: Maternal mortality rate 3.3.5: People requiring interventions against NTD	Relatively, ODA for health is much greater in countries with highest levels of maternal (and child) mortality (GLAAS, 2017; Pitt et al., 2010) ODA for water and sanitation is greater in countries with higher rates of maternal mortality and more interventions against NTD (see Annexes Table A11) Some authors consider increasing the share of ODA for NTD control to be necessary (Liese and Schubert, 2009)
6.4.1: Water–use efficiency	Support for water efficiency programmes included in Target 6.a definition More than 40% of surveyed agencies consider it as a “very high” priority area (GLAAS, 2017) ODA effectiveness might become negative as countries scale up the income ladder (Gopalan and Rajan, 2016)
10.1.1: Growth rates inequalities	Service delivery to the most vulnerable as a “very high” priority for 67% of the surveyed agencies (GLAAS, 2017) ODA plays an important role in reducing gender inequalities and rural–urban disparities in social and human development (Ndikumana and Pickbourn, 2017)
11.6.1: Urban solid waste collection	Existing connection with SDG 11 is established through Target 11.6 (reduction environmental impact of cities) (UN–Habitat, 2018)
12.2.1: Material footprint	Countries with higher levels of material footprint receive more ODA for water and sanitation (see Annexes Table A12) Connection between material and water footprint suggests that increasing water–use efficiency supports their reduction

4.4.4. Potential applications in decision–making processes

We have demonstrated the potentiality of this data–driven BNs approach to identify relationships among global development indicators. Understanding these linkages enables the full exploitation of synergies, conflict resolution, and trade–offs balances. On the basis of these linkages, integrated planning and management can support decision–making, reduce investment costs and facilitate implementation of a number of strategies that are geared towards sustainable development.

Nonetheless, current data gaps for a number of indicators and countries clearly limit the scope of the study and the lessons learnt. We have tested the robustness of our approach, showing that its performance is positive until a specific side of the sample. Credible data are the lifeblood of decision–making (IEAG, 2014), and are needed to underpin sector advocacy, stimulate political commitment, and trigger well–placed investments towards optimum health, environment, and economic gains (UN–Water, 2016). Moreover, data are the raw material for BNs models, as the validity of their outputs is directly dependant on both data quality and quantity. At present, there are several global initiatives that monitor different aspects of the development Agenda, yet a coherent framework is missing. To the extent that existing efforts expands to ensure harmonized and integrated monitoring of SDGs, increasing high–quality data availability, it is expected that a wide range of potential uses may emerge in relation to BNs applications.

The BNs approach presented here is a flexible tool that could be adapted to a specific context, such as focusing at the sub–national level, where decisions are taken by decentralized administrations. In fact, the 2030 Agenda resolution encourages each government to set “its own national targets guided by the global level of ambition but taking into account national circumstances” (United Nations General Assembly, 2015). Specifically, it opens the possibility to simulate different scenarios and to infer the impact of potential interventions. Different levels of improvement (investments) regarding node 6.2.1 (access to “at least basic” sanitation services) might be simulated (through CPTs modification) (see for example Figure 4.2). Here, the impact on immediate nodes 6.1.1 (access to drinking water services), 3.9.2 (mortality rate due to unsafe WaSH), 3.8.1 (coverage of essential health services), and 7.1.1 (access to electricity) could be evaluated. Similarly, further connected nodes could be analyzed as well. This requires a shift in the way that potential interventions are assessed and encourages decision–makers to integrate interdisciplinary perspectives, which, in turn, are essential for sustainable development.

In this scenario–based analysis, and considering the difficulty of countries to collect all the information related to the 17 SDGs, BNs might be also especially helpful when there is scarcity or some degree of uncertainty in the data. For example, if no information related to the access to sanitation services is available, different hypotheses can be made, and their potential impacts on associated nodes can then be assessed.

Another potential application of BNs is based on its inverse use (Li et al., 2019; Requejo-Castro et al., 2019; Song et al., 2018). In contrast to methodology for a scenario simulation, where one or more nodes can be modified to assess the impact in subsequent nodes, inverse use allows a desirable value in an objective node to be established and the new values of connected nodes to be obtained that would reach that value (see Section 2.2.2). Thus, specific interventions can be designed, assessed, and implemented. This possibility might be useful for planning purposes, allowing decision–makers to optimize these interventions in order to achieve the expected results.

4.5. KEY MESSAGES

As per definition, the SDGs are presented as integrated and indivisible. Therefore, conventional indicator–based frameworks need to be combined with innovative approaches for an accurate assessment of interlinkages and interdependencies between targets and indicators.

In this Chapter, we tested the validity of a data–driven BNs approach to elucidate SDGs interlinkages. In particular, we applied our approach to explore the relationships of SDG 6 across the 2030 Agenda.

Some key messages can be highlighted from this Chapter:

– We demonstrated the robustness of the approach for identifying indicator interlinkages, as results were consistently obtained up to a sample size of 130 countries. This aspect is particularly important when considering that results are spurred on by the data used. Furthermore, this sample size represents the potentiality of this approach for dealing with a relative low amount of data. However, a limitation of this approach that should be noted was that it did not identify the cause–effect relationships, which might be of interest. In any case, these results might be considered as a potential starting point for further discussion.

– We further demonstrated that the results obtained are coherent. Taking as a starting point the UN–Water Analytical Brief, we have compared the results provided by the BN model with the main water and sanitation interlinkages on the SDGs identified by this study. Our results have reached different levels of coincidence when considering both “first order” (direct) and “second order” (indirect) relationships. Notably, relationships regarding SDG Target 6.4 have reached 75% of coincidence. In contrast, lower levels of concurrence were obtained for Targets 6.1 (30%), 6.2 (48%), and 6.5 (33%). Further, and as an added value of our approach, we identified linkages that were not reflected in the UN Water Analytical Brief, which have been positively contrasted against the existing literature.

– A data–driven BNs approach complements existing approximations and is needed to increase both the understanding and the interpretation of the complexities and interdependencies of the SDGs.

CHAPTER V. CONCLUSIONS AND WAYS FORWARD

The complex and interconnected nature of the world we live in permeates different scales, sectors or decision problems. This fact is acknowledged by the United Nations 2030 Agenda for Sustainable Development, which underscores current global challenges, recognizes their interconnectivity and calls for international action. However, established "silo" approaches in which different institutions, sectors, governments and international agencies operate have been perceived as a weakness towards a sustainable future. In this sense, it is widely recognized as well the need of a major shift in decision–making processes towards more holistic and integrated approaches. Evidence–based decision–making involves complex processes of considering a wide range of information of different nature. Nowadays, available data can support these processes, but methodologies to effectively integrate these data are lacking.

This thesis has focused on the increasing use of Bayesian Networks modelling as an approach to accommodate complex problems and, ultimately, to support decision–making. Some of the features that characterize these models include, but not limited to, i) incorporating data and knowledge from different sources and domains, ii) estimating more accurately uncertainty, as the variables at hand are modeled by means of probability distributions, iii) computing automatically the probability of a particular hypothesis or scenario, and iv) obtaining the probability distribution of a variable given another (set of) variable(s), applying as well for the way round.

In practice, expert knowledge and empirical data to build and apply Bayesian Networks models are employed separately. Despite of the demonstrated utility of this practice, this dissertation has proposed a data–driven Bayesian Networks approach to combine expert opinion and quantitative data to support informed decision–making.

We have laid out the content of this thesis along a pair of interconnected research questions, both aimed at providing answers to the potential usefulness of the proposed approach to ultimately support decision–making. The first research question – *how can be combined expert knowledge and data–driven Bayesian Network approaches?* – deals with the development of a systematic methodology based on the replication of composite indicators–based conceptual frameworks, through the use of structure learning algorithms (implicit in BNs modelling). The second research question – *to which extent are data–driven Bayesian Network approaches robust in capturing the complexities and interdependencies of a given context?* – proposes a pure data–driven Bayesian Network approach, coupled with a statistical technique to reduce results uncertainty and with a comprehensive result robustness analysis.

Both approaches have been tested and validated taking the Sustainable Development Goal 6 as a reference point, with particular attention to the water, sanitation and hygiene sector.

Overall, this thesis offers systematic methods to combine qualitative and quantitative available data and to deal with the identification of interlinkages associated with a complex context. Both contributions might expand the use of BNs modelling as a tool to support decision–making processes. Hereafter a summary of the main contributions is presented. In addition, the limitations of this research are detailed. Some directions for future research are pointed out at the end of this Chapter.

5.1. MAIN CONCLUSIONS

The main conclusion of this thesis is that **expert knowledge and quantitative data available complement each other**. This idea might be far from being original, but it is the way in which both sources of information have been combined. We have taken a step forward the flexibility of Bayesian Networks modelling to deal with complex problems and from a data–driven approach. First, in Chapter III, we have demonstrated that the step–by–step methodology proposed is able to reproduce composite indicators (CI)–based conceptual frameworks that integrate a hierarchical structure. Furthermore, the results obtained reveal how expert knowledge (in terms of network structure) improves model inference capacity. Second, in Chapter IV, we demonstrated the robustness of the data–driven BNs approach for identifying indicator interlinkages. Although combining this analysis with an exhaustive literature review is expected for any research field, we provided an illustrative example on how to combine expert knowledge and the proposed approach.

The methodology proposed for combining expert knowledge and data to replicate hierarchical CI–based conceptual frameworks brings together further significant advantages. First, the models obtained allowed us to identify the key variables that explain the objective one (in this case, the general index of the selected conceptual framework). As detailed in Chapter III and as far the case study introduced, there are important difficulties in data collection for the member countries of the initiative assessed. Indeed, after ten years since it was launched, only one country has carried out a baseline of its rural communities, systems and service providers. The finding of key variables identification is then especially important when updating the required data. A direct consequence is translated into important savings, both in terms of time and economic resources. In addition to this identification, the flexibility of BNs permitted us as well to quantify, for each context assessed, to which extent the key variables might be improved as to reach a desirable value associated with the general index of this initiative. Thus, this feature represents a useful starting point for planning purposes.

The proposed data–driven BNs approach is also able to identify the interdependencies of the variables that define complex contexts. We have applied and tested this feature to two different contexts which represent a significant spectrum for analysis, namely large dataset and discrete variables (Chapter III) and small dataset and continuous variables (Chapter IV). In both cases, and through the combination of structure learning algorithms (SLAs) and conditional independence (C–Ind) tests, we have demonstrated the coherency of the results obtained. Interlinkages identification makes this approach more suitable than the use of composite indicators. In this sense, using BNs might enhance multi– and trans–disciplinary actions. In addition, this BNs approach complements existing approximations and is needed to increase both the understanding and the interpretation of the complexities and interdependencies of the problem at hand. Further, and as an added value of this approach shown in Chapter IV, we identified linkages that were not reflected in the analytical brief taken as a reference, which have been positively contrasted against the existing literature. On the basis of the linkages identified, integrated planning and management can support decision–making, reduce investment costs and facilitate implementation of a number of strategies that are geared towards sustainable development.

This research might expand and deepen the knowledge about the validity, reliability and accuracy of using BNs modelling. One remarkable output of this thesis relies on the systematic nature of the methodological contributions. These are defined by step–by–step processes, making them self–explanatory. Specifically, we provided the guidance to pre–process the data of interest, to select and apply the proposed SLA, and to test and validate the obtained results. The case studies selected represent potential applications, but the contribution of this thesis goes beyond the application to a specific context. Therefore, the proposed methods can be applied to any field of interest.

The proposed approach includes as well some weaknesses. On the one hand, the method proposed in Chapter III is only applicable to composite indicator–based conceptual frameworks that integrate a hierarchical structure. Furthermore, although the overall results can be considered as positive, the desired goodness of the model was not fully achieved. On the other hand, when dealing with small datasets as illustrated in Chapter IV, there is a constraint associated with the sample size as to obtain robust results. In addition, this approach was not able to identify the cause–effect relationships, which might be of interest.

5.2. LIMITATIONS OF THE RESEARCH

In addressing the research questions initially formulated, two key issues have impacted the extent of the research.

On the one hand, we ackowledge the **reduced number of contexts studied** within this thesis. For instance, we have not reproduced the analysis presented in Chapter III in other contexts (i.e. countries), which would be however of interest for providing a more general methodology. Similarly, we have not extended this research to compare the results of using, for example, a higher number of variable states. We are concerned that this aspect might be sensitive to the structure learning process (Alameddine et al., 2011). Furthermore, although having a lower number of variable states facilitates node CPTs management, it represents a potential loss of statistical accuracy (Chen and Pollino, 2012). As far as the analysis carried out in Chapter IV, it is important to emphasize the reduced nature of the dataset considered. In this context, and at the time of the study, existing data gaps for a number of indicators and countries clearly limited the scope of the study and the lessons learnt. At present, however, there are several global initiatives that monitor different aspects of the development Agenda, yet a coherent framework is missing. To the extent that existing efforts expands to ensure harmonized and integrated monitoring of SDGs, increasing high–quality data availability, it is expected that a wide range of potential uses may emerge in relation to Bayesian Networks applications.

On the other hand, we acknowledge the **lack of practical implementation** associated with the proposed methodologies into the real–world. This thesis falls short of showing how the developed methodologies might be specifically applied in practice and integrated into existing decision–making processes. Indeed, despite the implementation of real–life case studies, they hardly suffice to give conclusive information on how are effectively used to improve decision–making. In practice, decision–making is related to the process by which the choice of an alternative among the available options is made, in order to solve a current or potential problem. Taking as a reference the model obtained in Chapter III, the following step would rely on validating the model with the potential stakeholders involved, specifically as regard the interlinkages identified based on the data. In this sense, it is remarkable that the graphical nature of network presentation facilitates this process and makes it easier to illustrate the impact of a range of different actions and strategies to stakeholders. Once this step is carried out, the features of BNs models could be exploited. As detailed, one of these advantages relies on the explicit representation of the uncertainty (i.e. results are given as a probability distribution). This allows decision makers to first estimate the chance that a specific intervention will have a particular effect, and then to investigate the consequences of their uncertainty. Due to the stochastic nature of BNs models, the outcomes produced are more flexible than those produced by deterministic approaches (e.g. a composite index). As a last step, results could then be analyzed for a range of scenarios and/or conditions, enabling decision makers to identify the combination of actions in which to direct their efforts for maximum impact. In addition to this reflection, it is noteworthy to mention that even if there is no need to be an expert in mathematics or statistics to use BNs, it is obviously beneficial to understand some of the general principles on which models are based, and to be aware of what is possible to do and what is not. In this sense, we acknowledge that the learning process for using BNs models is not trivial. This hinders to a certain extent its implementation in certain contexts, where resources are limited and stakeholders often lack capacities to profit from the BNs models once developed.

5.3. THE WAY FORWARD

This thesis has proposed a data–driven Bayesian Networks approach to combine existing expert knowledge and data availability, as well as to identify the interdependencies of the context of interest. The overall aim of this proposal relies on the improvement of decision–making processes associated to inherent complexity of the problems at hand. For this purpose, we have provided systematic methods that might expand the use the proposed approach. In this sense, we have tested the validity of the approach, as well as the robustness of the results obtained. We acknowledge that approach validation has not been exhaustive but provides the starting point for further exploration. Thus, the proposed way forward focuses on giving more light to validate the proposed data–driven Bayesian Networks approach and associated methods developed.

First, **the proposed approach must be tested in further contexts**. Besides the results presented in this research are considered as positive, more evidences as regards approach validity are required. We have applied the BNs approach to two specific case studies but the proposed methods can be applied to any field of interest. Due to the systematic nature of the proposed methods (i.e. defined by step–by–step processes), these are presented as self–explanatory. On the one hand, the method developed to replicate hierarchical CI–based frameworks might be applied to any context that includes similar characteristics. Furthermore, it would be suitable a further assessment that tests to which extend more hierarchical levels within the framework improves or not the inference capacity of the BN model. On the other hand, the method employed for interlinkages identification across the 2030 Agenda for Sustainable Development might be focused on a different SDG of interest. In addition, and considering that the amount of data available is increasing, a more complete analysis can be done as missing information associated with SDG indicators is now available. Moreover, further analyses might be focused at sub–national level. Overall, the application of the proposed approach has been focused at national level. Despite the likely usefulness of the results obtained, we acknowledge that scaling down the analysis would be appropriate as decisions are taken by decentralized administrations. In fact, the 2030 Agenda resolution encourages each government to set “its own national targets guided by the global level of ambition but taking into account national circumstances” (United Nations General Assembly, 2015). As pointed out in previous Section, data are the raw material for the proposed data–driven BNs approach. Thus, the validity of their outputs is directly dependant on both data quality and quantity. From the existing efforts to increase high–quality data availability, we expect this line of research to be explored, as well as deepen on the potential uses that might emerge in relation to BNs applications.

Second, **the proposal must be extended to work directly with the raw variables**. Recalling the case study of Chapter III, the selected CI–based framework includes a general index, two partial indices, four dimensions and sixteen components. In this case, the raw variables refer to the list of single indicators that fed each component. As a result, a more complex framework with a new level of hierarchy would be obtained. Nevertheless, this new framework offers the possibility to exploit BNs features directly to the indicators in which decisions fall upon. At any context of analysis, the output might be translated into informed decisions to tackle the problem at hand.

Last but not least, **both proposed methods might be merged into a single one**. Specifically, a first step would rely on the identification of the interlinkages of the variables at hand (i.e. strong links), following the procedure detailed in Chapter IV. Then, these links are introduced automatically as fixed ones when applying the method detailed in Chapter III. As detailed in this last Chapter, we developed a semi-automatic procedure (with manual decisions in one step of the method). Preliminary research on this line suggests that the manual decisions to make are reduced significantly. Recalling the case studies employed in this thesis, the combined method might be applied to the SIASAR conceptual framework, using as well the raw variables it comprises. In the case of the SDGs framework, it would be necessary to organize the indicators in a hierarchical way. A potential application might take as a starting point the development of an unofficial SDG Index (Sachs et al., 2018). By organizing the indicators it comprises in composites associated with SDG targets and goals, then it would be established the framework needed for replication.

These different lines of research suggest a potential way forward.

REFERENCES

Aguilera, P.A., Fernández, A., Fernández, R., Rumí, R., Salmerón, A., 2011. Bayesian networks in environmental modelling. Environ. Model. Softw. 26, 1376–1388. https://doi.org/10.1016/j.envsoft.2011.06.004.

Aguilera, P.A., Fernández, A., Ropero, R.F., Molina, L., 2013. Groundwater quality assessment using data clustering based on hybrid Bayesian networks. Stoch. Environ. Res. Risk Assess. 27, 435–447. https://doi.org/10.1007/s00477-012-0676-8.

Alameddine, I., Cha, Y.K., Reckhow, K.H., 2011. An evaluation of automated structure learning with Bayesian networks: An application to estuarine chlorophyll dynamics. Environ. Model. Softw. 26, 163–172. https://doi.org/10.1016/j.envsoft.2010.08.007.

Albrecht, T.R., Crootof, A., Scott, C.A., 2018. The water-energy-food nexus: a systematic review of methods for nexus assessment. Environ. Res. Lett. 13, 043002. https://doi.org/10.1088/1748-9326/aaa9c6.

Alkire, S., Foster, J., 2008. Counting and multidimensional poverty measurement. OPHI Working Paper 7. University of Oxford, United Kingdom. https://www.ophi.org.uk/wp-content/uploads/ophi-wp7_vs2.pdf.

Alkire, S., Jahan, S., 2018. The new global MPI 2018: aligning with the sustainable development goals. HDRO Occasional Paper. United Nations Development Programme (UNDP). http://hdr.undp.org/sites/default/files/2018_mpi_jahan_alkire.pdf.

Alkire, S., Santos, M.E., 2014. Measuring acute poverty in the developing world: Robustness and scope of the Multidimensional Poverty Index. World Dev. 59, 251–274. https://doi.org/10.1016/j.worlddev.2014.01.026.

Allen, C., Graciela, M., Wiedmann, T., 2018. Initial progress in implementing the Sustainable Development Goals (SDGs): a review of evidence from countries. Sustain. Sci. 13, 1453–1467. https://doi.org/10.1007/s11625-018-0572-3.7.

Alok, K., Mazumdar, K., 2002. Use of Bayesian networks for monitoring total sanitation campaign projects, India. In Proceedings of the 28th WEDC Conference. WEDC – Water, Engineering and Development Centre. Kolkata, India.

ATAG (Air Transport Action Group), 2018. Aviation: Benefits without Borders. Geneva, Switzerland. https://aviationbenefits.org/media/166344/abbb18_full-report_web.pdf.

Backman, G., Hunt, P., Khosla, R., Jaramillo-Strouss, C., Fikre, B.M., Rumble, C., Pevalin, D., Acurio Páez, D., Armijos Pineda,M., Frisancho, A., Tarco, D.,Motlagh,M., Farcasanu, D., Vladescu, C., 2008. Health systems and the right to health: an assessment of 194 countries. Lancet 372, 2047–2085. https://doi.org/10.1016/S0140-6736(08)61781-X.

Bandura, R., 2006. A survey of composite indices measuring country performance: 2006 Update. United Nations Development Programme – Office of Development Studies. New York, United States.

Bangert, M., Molyneux, D.H., Lindsay, S.W., Fitzpatrick, C., Engels, D., 2017. The crosscutting contribution of the end of neglected tropical diseases to the sustainable development goals. Infect. Dis. Poverty 6, 73. https://doi.org/10.1186/s40249-017-0288-0.

Bartram, J., Brocklehurst, C., Fisher, M.B., Luyendijk, R., Hossain, R., Wardlaw, T., Gordon, B., 2014. Global monitoring of water supply and sanitation: history, methods and future challenges. Int. J. Environ. Res. Public Health 11, 8137–8165. https://doi.org/10.3390/ijerph110808137.

Bartram, J., Lewis, K., Lenton, R., Wright, A., 2005. Focusing on improved water and sanitation for health. Lancet 365, 810–812. https://doi.org/10.1016/S0140-6736(05)17991-4.

Bordalo, A.A., Teixeira, R.,Wiebe, W.J., 2006. A water quality index applied to an international Shared River Basin: the case of the Douro River. Environ. Manag. 38, 910–920. https://doi.org/10.1007/s00267-004-0037-6.

Bromley, J., 2005. Guidelines for the use of Bayesian networks as a participatory tool for water resource. Walliford, United Kingdom.

Bromley, J., Jackson, N.A., Clymer, O.J., Giacomello, A.M., Jensen, F.V., 2005. The use of Hugin® to develop Bayesian networks as an aid to integrated water resource planning. Environ. Model. Softw. 20, 231–242. https://doi.org/10.1016/j.envsoft.2003.12.021.

Brown, J., Cavill, S., Cumming, O., Jeandron, A., 2012. Water, sanitation, and hygiene in emergencies: summary review and recommendations for further research. Waterlines 31, 11–29. https://doi.org/10.3362/1756-3488.2012.004.

Cain, J., 2001. Planning improvements in natural resources management: Guidelines for using Bayesian Networks to support the planning and management of development programmes in the water sector and beyond. Centre for Ecology and Hydrology. Wallingford, United Kingdom. ISBN: 0-903741-00-9.

Cairncross, S., Hunt, C., Boisson, S., Bostoen, K., Curtis, V., Fung, I.C., Schmidt, W.P., 2010. Water, sanitation and hygiene for the prevention of diarrhoea. Int. J. Epidemiol. 39, i193–i205. https://doi.org/10.1093/ije/dyq035.

Carriger, J.F., Barron, M.G., Newman, M.C., 2016. Bayesian networks improve causal environmental assessments for evidence-based policy. Environ. Sci. Technol. 50, 13195–13205. https://doi.org/10.1021/acs.est.6b03220.

Castelletti, A., Soncini-Sessa, R., 2007. Bayesian networks and participatory modelling in water resource management. Environ. Model. Softw. 22, 1075–1088. https://doi.org/10.1016/j.envsoft.2006.06.003.

Chan, T., MacDonald, M.C., Kearton, A., Elliott, M., Shields, K.F., Powell, B., Bartram, J.K., Hadwen, W.L., 2020. Climate adaptation for rural water and sanitation systems in the Solomon Islands: A community scale systems model for decision support. Sci. Total Environ. 714, 136681. https://doi.org/10.1016/j.scitotenv.2020.136681.

Chandrakumar, C., McLaren, S.J., 2018. Towards a comprehensive absolute sustainability assessment method for effective earth system governance: Defining key environmental indicators using an enhanced-DPSIR framework. Ecol. Indic. 90, 577–583. https://doi.org/10.1016/j.ecolind.2018.03.063.

Chao, Y.-S., Scutari, M., Chen, T.-S.,Wu, C.-J., Durand, M., Boivin, A.,Wu, H.-C., Chen,W.-C., 2018. A network perspective of engaging patients in specialist and chronic illness care: The 2014 International Health Policy Survey. PLoS One 13, e0201355. https://doi.org/10.1371/journal.pone.0201355.

Chen, S.H., Pollino, C.A., 2012. Good practice in Bayesian network modelling. Environ. Model. Softw. 37, 134–145. https://doi.org/10.1016/j.envsoft.2012.03.012.

Cheng, J.J., Schuster-Wallace, C.J., Watt, S., Newbold, B., Mente, A., 2012. An ecological quantification of the relationships between water, sanitation and infant, child, and maternal mortality. Environ. Health 11, 4. https://doi.org/10.1186/1476-069X-11.

Cho, D.I., Ogwang, T., Opio, C., 2010. Simplifying the water poverty index. Soc. Indic. Res. 97, 257–267. https://doi.org/10.1007/s11205-009-9501-2.

Chung, E.S., Lee, K.S., 2009. Prioritization of water management for sustainability using hydrologic simulation model and multicriteria decision making techniques. Environ. Manag. 90, 1502–1511. https://doi.org/10.1016/j.jenvman.2008.10.008.

Cohen, A., Sullivan, C.A., 2010. Water and poverty in rural China: Developing an instrument to assess the multiple dimensions of water and poverty. Ecol. Econ. 69, 999–1009. https://doi.org/10.1016/j.ecolecon.2010.01.004.

Collste, D., Pedercini, M., Cornell, S.E., 2017. Policy coherence to achieve the SDGs: using integrated simulation models to assess effective policies. Sustain. Sci. 12, 921–931. https://doi.org/10.1007/s11625-017-0457-x.

Coopman, A., Osborn, D., Ullah, F., Auckland, E., Long, G., 2016. Seeing the whole: implementing the SDGs in an integrated and coherent way. Stakeholder forum, Bioregional and Newcastle University (United Kingdom). https://sf.stakeholderforum.org/fileadmin/files/SeeingTheWhole.ResearchPilotReportOnSDGsImplementation.pdf.

Costanza, R., Daly, L., Fioramonti, L., Giovannini, E., Kubiszewski, I., Mortensen, L.F., Pickett, K.E., Ragnarsdottir, K.V., De Vogli, R., Wilkinson, R., 2016. Modelling and measuring sustainable wellbeing in connection with the UN Sustainable Development Goals. Ecol. Econ., 130, 350–355. https://doi.org/10.1016/j.ecolecon.2016.07.009.

Cronk, R., Bartram, J., 2017. Factors influencing water system functionality in Nigeria and Tanzania: a regression and Bayesian network analysis. Environ. Sci. Technol. 51, 11336–11345. https://doi.org/10.1021/acs.est.7b03287.

Cronk, R., Bartram, J., 2018. Identifying opportunities to improve piped water continuity and water system monitoring in Honduras, Nicaragua, and Panama: Evidence from Bayesian networks and regression analysis. J. Clean. Prod. 196, 1–10. https://doi.org/10.1016/j.jclepro.2018.06.017.

Dang, K.B., Windhorst, W., Burkhard, B., Müller, F., 2019. A Bayesian Belief Network–based approach to link ecosystem functions with rice provisioning ecosystem services. Ecol. Indic. 100, 30–44. https://doi.org/10.1016/j.ecolind.2018.04.055.

Dangour, A.D., Watson, L., Cumming, O., Boisson, S., Che, Y., Velleman, Y., Cavill, S., Allen, E., Uauy, R., 2013. Interventions to improve water quality and supply, sanitation and hygiene practices, and their effects on the nutrition status of children. Cochrane DB. Syst. Rev. 8. Art. No.: CD009382. https://doi.org/10.1002/14651858.CD009382.PUB2.

Desai, S., Alva, S., 1998. Maternal education and child health: is there a strong causal relationship? Demography 35, 71–81.

Dondeynaz, C., López Puga, J., Carmona Moreno, C., 2013. Bayesian networks modelling in support to cross-cutting analysis of water supply and sanitation in developing countries. Hydrol. Earth Syst. Sci. 17, 3397–3419. https://doi.org/10.5194/hess-17-3397-2013.

EEA (European Environment Agency), 1999. Environmental indicators: Typology and overview. Technical Report nº 25. Copenhagen, Denmark. https://www.eea.europa.eu/publications/TEC25.

El Khanji, S., 2016. An exploration of the interaction between socio-economic productivity and water withdrawal. Environ. Dev. Sustain. 19, 653–677. https://doi.org/10.1007/s10668-016-9757-z.

Eldridge, D.J., Paul, K.I., Roxburgh, S., Butler, D.W., Ramp, D., 2019. Risks to carbon dynamics in semi-arid woodlands of eastern Australia under current and future climates. J. Environ. Manag. 235, 500–510. https://doi.org/10.1016/j.jenvman.2019.01.076.

Ellison, D., Futter, M.N., Bishop, K., 2012. On the forest cover-water yield debate: from demand- to supply-side thinking. Glob. Chang. Biol. 18, 806–820. https://doi.org/10.1111/j.1365-2486.2011.02589.x.

Ellison, D., Morris, C.E., Locatelli, B., Sheil, D., Cohen, J., Murdiyarso, D., Gutierrez, V., van Noordwijk, M., Creed, I.F., Pokorny, J., Gaveau, D., Spracklen, D.V., Bargués Tobella, A., Ilstedt, U., Teuling, A.J., Gebreyohannis Gebrehiwot, S., Sands, D.C., Muys, B., Verbist, B., Springgay, E., Sugandi, Y., Sullivan, C.A., 2017. Trees, forests and water: Cool insights for a hot world. Glob. Environ. Chang. 43, 51–61. https://doi.org/10.1016/j.gloenvcha.2017.01.002.

Ercin, A.E., Hoekstra, A.Y., 2014.Water footprint scenarios for 2050: A global analysis. Environ. Int. 64, 71–82. https://doi.org/10.1016/j.envint.2013.11.019.

Esrey, S.A., Potash, J.B., Roberts, L., Shiff, C., 1991. Effects of improved water supply and sanitation on ascariasis, diarrhoea, dracunculiasis, hookworm infection, schistosomiasis, and trachoma. Bull. World Health Organ. 69, 609–621.

Fader, M., Cranmer, C., Lawford, R., Engel-Cox, J., 2018. Toward an understanding of synergies and trade-offs between water, energy, and food SDG targets. Front. Environ. Sci. 6, 112, 1–11. https://doi.org/10.3389/fenvs.2018.00112.

FAO (Food and Agriculture Organization), 2015. Mapping the vulnerability of mountain peoples to food insecurity. Rome, Italy. http://www.fao.org/3/a-i5175e.pdf.

FAO (Food and Agriculture Organization), 2018. Progress on water use efficiency - global baseline for SDG 6 indicator 6.4.1 2018. Rome, Italy. http://www.unwater.org/publications/progress-on-water-use-efficiency-641.

Feachem, R.G., 1984. Interventions for the control of diarrhoeal diseases among young children: promotion of personal and domestic hygiene. Bull. World Health Organ. 62, 467–476.

Fisher, J., 2008. Women in water supply, sanitation and hygiene programmes. Proceedings of the ICE: Municipal Engineer. 161, pp. 223–229. https://dspace.lboro.ac.uk/dspace-jspui/bitstream/2134/9920/13/muen161-223.pdf.

Fisher, M.B., Shields, K.F., Chan, T.U., Christenson, E., Cronk, R.D., Leker, H., Samani, D., Apoya, P., Lutz, A., Bartram, J., 2015. Understanding handpump sustainability: Determinants of rural water source functionality in the Greater Afram Plains Region of Ghana. Water Resour. Res. 51, 8431–8449. https://doi.org/10.1002/2014WR016770.

Fitzpatrick, C., Engels, D., 2016. Leaving no one behind: a neglected tropical disease indicator and tracers for the Sustainable Development Goals. Int. Health 8, i15–i18. https://doi.org/10.1093/inthealth/ihw002.

Flores-Baquero, O., Gallego Ayala, J., Giné-Garriga, R., Jiménez, A., Pérez-Foguet, A., 2016a. The influence of the Human Rights to Water and Sanitation normative content in measuring the level of service. Soc. Indic. Res. 133, 763–786. https://doi.org/10.1007/s11205-016-1374-6.

Flores-Baquero, O., Jiménez Fdez. de Palencia, A., Pérez-Foguet, A., 2016b. Measuring disparities in access to water based on the normative content of the Human Right. Soc. Indic. Res. 127, 741–759. https://doi.org/10.1007/s11205-015-0976-8.

Foley, J.A., DeFries, R., Asner, G.P., Barford, C., Bonan, G., Carpenter, S.R., Chapin, F.S., Coe, M.T., Daily, G.C., Gibbs, H.K., Helkowski, J.H., Holloway, T., Howard, E.A., Kucharik, C.J., Monfreda, C., Patz, J.A., Prentice, I.C., Ramankutty, N., Snyder, P.K., 2005. Global consequences of land use. Science 309, 570–574. https://doi.org/10.1126/science.1111772.

Gama, J., 2012. A survey on learning from data streams: Current and future trends. Prog. Artif. Intell. 1, 45–55. http://dx.doi.org/10.1007/s13748-011-0002-6.

Gao, L., Bryan, Br.A., 2017. Finding pathways to national-scale land-sector sustainability. Nature 544, 217–235. https://doi.org/10.1038/nature21694.

Garcia-Prats, A., González-Sanchis, M., Del Campo, A.D., Lull, C., 2018. Hydrology-oriented forest management trade-offs. A modeling framework coupling field data, simulation results and Bayesian networks. Sci. Total Environ. 639, 725–741. https://doi.org/10.1016/j.scitotenv.2018.05.134.

García-Santos, G., Madruga De Brito, M., Höllermann, B., Taft, L., Almoradie, A., Evers, M., 2018. Methodology to explore emergent behaviours of the interactions between water resources and ecosystem under a pluralistic approach. P. Int. Ass. Hydrol. Sci. 379, 83–87. https://doi.org/10.5194/piahs-379-83-2018.

Giné-Garriga, R., 2015. Monitoring water, sanitation and hygiene services: Developing tools and methods to measure sustainable access and practice at the local level. Universitat Politècnica de Catalunya. http://www.tdx.cat/handle/10803/334692.

Giné-Garriga, R., de Palencia, A. J. F., Pérez-Foguet, A., 2013. Water-sanitation-hygiene mapping: an improved approach for data collection at local level. Sci. Total Environ. 463–464C, 700–711. https://doi.org/10.1016/j.scitotenv.2013.06.005.

Giné-Garriga, R., Flores-Baquero, O., Jiménez-Fdez. de Palencia, A., Pérez-Foguet, A., 2017. Monitoring sanitation and hygiene in the 2030 Agenda for Sustainable Development: A review through the lens of human rights. Sci. Total Environ. 580, 1108–1119. https://doi.org/10.1016/j.scitotenv.2016.12.066.

Giné-Garriga, R., Pérez-Foguet, A., 2010. Improved method to calculate a water poverty index at local scale. J. Environ. Eng. 136, 1287–1298. https://doi.org/10.1061/(ASCE)EE.1943-7870.0000255.

Giné-Garriga, R., Pérez-Foguet, A., 2011. Application of a revised water poverty index to target the water poor. Water Sci. Technol. 63 (6), 1099–1110. https://doi.org/10.2166/wst.2011.347.

Giné-Garriga, R., Pérez-Foguet, A., 2013a. Unravelling the linkages between water, sanitation, hygiene and rural poverty: The WaSH poverty index. Water Resour. Manag. 27, 1501–1515. https://doi.org/10.1007/s11269-012-0251-6.

Giné-Garriga, R., Pérez-Foguet, A., 2013b Water, sanitation, hygiene and rural poverty: Issues of sector planning and the role of aggregated indicators. Water Policy 15, 1018–1045. https://doi.org/10.2166/wp.2013.037.

Giné-Garriga, R., Pérez-Foguet, A., 2018. Measuring sanitation poverty: A multidimensional measure to assess delivery of sanitation and hygiene services at the household level. OPHI Working Paper 116. University of Oxford, United Kingdom. https://ophi.org.uk/measuring-sanitation-poverty-a-multidimensional-measure-to-assess-delivery-ofsanitation-and-hygiene-services-at-the-household-level/.

Giné-Garriga, R., Pérez-Foguet, A., 2019. Monitoring and targeting the sanitation poor: A multidimensional approach. Nat. Resour. Forum 43, 82–94. https://doi.org/10.1111/1477-8947.12171.

Giné-Garriga, R., Requejo-Castro, D., Molina, J.L., Pérez-Foguet, A., 2018. A novel planning approach for the water, sanitation and hygiene (WaSH) sector: The use of object-oriented Bayesian Networks. Environ. Model. Softw. 103, 1–15. https://doi.org/10.1016/j.envsoft.2018.01.021.

GLAAS (Global Analysis and Assessment of Sanitation and Drinking-water), 2017. Financing universal water, sanitation and hygiene under the Sustainable Development Goals. Geneva, Switzerland. http://www.unwater.org/publications/un-water-glaas-2017-financing-universal-water-sanitation-hygiene-sustainable-development-goals.

GLAAS (Global Analysis and Assessment of Sanitation and Drinking-water), 2019. National systems to support drinking-water, sanitation and hygiene. Global status report. Geneva, Switzerland. https://www.unwater.org/publications/un-water-glaas-2019-national-systems-to-support-drinking-water-sanitation-and-hygiene-global-status-report-2019/

Godfrey, L., Tood, C., 2001. Defining thresholds for freshwater sustainability indicators within the context of South African water resource management. In 2nd WARFSA/WaterNet Symposium: Integrated Water Resource Management: Theory, Practice, Cases. Cape Town, South Africa.

Godfrey, S., van der Velden, M., Muianga, A., Xavier, A., Downs, K., Morgan, C., Bartram, J., 2014. Sustainability check: Five-year annual sustainability audits of the water supply and open defecation free status in the 'one million initiative', Mozambique. J. Water Sanit. Hyg. Dev. 4, 471–483. https://doi.org/10.2166/washdev.2014.118.

Gonzalez-Redin, J., Gordon, I.J., Hill, R., Polhill, J.G., Dawson, T.P., 2019. Exploring sustainable land use in forested tropical social-ecological systems: a case-study in thewet tropics. J. Environ. Manag. 231, 940–952. https://doi.org/10.1016/j.jenvman.2018.10.079.

Gopalan, S., Rajan, R.S., 2016. Has foreign aid been effective in the water supply and sanitation sector? Evidence from panel data. World Dev. 85, 84–104. https://doi.org/10.1016/j.worlddev.2016.04.010.

Grosh, M., 1997. The policymaking uses of multitopic household survey data: A primer. World Bank Res. Obser. 12, 137–160. https://doi.org/10.1093/wbro/12.2.137.

GWA (Gender and Water Alliance), 2003. The gender and water development report 2003: gender perspectives on policies in the water sector. Delft, Netherlands. http://genderandwater.org/en/gwa-products/policy-influencing/gender-perspectives-onpolicies-in-the-water-sector/view.

GWP (Global Water Partnership), 2000. Integrated water resource management. TAC background papers no. 4. Stockholm, Sweeden. https://www.gwp.org/globalassets/global/toolbox/publications/background-papers/04-integrated-water-resources-management-2000-english.pdf.

Hall, N.L., Ross, H., Richards, R., Barrington, D.J., Dean, A.J., Head, B.W., Jagals, P., Reid, S., Hill, P.S., 2018. Implementing the United Nations' Sustainable Development Goals for water and beyond in Australia: A proposed systems approach. Australasian J. Water Resour. 22, 29–38. https://doi.org/10.1080/13241583.2018.1481563.

Henderson, A.R., 2005. The bootstrap: a technique for data-driven statistics. Using computer-intensive analyses to explore experimental data. Clin. Chim. Acta 359, 1–2, 1–26. https://doi.org/10.1016/j.cccn.2005.04.002.

Henriksen, H.J., Barlebo, H.C., 2008. Reflections on the use of Bayesian belief networks for adaptive management. J. Environ. Manag. 88, 1025–1036. https://doi.org/10.1016/j.jenvman.2007.05.009.

Herrera, V., 2019. Reconciling global aspirations and local realities: Challenges facing the Sustainable Development Goals for water and sanitation. World Dev. 118, 106–117. https://doi.org/10.1016/j.worlddev.2019.02.009.

Hoekstra, A.Y., Hung, P.Q., 2002. Virtual water trade: a quantification of virtual water flows between nations in relation to international crop trade. Value of Water Research Report Series No. 11. Delft, Netherlands. http://www.ayhoekstra.nl/pubs/Report11.pdf.

Hoekstra, Y.A.,Wiedmann, T.O., 2014. Humanity's unsustainable environmental footprint. Science 344, 1114–1117. https://doi.org/10.1126/science.1248365.

Hotez, P.J., Bottazzi, M.E., Strych, U., Chang, L.Y., Lim, Y.A.L., Goodenow, M.M., AbuBakar, S., 2015. Neglected tropical diseases among the Association of Southeast Asian Nations (ASEAN): overview and update. PLoS Negl. Trop. Dis. 9, e0003575. https://doi.org/10.1371/journal.pntd.0003575.

Hou, Y., Zhou, S., Burkhard, B., Müller, F., 2014. Socioeconomic influences on biodiversity, ecosystem services and human well-being: a quantitative application of the DPSIR model in Jiangsu, China. Sci. Total Environ. 490, 1012–1028. https://doi.org/10.1016/j.scitotenv.2014.05.071.

ICSU–ISSC (International Council for Science–International Social Science Council), 2015. Review of the Sustainable Development Goals: The science perspective. Paris, France. https://council.science/wp-content/uploads/2017/05/SDG-Report.pdf.

ICSU – ISSC (International Council for Science–International Social Science Council), 2017. A Guide to SDG Interactions: From Science to Implementation. International Council for Science/International Social Science Council. Paris, France. https://council.science/publications/a-guide-to-sdg-interactions-from-science-to-implementation.

ILO (International Labour Organization), 2018. World Employment Social Outlook 2018: Greening with Jobs. Geneva, Switzerland. https://www.ilo.org/weso-greening/documents/WESO_Greening_EN_web2.pdf.

ILO (International Labour Organization), 2019. A quantum leap for gender equality: for a better future of work for all. Geneva, Switzerland. https://www.ilo.org/wcmsp5/groups/public/—dgreports/—dcomm/—publ/documents/publication/wcms_674831.pdf.

Ioannis Tsamardinos, I., Brown, L.E., Aliferis, C.F., 2006. The max-min hill-climbing Bayesian Network structure learning algorithm. Mach. Learn. 65, 31–78. https://doi.org/10.1007/s10994-006-6889-7.

IPCC (Intergovernmental Panel on Climate Change), 2014. Climate Change 2014: Synthesis Report. Geneva, Switzerland. https://www.ipcc.ch/site/assets/uploads/2018/05/SYR_AR5_FINAL_full_wcover.pdf.

Ivens, S., 2008. Does increased water access empower women? Development 51, 63–67. https://doi.org/10.1057/palgrave.development.1100458.

Jiménez, A., Panchali, S., Giné-Garriga, R., Avello, P., Leten, J., Lymer, B.L., Schneider, K., Ward, R., 2020. Unpacking water governance: A framework for practitioners. Water 12, 827. https://doi.org/10.3390/w12030827.

JMP (Joint Monitoring Programme), 2000. Global water supply and sanitation assessment 2000 report. New York, United States / Geneva, Switzerland. https://washdata.org/sites/default/files/documents/reports/2017-06/Global%20Water%20Supply%20and%20Sanitation%20Assessment%202000.pdf.

JMP (Joint Monitoring Programme), 2008. Progress on drinking water and sanitation: Special focus on sanitation. New York, United States / Geneva, Switzerland. https://washdata.org/sites/default/files/documents/reports/2017-06/JMP-2008-Report_0.pdf.

JMP (Joint Monitoring Programme), 2015. Progress on sanitation and drinking water: 2015 update and MDG assessment. New York / Geneva, Unites States / Switzerland. https://washdata.org/sites/default/files/documents/reports/2017-06/JMP-2015-Report.pdf.

JMP (Joint Monitoring Programme), 2017a. Progress on drinking water, sanitation and hygiene: 2017 update and SDG baselines. New York, United States / Geneva, Switzerland. https://washdata.org/sites/default/files/documents/reports/2019-05/JMP-2017-report-final.pdf.

JMP (Joint Monitoring Programme), 2017b. WaSH in the Agenda 2030: New Global Indicators for Drinking Water, Sanitation and Hygiene. New York / Geneva, Unites States / Switzerland. https://washdata.org/sites/default/files/documents/reports/2017-07/JMP-2017-WASH-in-the-2030-agenda.pdf.

JMP (Joint Monitoring Programme), 2019. Progress on household drinking water, sanitation and hygiene 2000-2017. Special focus on inequalities. New York / Geneva, Unites States / Switzerland. https://washdata.org/sites/default/files/documents/reports/2019-07/jmp-2019-wash-households.pdf.

JMP (Joint Monitoring Programme), 2020. Progress on drinking water, sanitation and hygiene in schools: Special focus on COVID-19. New York / Geneva, Unites States / Switzerland. https://washdata.org/sites/default/files/2020-09/JMP-2020-WASH-schools.pdf.

Kanter, D.R., Schwoob, M.H., Baethgen, W.E., Bervejillo, J.E., Carriquiry, M., Dobermann, A., Ferraro, B., Lanfranco, B., Mondelli, M., Penengo, C., Saldias, R., Silva, M.E., de Lima, J.M.S., 2016. Translating the Sustainable Development Goals into action: a participatory backcasting approach for developing national agricultural transformation pathways. Glob. Food Secur-Agr. 10, 71–79. https://doi.org/10.1016/j.gfs.2016.08.002.

Kevani, K., Huisingh, D., 2013. A review of progress in empowerment of women in rural water management decision-making processes. J. Clean. Prod. 60, 53–64. https://doi.org/10.1016/j.jclepro.2013.03.041.

Khalili, N.R., Cheng, W., McWilliams, A., 2017. A methodological approach for the design of sustainability initiatives: in pursuit of sustainable transition in China. Sustain. Sci. 12, 933–956. https://doi.org/10.1007/s11625-017-0463-z.

Kim, K.H., Kabir, E., Kabir, S., 2015. A review on the human health impact of airborne particulate matter. Environ. Int. 74, 136–143. https://doi.org/10.1016/j.envint.2014.10.005.

Kirchhoff, M., Thomas, P., Palacios, E., Friston, K., Kiverstein, J., 2018. The Markov blankets of life: autonomy, active inference and the free energy principle. J. R. Soc. Interface 15: 20170792. https://doi.org/10.1098/rsif.2017.0792.

Kjærulff, U.B., Madsen, A.L., 2005. Probabilistic networks: An introduction to Bayesian Networks and Influence Diagrams. Aalborg University, Denmark.

Korb, K., Nicholson, A., 2004. Bayesian Artificial Intelligence. Chapman and Hall/CRC. Florida, United States. ISBN: 978-1-58488-387-1.

Kumpel, E., Nelson, K.L., 2016. Intermittent water supply: Prevalence, practice, and microbial water quality. Environ. Sci. Technol. 50, 542–553. https://doi.org/10.1021/acs.est.5b03973.

Landuyt, D., Broekx, S., D'hondt, R., Engelen, G., Aertsens, J., Peter L.M. Goethals, P.L.M., 2013. A review of Bayesian belief networks in ecosystem service modelling. Environ. Model. Softw. 46, 1–11. https://doi.org/10.1016/j.envsoft.2013.03.011.

Le Blanc, D., 2015. Towards integration at last? The Sustainable Development Goals as a network of targets. Sustain. Dev. 23, 176–187. https://doi.org/10.1002/sd.1582.

Li, J., Song, G., Semakula, H.M., Zhang, S., 2019. Climatic burden of eating at home against away-from-home: A novel Bayesian Belief Network model for the mechanism of eating-out in urban China. Sci. Total Environ. 650, 224–232. https://doi.org/10.1016/j.scitotenv.2018.09.015.

Li, X., Feng, K., Siu, Y.L., Hubacek, K., 2012. Energy-water nexus of wind power in China: The balancing act between CO2 emissions and water consumption. Energ Policy 45, 440–448. https://doi.org/10.1016/j.enpol.2012.02.054.

Liese, B.H., Schubert, L., 2009. Official development assistance for health-how neglected are neglected tropical diseases? An analysis of health financing. Int. Health 1, 141–147. https://doi.org/10.1016/j.inhe.2009.08.004.

Lin, T., Lin, J., Cui, S., Cameron, S., 2009. Using a network framework to quantitatively select ecological indicators. Ecol. Indic. 9, 1114–1120. https://doi.org/10.1016/j.ecolind.2008.12.009.

Liu, H., Zhou, S., Lam,W., Guan, J., 2017. A new hybrid method for learning Bayesian networks: Separation and reunion. Knowl.-Based Syst. 121, 185–197. https://doi.org/10.1016/j.knosys.2017.01.029.

Liu, J., Hull, V., Godfray, H. Ch.J., Tilman, D., Gleick, P., Hoff, H., Pahl-Wostl, C., Xu, Z., Chung, M. G., Sun, J., Li, Sh., 2018. Nexus approaches to global sustainable development. Nat. Sustain. 1, 466–476. https://doi.org/10.1038/s41893-018-0135-8.

Lockwood, H., Smits, S., Schouten, T., Moriarty, P., 2010. Sustainable water services at scale. In Proceedings: International Symposium on rural water services: Providing sustainable water services at scale. Kampala, Uganda.

Longo, S.B., York, R., 2009. Structural influences on water withdrawals: an exploratory macro-comparative analysis. Hum. Ecol. Rev. 16, 75–83. https://www.jstor.org/stable/24707738.

Luh, J., Baum, R., Bartram, J., 2013. Equity in water and sanitation: Developing an index to measure progressive realization of the human right. Int. J. Hyg. Environ. Health 216, 662–671. https://doi.org/10.1016/j.ijheh.2012.12.007.

Madsen, A.L., Jensen, F., Salmerón, A., Langseth, H., Nielsen, T.D., 2016. A parallel algorithm for Bayesian network structure learning from large data sets. Knowl.-Based Syst. 117, 46–55. https://doi.org/10.1016/j.knosys.2016.07.031.

Mainali, B., Luukkanen, J., Silveira, S., Kaivo-Oja, J., 2018. Evaluating synergies and tradeoffs among Sustainable Development Goals (SDGs): explorative analyses of development paths in South Asia and sub-Saharan Africa. Sustainability 10, 815. https://doi.org/10.3390/su10030815.

Makarieva, A.M., Gorshkov, V.G., 2007. Biotic pump of atmospheric moisture as driver of the hydrologicalcycle on land. Hydrol. Earth Syst. Sci. 11, 1013–1033. https://doi.org/10.5194/hess-11-1013-2007.

Marcot, B.G., 2017. Common quandaries and their practical solutions in Bayesian network modelling. Ecol. Model. 358, 1–9. https://doi.org/10.1016/j.ecolmodel.2017.05.011.

Marcot, B.G., Penman, T.D., 2019. Advances in Bayesian network modelling: Integration of modelling technologies. Environ. Model. Softw. 111, 386–393. https://doi.org/10.1016/j.envsoft.2018.09.016.

Margaritis, D., 2003. Learning Bayesian Network model structure from data. Ph.D. thesis. School of Computer Science, Carnegie-Mellon University. Pittsburgh, United States. http://reports-archive.adm.cs.cmu.edu/anon/2003/CMU-CS-03-153.pdf.

Mekonnen, M.M., Hoekstra, Y.A., 2016. Four billion people facing severe water scarcity. Sci. Adv. 2, e1500323. https://doi.org/10.1126/sciadv.1500323.

Mohajerani, H., Kholghi, M.,Mosaedi, A., Farmani, R., Sadoddin, S., Casper, M., 2017. Application of Bayesian Decision Networks for groundwater resourcesmanagement under the conditions of high uncertainty and data scarcity. Water Resour. Manag. 31, 1859–1879. https://doi.org/10.1007/s11269-017-1616-7.

Molina, J.L., Bromley, J., García-Arostegui, J.L., Sullivan, C.A., Benavente, J., 2010. Integrated water resources management of overexploited hydrogeological systems using object-oriented Bayesian networks. Environ. Model. Softw. 25, 383–397. https://doi.org/10.1016/j.envsoft.2009.10.007.

Molina, J.L., García Aróstegui, J.L., Benavente, J., Varela, C., de la Hera, A., López Geta, J.A., 2009. Aquifers overexploitation in SE Spain: a proposal for the integrated analysis of water management. Water Resour. Manag. 23, 2737–2760. https://doi.org/10.1007/s11269-009-9406-5.

Molina, J.L., Pulido-Velázquez, D., García Aróstegui, J.L., Pulido-Velázquez, M., 2013. Dynamic Bayesian networks as a decision support tool for assessing climate change impacts on highly stressed groundwater systems. J. Hydrol. 479, 113–129. https://doi.org/10.1016/j.jhydrol.2012.11.038.

Mugagga, F., Nabaasa, B.B., 2016. The centrality of water resources to the realization of Sustainable Development Goals (SDG). A review of potentials and constraints on the African continent. Int. Soil Water Conserv. Res. 4, 215–223. https://doi.org/10.1016/j.iswcr.2016.05.004.

Mukkala, K., Tervo, H., 2013. Air transportation and regional growth: which way does the causality run? Environ. Plann. A 45 (6), 1508–1520. https://doi.org/10.1068/a45298.

Nardo, M., Saisana, M., Saltelli, A., Tarantola, S., Hoffman, A., Giovannini, E., 2005. Handbook on constructing composite indicators: Methodology and user guide. OECD Statistics Working Paper. Paris, France. https://www.oecd.org/sdd/42495745.pdf.

Ndikumana, L., Pickbourn, L., 2017. The impact of foreign aid allocation on access to social services in sub-Saharan Africa: the case of water and sanitation. World Dev. 90, 104–114. https://doi.org/10.1016/j.worlddev.2016.09.001.

Nhamo, L., Ndlela, B., Nhemachena, C., Mabhaudhi, T., Mpandeli, S., Matchaya, G., 2018. The Water-Energy-Food Nexus: Climate risks and opportunities in Southern Africa. Water 10, 567. https://doi.org/10.3390/w10050567.

Niemeijer, D., De Groot, R.S., 2008. Framing environmental indicators: Moving from causal chains to causal networks. Environ. Dev. Sustain. 10, 89–106. https://doi.org/10.1007/s10668-006-9040-9.

Nilsson,M., Chisholm, E., Griggs,D., Howden-Chapman, P.,McCollum, D., Messerli, P., Neumann, B., Stevance, A.S., Visbeck, M., Stafford-Smith, M., 2018. Mapping interactions between the Sustainable Development Goals: Lessons learned and ways forward. Sustain. Sci. 13, 1489–1503. https://doi.org/10.1007/s11625-018-0604-z.

Obersteiner, M., Walsh, Br., Frank, St., Havlík, P., Cantele, M., Liu, J., Palazzo, A., Herrero, M., Lu, Y., Mosnier, A., Valin, H., Riahi, K., Kraxner, Fl., Fritz, St., Van Vuuren, D., 2016. Assessing the land resource–food price nexus of the Sustainable Development Goals. Sci. Adv. 2 (9). https://doi.org/10.1126/sciadv.1501499.

OECD (Organisation for Economic Co-operation and Development), 1993. OECD core set of indicators for environmental performance reviews: A synthesis report by the group on the state of the Enviroment. OECD Environmental Directorate Monographs n° 83. Paris, France. https://www.oecd.org/officialdocuments/publicdisplaydocumentpdf/?cote=OCDE/GD(93)179&docLanguage=En.

OECD–IIASA (Organisation for Economic Co-operation and Development–International Institute for Applied Systems Analysis), 2020. Systemic thinking for policy making: The potential of systems analysis for addressing global policy challenges in the 21st Century. OECD Publishing. Paris, France. https://doi.org/10.1787/879c4f7a-en.

Ordónez-Galán, C., Matías, J.M., Rivas, T., Bastante, F.G., 2009. Reforestation planning using Bayesian networks. Environ. Model. Softw. 24, 1285–1292. https://doi.org/10.1016/j.envsoft.2009.05.009.

Ortiz-Lozano, L., 2012. Identification of priority conservation actions in marine protected areas: Using a causal networks approach. Ocean Coast. Manage. 55, 74–83. https://doi.org/10.1016/j.ocecoaman.2011.10.013.

Pahl-Wostl, C., 2017. Governance of the water-energy-food security nexus: A multi-level coordination challenge. Environ. Sci. Pol. 92, 356–367. https://doi.org/10.1016/j.envsci.2017.07.017.

Panda, S.M., 2007. Mainstreaming gender in water management: a critical view. Gender Technol. Dev. 11, 321–338. https://doi.org/10.1177/097185240701100302.

Pearl, J., 1988. Probabilistic reasoning in intelligent systems: Networks of plausible inference. Morgan Kaufmann Publishers. California, United States. ISBN: 1-55860-479-0.

Pearson, A.L., Zwickle, A., Namanya, J., Rzotkiewicz, A.,Mwita, E., 2016. Seasonal shifts in primary water source type: A comparison of largely pastoral communities in Uganda and Tanzania. Int. J. Env. Res. Pub. He. 13, 169. https://doi.org/10.3390/ijerph13020169.

Pena, L., Michaud, D., Biau, J., Stip, C., Rodríguez, A., Martínez, G., Simon, Y., Madrid, M. L., 2014. The SIASAR Initiative. An information system for more sustainable rural water and sanitation services. The World Bank. Washington D. C., United States.

Pérez-Foguet, A., Flores-Baquero, O., 2015. Decision support model for SIASAR. Technical proposal (v. 2015.07). Universitat Politècnica de Catalunya. Barcelona, Spain. http://hdl.handle.net/2117/77587.

Pérez-Foguet, A., Giné-Garriga, R., 2011. Analyzing water poverty in basins. Water Resour. Manag. 25, 3595–3612. https://doi.org/10.1007/s11269-011-9872-4.

Pérez-Miñana, E., 2016. Improving ecosystem services modelling: Insights from a Bayesian network tools review. Environ. Model. Softw. 85, 184–201. http://dx.doi.org/10.1016/j.envsoft.2016.07.007.

Phan, Th.D., Smart, C.R.J., Capon, S.J., Hadwen, W.L., Sahin, O., 2016. Applications of Bayesian belief networks in water resource management: A systematic review. Environ. Model. Softw. 85, 98–111. https://doi.org/10.1016/j.envsoft.2016.08.006.

Pirrone, N., Trombino, G., Cinnirella, S., Algieri, A., Bendoricchio, G., Palmeri, L., 2005. The driver-pressure-state-impact-response (DPSIR) approach for integrated catchment coastal zone management: preliminary application to the Po catchment-Adriatic Sea coastal zone system. Reg. Environ. Chang. 5, 111–137. https://doi.org/10.1007/s10113-004-0092-9.

Pitt, C., Greco, G., Powell-Jackson, T., Mills, A., 2010. Countdown to 2015: assessment of official development assistance to maternal, newborn, and child health, 2003–08. Lancet 376, 1485–1496. https://doi.org/10.1016/S0140-6736(10)61302-5.

Pramova, E., Locatelli, B., Brockhaus, M., Fohlmeister, S., 2012. Ecosystem services in the national adaptation programmes of action. Clim. Policy 12, 393–409. https://doi.org/10.1080/14693062.2011.647848.

Ramos-Quintana, F., Ortíz-Hernández, M.L., Sánchez-Salinas, E., Úrsula-Vázquez, E., Guerrero, J.A., Zamorano, M., 2018. Quantitative-qualitative assessments of environmental causal networks to support the DPSIR framework in the decision-making process. Environ. Impact Asses. 69, 42–60. https://doi.org/10.1016/j.eiar.2017.11.004.

Rasul, G., 2016. Managing the food, water, and energy nexus for achieving the Sustainable Development Goals in South Asia. Environ. Dev. 18, 14–25. https://doi.org/10.1016/j.envdev.2015.12.001.

Requejo-Castro, D., Giné-Garriga, R., Flores-Baquero, O., Martínez, G., Rodríguez, A., de Palencia, Jimenez-Fdez., 2017. A., Pérez-Foguet, A. SIASAR: A country-led indicator framework for monitoring the rural water and sanitation sector in Latin America and the Caribbean. Water Pract. Technol. 12, 372–385. https://doi.org/10.2166/wpt.2017.041.

Requejo-Castro, D., Giné-Garriga, R., Pérez-Foguet, A., 2019. Bayesian network modelling of hierarchical composite indicators. Sci. Total Environ. 668, 936–946. https://doi.org/10.1016/j.scitotenv.2019.02.282.

Ringler, C., Bhaduri, A., Lawford, R., 2013. The nexus across water, energy, land and food (WELF): potential for improved resource use efficiency? Curr. Opin. Environ. Sustain. 5, 617–624. https://doi.org/10.1016/j.cosust.2013.11.002.

Rothausen, S.G.S.A., Conway, D., 2011. Greenhouse-gas emissions from energy use in the water sector. Nat. Clim. Chang. 1, 210–219. https://doi.org/10.1038/nclimate1147.

Saaty, T.L., 2001. Decision making with dependence and feedback: The Analytic Network Process. RWS Publishing, University of Pittsburgh. Pennsylvania, United States. ISBN: 978-0-387-33987-0.

Sachs, J., Schmidt-Traub, G., Kroll, C., Lafortune, G., Fuller, G., 2018. SDG index and dashboards report 2018. Bertelsmann Stiftung and Sustainable Development Solutions Network (SDSN). New York, United States. https://www.sdgindex.org/assets/files/2018/01%20SDGS%20GLOBAL%20EDITION%20WEB%20V9%20180718.pdf.

Scharin, H., Ericsdotter, S., Elliott, M., Turner, R.K., Niiranen, S., Blenckner, T., Hyytiäinen, K., Ahlvik, L., Ahtiainen, H., Artell, J., Hasselström, L., Söderqvist, T., Rockström, J., 2016. Processes for the sustainable stewardship of marine environments. Ecol. Econ. 128, 55–67. https://doi.org/10.1016/j.ecolecon.2016.04.010.

Schmalzbauer, B., Visbeck, M. (Eds.), 2016. The Contribution of Science in Implementing the Sustainable Development Goals. German Committee Future Earth. Stuttgart/Kiel, Germany. http://futureearth.org/sites/default/files/2016_report_contribution_science_sdgs.pdf.

Scutari, M., 2010. Learning Bayesian networks with the bnlearn R package. J. Stat. Softw. 35, 1–22. https://doi.org/10.18637/jss.v035.i03.

Scutari, M., Auconi, P., Caldarelli, G., Franchi, L., 2017. Bayesian networks analysis of malocclusion data. Sci. Rep-UK 7, 1–11. https://doi.org/10.1038/s41598-017-15293-w.

Scutari, M., Denis, J.B., 2015. Bayesian networks with examples in R. Taylor & Francis Group. Florida, United States. ISBN: 978-1-4822-2559-4.

Scutari, M., Graafland, C.E., Gutiérrez, J.M., 2018. Who learns better Bayesian network structures: constraint-based, score-based or hybrid algorithms? Proceedings of Machine Learning Research (72, PGM 2018), pp. 416–427. Prague, Czech Republic. http://proceedings.mlr.press/v72/scutari18a/scutari18a.pdf.

SDSN (Sustainable Development Solutions Network), 2015. Indicators and a monitoring framework for Sustainable Development Goals: launching a data revolution for the SDGs. http://unsdsn.org/wp-content/uploads/2015/05/FINAL-SDSN-Indicator-Report-WEB.pdf.

SDSN (Sustainable Development Solutions Network), 2016. SDG Index and dashboards: a global report. https://www.sdgindex.org/assets/files/sdg_index_and_dashboards_compact.pdf.

Sheil, D., Cohen, J., Colfer, C.J.P., Price, D., Puri, R., Ruíz-Pérez, M., Sugandi, Y., Vedeld, P., Wollenberg, E., Yasmi, Y., 2016. The moral basis for conservation–reflections on Dickman et al. Front. Ecol. Environ. 14, 67–69. https://doi.org/10.1002/fee.1224.

SIASAR, 2016. Reglamento del Sistema de Información de Agua y Saneamiento Rural (Normative of the Rural Water and Sanitation Information System). http://globalsiasar.org/sites/default/files/documents/reglamento_siasar_2016.pdf.

Singh, G.G., Cisneros-Montemayor, A.M., Swartz, W., Cheung, W., Guy, J.A., Kenny, T.A., McOwen, C.J., Asch, R., Geffert, J.L., Wabnitz, C.C.C., Sumaila, R., Hanich, Q., Ota, Y., 2018. A rapid assessment of co-benefits and trade-offs among Sustainable Development Goals. Mar. Policy 93, 223–231. https://doi.org/10.1016/j.marpol.2017.05.030.

Singh, R.K., Murty, H.R., Gupta, S.K., Dikshit, A.K, 2009. An overview of sustainability assessment methodologies. Ecol. Indic. 9, 189–212. https://doi.org/10.1016/j.ecolind.2008.05.011.

Song, G., Semakula, H.M., Fullana-i-Palmer, P., 2018. Chinese household food waste and its' climatic burden driven by urbanization: A Bayesian belief network modelling for reduction possibilities in the context of global efforts. J. Clean. Prod. 202, 916–924. https://doi.org/10.1016/j.jclepro.2018.08.233.

Spaiser, V., Ranganathan, S., Swain, R.B., Sumpter, D.J.T., 2017. The sustainable development oxymoron: quantifying and modelling the incompatibility of sustainable development goals. Int J Sust Dev World 24, 457–470. https://doi.org/10.1080/13504509.2016.1235624.

Stålgren, P., 2006. Corruption in the water sector: causes, consequences and potential reform. Swedish Water House Policy Brief Nr. 4. Stockholm International Water Institute (SIWI). Stockholm, Sweeden. http://www.swedishwaterhouse.se/wp-content/uploads/20060906171639CorruptionPB_low.pdf.

Sullivan, C.A., Meigh, J.R., Giacomello, A.M., Fediw, T., Lawrence, P., Samad, M., Mlote, S., Hutton, C., Allan, J.A., Schulze, R.E., Dlamini, D.J., Cosgrove, W., Delli Priscoli, J., Gleick, P., Smout, I., Cobbing, J., Calow, R., Hunt, C., Hussain, A., Acreman, M.C., King, J., Malomo, S., Tate, E.L., O'Regan, D., Milner, S., Steyl, I., 2003. The water poverty index: Development and application at the community scale. Nat. Resour. Forum 27, 189–199. https://doi.org/10.1111/1477-8947.00054.

Taft, L., Evers, M., 2016. A review of current and possible future human-water dynamics in Myanmar's river basins. Hydrol. Earth Syst. Sci. 20, 4913–4928. https://doi.org/10.5194/hess-20-4913-2016.

Transparency International, 2008. Global corruption report 2008: corruption in the water sector. Cambridge, United Kingdom. https://www.transparency.org/whatwedo/publication/global_corruption_report_2008_corruption_in_the_water_sector.

Tsamardinos, I., Aliferis, C.F., Statnikov, A,. 2003. Algorithms for large scale Markov Blanket discovery. In Proceedings: Sixteenth International Florida Artificial Intelligence Research Society Conference, pp. 376–381.

UN–DESA (United Nations Department of Economic and Social Affairs), 1996. Indicators of sustainable development: Framework and methodologies. United Nations Sales Publication No E 96 II A 16, New York, United States. https://www.un.org/esa/sustdev/csd/csd9_indi_bp3.pdf.

UNDP (United Nations Development Programme), 2006a. Human Development Report 2006 - Beyond Scarcity: Power, Poverty and the Global Water Crisis. New York, United States. https://www.undp.org/content/dam/undp/library/corporate/HDR/2006%20Global%20HDR/HDR-2006-Beyond%20scarcity-Power-poverty-and-the-global-water-crisis.pdf.

UNDP (United Nations Development Programme), 2006b. Resource Guide: Mainstreaming Gender in Water Management. New York, United States. https://www.undp.org/content/dam/aplaws/publication/en/publications/environment-energy/www-ee-library/water-governance/resource-guide-mainstreaming-gender-in-water-management/IWRMGenderResourceGuide-English-200610.pdf.

UNDP (United Nations Development Programme), 2018. Human Development Data (1990–2015). http://hdr.undp.org/en/data.

UN–EMG (United Nations Environment Management Group), 2011. Working towards a balanced and inclusive Green Economy: a United Nations system-wide perspective. Geneve, Switzerland. http://wedocs.unep.org/bitstream/handle/20.500.11822/8065/-Working%20towards%20a%20Balanced%20and%20Inclusive%20Green%20Economy_%20A%20United%20Nations%20System-wide%20Perspective%20%20-20111109.pdf?sequence=3&isAllowed=y.

UNEP (United Nations Environment Programme), 2018. Progress on integrated water resources management. Global baseline for SDG 6 Indicator 6.5.1: degree of IWRM implementation. Washington D.C., United States. http://www.unwater.org/publications/progresson-integrated-water-resources-management-651.

UNEP–WCMC (United Nations Environment Programme World Conservation Monitoring Centre), IUCN (International Union for Conservation of Nature), 2016. Protected Planet Report 2016: How Protected Areas Contribute to Achieving Global Targets for Biodiversity. Cambridge, United Kingdom. https://wdpa.s3.amazonaws.com/Protected_Planet_Reports/2445%20Global%20Protected%20Planet%202016_WEB.pdf.

UNEP–WCMC (United Nations Environment Programme World Conservation Monitoring Centre), IUCN (International Union for Conservation of Nature), NGS (National Geographic Society), 2018. Protected Planet Report 2018: Tracking Progress towards Global Targets for Protected Areas. Cambridge; Gland; Washington D.C., United States. https://www.unep-wcmc.org/system/comfy/cms/files/files/000/001/445/original/Global_Protected_Planet_2018.PDF.

UN–ESCAP (United Nations Economic and Social Commission for Asia and the Pacific), 2016. Analytical framework for integration of water and sanitation SDGs and targets using a systems thinking approach. Working paper. Bangkok, Thailand. http://sdghelpdesk.unescap.org/sites/default/files/2018-02/integration%20sdg6.pdf.

UN–Habitat (United Nations Human Settlements Programme), 2010. Solid waste management in the world's cities: water and sanitation in the world cities 2010. Nairobi, Kenya. https://unhabitat.org/books/solid-waste-management-in-the-worlds-cities-waterand-sanitation-in-the-worlds-cities-2010-2.

UN–Habitat (United Nations Human Settlements Programme), 2015. Slum almanac 2015–2016: tracking improvement in the lives of slum dwellers. Nairobi, Kenya. https://unhabitat.org/wp-content/uploads/2016/02-old/Slum%20Almanac%202015-2016_EN.pdf.

UN–Habitat (United Nations Human Settlements Programme), 2018. SDG-11 synthesis report 2018: tracking progress towards inclusive, safe, resilient and sustainable cities and human settlements. Nairobi, Kenya. https://unhabitat.org/sdg-11-synthesis-report.

UN–IEAG (United Nations Secretary–General's Independent Expert Advisory Group on a Data Revolution for Sustainable Development), 2014. A world that counts: Mobilizing the data revolution for sustainable development. New York, United States. http://www.undatarevolution.org/wp-content/uploads/2014/11/A-World-That-Counts.pdf.

United Nations General Assembly, 2015. Transforming our world: the 2030 agenda for sustainable development. Resolution A/RES/70/1. New York, United States. https://www.un.org/en/development/desa/population/migration/generalassembly/docs/globalcompact/A_RES_70_1_E.pdf.

United Nations, 1996. Indicators of sustainable development: Framework and methodologies. United Nations Sales Publication No E 96 II A 16. New York, United States.

United Nations, 2018a. Sustainable Development Goal 6 synthesis report 2018 on water and sanitation. New York, United States. http://www.unwater.org/publication_categories/sdg-6-synthesis-report-2018-on-water-and-sanitation.

United Nations, 2018b. The Sustainable Development Goals Report 2018. New York, United States. https://unstats.un.org/sdgs/files/report/2018/TheSustainableDevelopmentGoalsReport2018-EN.pdf.

UNSD (United Nations Statistics Division), 2018. Sustainable Development Goal Indicators Website. https://unstats.un.org/sdgs/indicators/database/.

Unver, O., Bhaduri, A., Hoogeveen, J., 2017. Water-use efficiency and productivity improvements towards a sustainable pathway for meeting future water demand. Water Secur 1, 21–27. https://doi.org/10.1016/j.wasec.2017.05.001.

UN–Water, 2016. Water and Sanitation Interlinkages across the 2030 Agenda for Sustainable Development. Geneva, Switzerland. http://www.unwater.org/publications/water-sanitationinterlinkages-across-2030-agenda-sustainable-development.

UN–Women, 2018. Turning promises into action: gender equality in the 2030 agenda for sustainable development. New York, United States. http://www.unwomen.org/-/media/headquarters/attachments/sections/library/publications/2018/sdg-report-gender-equality-inthe-2030-agenda-for-sustainable-development-2018-en.pdf?la=en&vs=4332.

Uusitalo, L., 2007. Advantages and challenges of Bayesian Networks in environmental modelling. Ecol. Model. 203, 312–318. https://doi.org/10.1016/j.ecolmodel.2006.11.033.

Valcourt, N., Javernick-Will, A., Walters, J., Linden, K, 2020. System approaches to water, sanitation, and hygiene: A systematic literature review. Int. J. Environ. Res. Public Health 17, 702. https://doi.org/10.3390/ijerph17030702.

Vacik, H., Wolfslehner, B., Seidl, R., Lexer, M.J., 2007. Integrating the DPSIR-approach and the Analytic Network Process for the assessment of forest management strategies. In: Reynolds, K., Rennolls, K., Kohl, M., Thomson, A., Shannon, M., Ray, D. (Eds.). Sustainable forestry: From monitoring and modelling to knowledge management and policy science. CABI Publishing. Oxfordshire, United Kingdom. https://doi.org/10.1079/9781845931742.0393.

Vörösmarty, C.J., Green, P., Salisbury, J., Lammers, R.B., 2000. Global water resources: vulnerability from climate change and population growth contemporary population relative to demand per discharge. Science 289, 284–288. https://doi.org/10.1126/science.289.5477.284.

Watson, J.T., Gayer, M., Connolly, M.A., 2007. Epidemics after natural disasters. Emerg. Infect. Dis. 13, 1–5. https://doi.org/10.3201/eid1301.060779.

WB (The World Bank Group), 2017. Latin America - Consolidation, improvement and expansion of the rural water and sanitation information system (SIASAR). Washington D.C., United States. http://documents.worldbank.org/curated/en/930481514358304158/Latin-America-Consolidation-improvement-and-expansion-of-the-rural-water-and-sanitation-information-system-SIASAR.

WB–WSP (World Bank Water and Sanitation Programme), 2015. Developing business models for fecal sludge management in Maputo. Maputo, Mozambique.

Webb, A.L., Stein, A.D., Ramakrishnan, U., Hertzberg, V.S., Urizar, M., Martorell, R., 2006. A simple index to measure hygiene behaviours. Int. J. Epidemiol. 35, 1469–1477. https://doi.org/10.1093/ije/dyl165.

Weitz, N., Nilsson, M., & Davis, M., 2014. A Nexus approach to the Post-2015 Agenda: Formulating integrated water, energy, and food SDGs. SAIS Rev. Int. Aff. 34, 37–50. https://doi:10.1353/sais.2014.0022.

WHO (World Health Organization), 2015a.Water, sanitation and hygiene for accelerating and sustaining progress on neglected tropical diseases: a global strategy 2015–2020. Geneva, Switzerland. https://apps.who.int/iris/bitstream/handle/10665/182735/WHO_FWC_WSH_15.12_eng.pdf?sequence=1.

WHO (World Health Organization), 2015b. Tracking Universal Health Coverage: First Global Monitoring Report. Geneva, Switzerland. https://apps.who.int/iris/bitstream/handle/10665/174536/9789241564977_eng.pdf?sequence=1.

WHO (World Health Organization), 2018. World health statistics 2018: monitoring health for the Sustainable Development Goals. Geneva, Switzerland. https://apps.who.int/iris/bitstream/handle/10665/272596/9789241565585-eng.pdf?ua=1.

Wiedmann, T.O., Schandl, H., Lenzen, M., Moran, D., Suh, S., West, J., Kanemoto, K., 2015. The material footprint of nations. P. Natl. Acad. Sci. 112, 6271–6276. https://doi.org/10.1073/pnas.1220362110.

Willetts, J., Halcrow, G., Carrard, N., Rowland, C., Crawford, J., 2010. Addressing two critical MDGs together: gender in water, sanitation and hygiene initiatives. Pac. Econ. Bull. 25, 162–176. https://core.ac.uk/download/pdf/156642751.pdf.

Wolfslehner, B., Vacik, H., 2011. Mapping indicator models: From intuitive problem structuring to quantified decision-making in sustainable forest management. Ecol. Indic. 11, 274–283. https://doi.org/10.1016/j.ecolind.2010.05.004.

Woodhouse, P., Muller, M., 2017.Water governance: an historical perspective on current debates. World Dev. 92, 225–241. https://doi.org/10.1016/j.worlddev.2016.11.014.

World Bank, 2018. Tracking SDG-7: The Energy Progress Report 2018. International Bank for Reconstruction and Development/The World Bank. Washington D.C., United States. http://documents.worldbank.org/curated/en/495461525783464109/pdf/126026-WP-PUBLIC-P167379-tracking-sdg7-the-energy-progress-report-full-report.pdf.

WWAP (United NationsWorld Water Assessment Programme), 2014. The United Nations World Water Development Report 2014: Water and Energy. UNESCO. Paris, France. http://www.unwater.org/publications/world-water-development-report-2014-water-energy.

WWAP (United NationsWorld Water Assessment Programme), 2016. The United Nations WorldWater Development Report 2016:Water and Jobs. UNESCO. Paris, France. http://www.unwater.org/publications/world-water-development-report-2016.

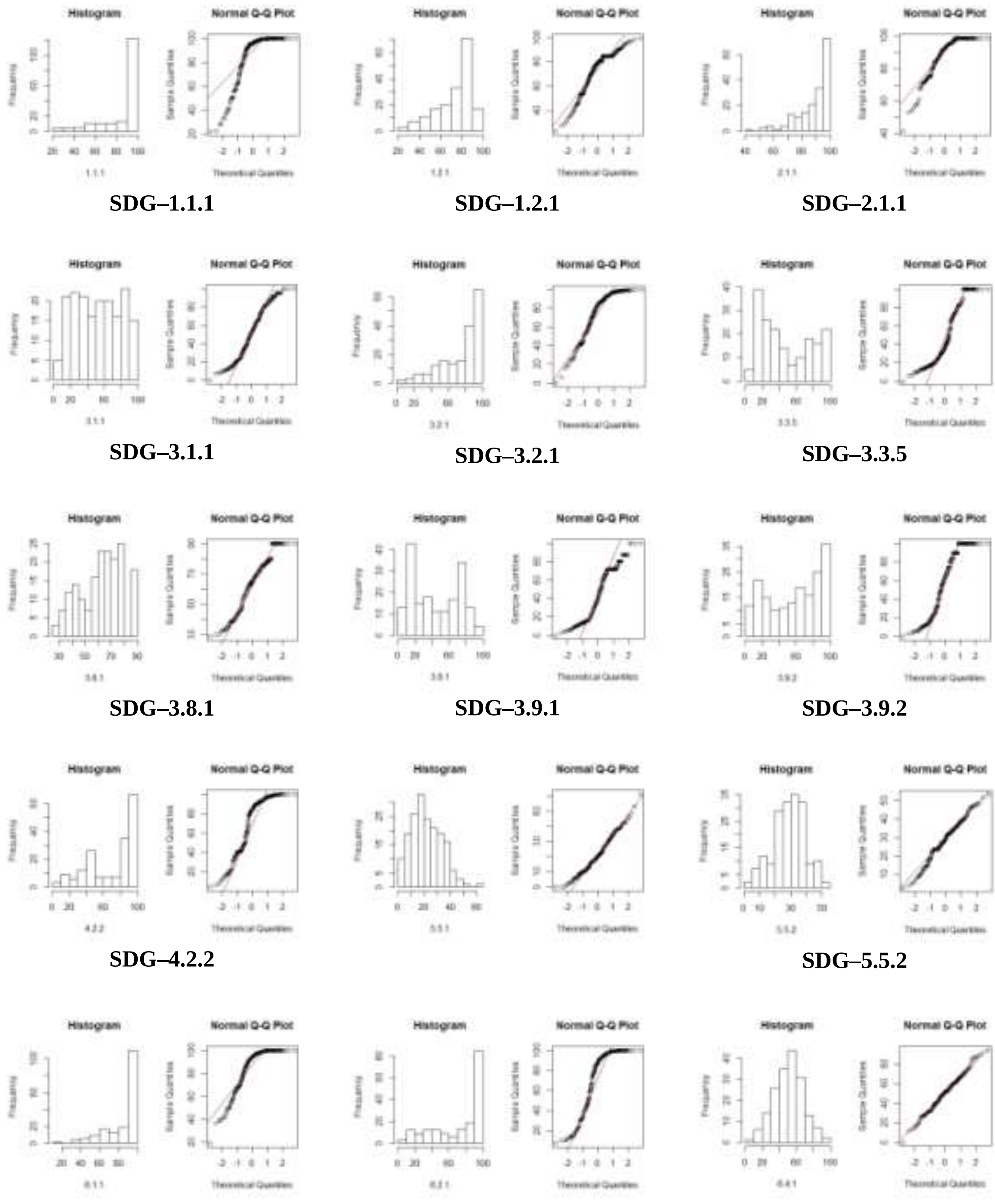
WWAP (United NationsWorldWater Assessment Programme), 2019. The United Nations world water development report 2019: leaving no one behind. UNESCO. Paris, France. http://www.unwater.org/publications/world-water-development-report-2019.

Yaramakala, S., Margaritis, D., 2005. Speculative Markov Blanket discovery for optimal feature selection. In Proceedings: Fifth IEEE International Conference on Data Mining, pp. 809–812.

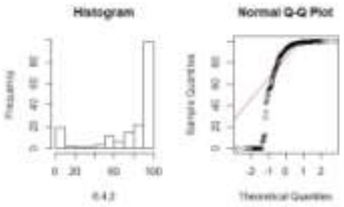
ANNEXES

SUPPLEMENTARY FIGURES

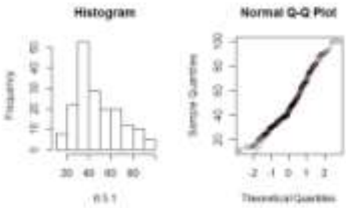
Figure A1. SDG indicators distributions (histograms) and associated normality check (Q–Q plot).



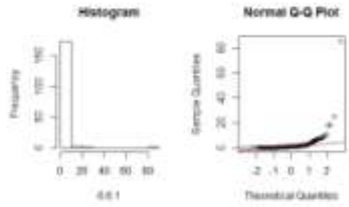
Continuation of Figure A1.



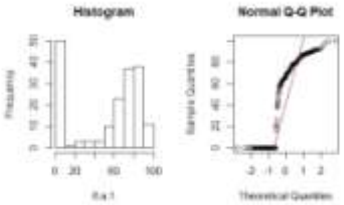
SDG–6.4.2



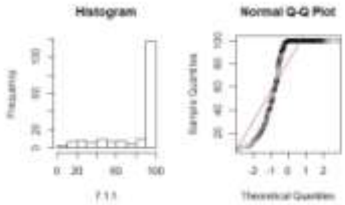
SDG–6.5.1



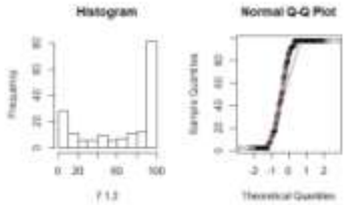
SDG–6.6.1



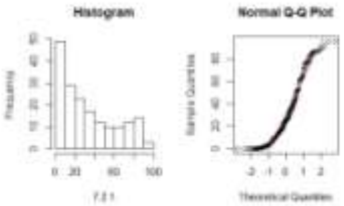
SDG–6.a.1



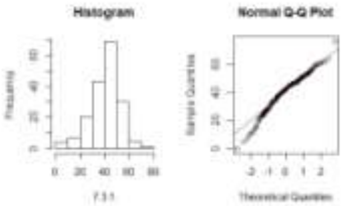
SDG–7.1.1



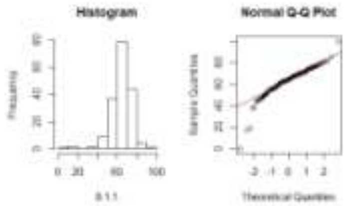
SDG–7.1.2



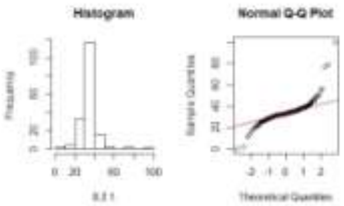
SDG–7.2.1



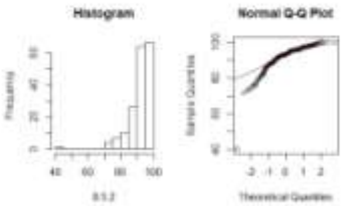
SDG–7.3.1



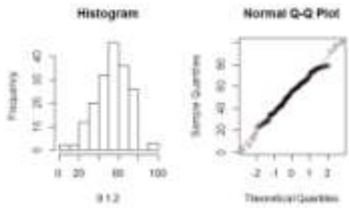
SDG–8.1.1



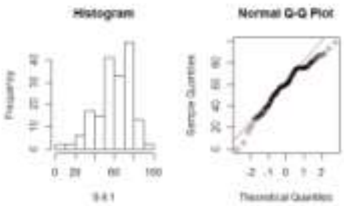
SDG–8.2.1



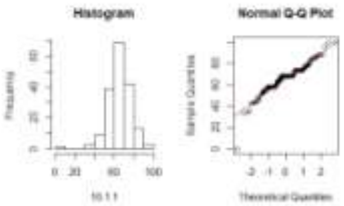
SDG–8.5.2



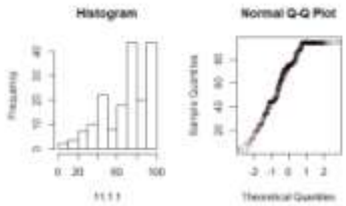
SDG–9.1.2



SDG–9.4.1

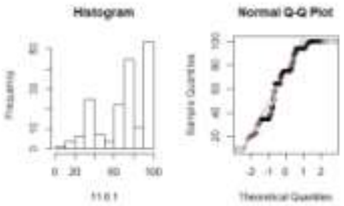


SDG–10.1.1

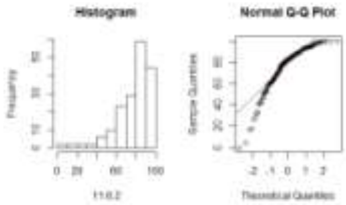


SDG–11.1.1

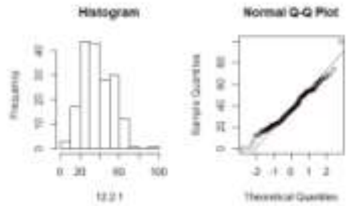
Continuation of Figure A1.



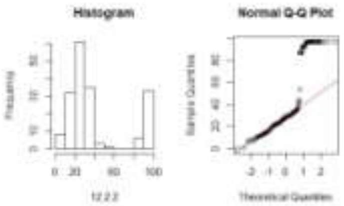
SDG–11.6.1



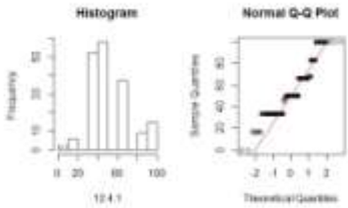
SDG–11.6.2



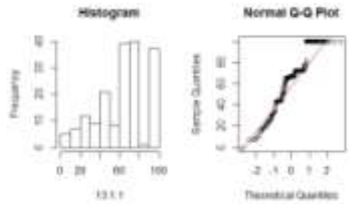
SDG–12.2.1



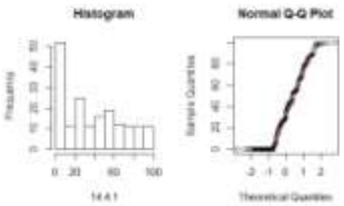
SDG–12.2.2



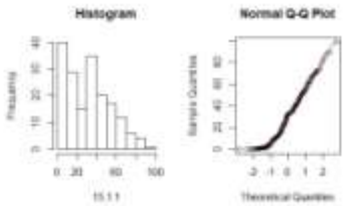
SDG–12.4.1



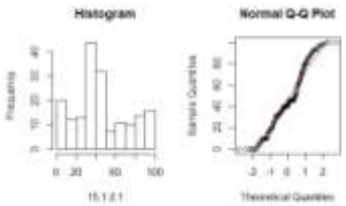
SDG–13.1.1



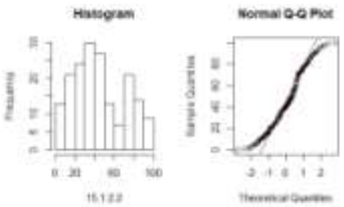
SDG–14.4.1



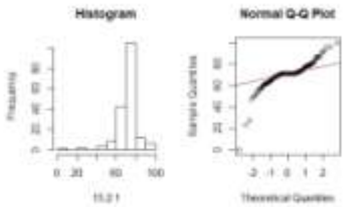
SDG–15.1.1



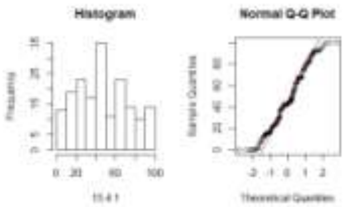
SDG–15.1.2.1



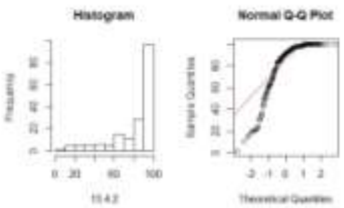
SDG–15.1.2.2



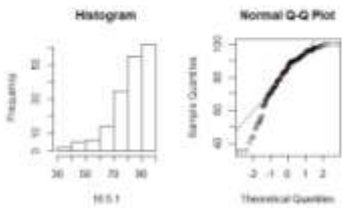
SDG–15.2.1



SDG–15.4.1



SDG–15.4.2



SDG–16.5.1

SUPPLEMENTARY TABLES

Table A1. Dimensions, components and indicators (including corresponding survey questionnaire) within SIASAR conceptual framework. Source: Pérez-Foguet and Flores-Baquero (2015).

Dimensions	Components	Indicators
Water service level (WSL)	Accessibility (ACC)	Improved water supply coverage [a] Access time [b]
	Continuity (CON)	Service hours per day [b]
	Seasonality (SEA)	Water system flow [b] Minimum water system flow [b] Sufficient water during summer [b] Number of households [a]
	Quality (QUA)	Physico–chemical quality [b] Bacteriological quality [b]
Sanitation and hygiene service level (SHL)	Sanitation service level (SSL)	Improved sanitation coverage [a]
	Personal hygiene (PER)	Hand–washing practice [a]
	Household hygiene (WAT)	Household safety water management [a]
	Community hygiene (COM)	Garbage and puddles presence [a] Open defecation [a]
Water system infrastructure (WSI)	System autonomy (AUT)	Service days without production [b] Number of households [a]
	Production infrastructure (INF)	Catchment area status [b] Conduction status [b] Storage status [b] Distribution status [b]
	Water catchment area protection (PRO)	Catchment protection area status [b]
	Treatment system (TRE)	Treatment system typology [b] Treatment system functionality [b]
Service provision (SEP)	Organization management (ORG)	Legalization and directive structure [c] Ordinary operation [c] Equity within the organization [c] Economic management and accountability [c]
	Operation & maintenance management (OPM)	O&M general assessment [c] Basic operation with chlorine [b]
	Economic management (ECO)	Collection efficiency rate [c] Cost coverage rate [c] Liquid assets rate [c]
	Environmental management (ENV)	Catchment attention measurements [c] Environmental sanitation promotion [c]

(a) Community questionnaire, (b) System questionnaire, and (c) Service provision questionnaire.

Table A2. Aggregation to construct the different dimensions, partial indices and general index.

Water and sanitation performance index for rural communities (WSP)

$$\mathbf{WSP} = \prod_{\mathbf{i,j=0}}^{\mathbf{i,j=1}} \mathbf{x_j}^{\mathbf{p_j}} = (\mathbf{WSHL} * \mathbf{WSSI})^{1/2}$$

WaSH service level index (WSHL)	**Water services sustainability index (WSSI)**
$\mathbf{WSHL} = \prod_{\mathbf{i,j=0}}^{\mathbf{i,j=1}} \mathbf{x_j}^{\mathbf{p_j}} = (\mathbf{WSL} * \mathbf{SHL})^{1/2}$	$\mathbf{WSSI} = \prod_{\mathbf{i,j=0}}^{\mathbf{i,j=1}} \mathbf{x_j}^{\mathbf{p_j}} = (\mathbf{WSI} * \mathbf{SEP})^{1/2}$
Water service level (WSL) $\mathbf{WSL} = \sum_{\mathbf{i,j=0}}^{\mathbf{i,j=1}} \mathbf{x_i}.\,\mathbf{p_j} = \frac{(\mathbf{ACC} + \mathbf{CON} + \mathbf{SEA} + \mathbf{QUA})}{\mathbf{4}}$ ACC – Accessibility CON – Continuity SEA – Seasonality QUA – Quality	**Water system infrastructure (WSI)** $\mathbf{WSI} = \sum_{\mathbf{i,j=0}}^{\mathbf{i,j=1}} \mathbf{x_i}.\,\mathbf{p_j} = \frac{(\mathbf{AUT} + \mathbf{INF} + \mathbf{PRO} + \mathbf{TRE})}{\mathbf{4}}$ AUT – System autonomy INF – Production infrastructure PRO – Water catchment area protection TRE – Treatment system
Sanitation and hygiene service level (SHL) $\mathbf{SHL} = \sum_{\mathbf{i,j=0}}^{\mathbf{i,j=1}} \mathbf{x_i}.\,\mathbf{p_j} = \frac{(\mathbf{SSL} + \mathbf{PER} + \mathbf{WAT} + \mathbf{COM})}{\mathbf{4}}$ SSL – Sanitation service level PER – Personal hygiene WAT – Household hygiene COM – Community hygiene	**Service provision (SEP)** $\mathbf{SEP} = \sum_{\mathbf{i,j=0}}^{\mathbf{i,j=1}} \mathbf{x_i}.\,\mathbf{p_j} = \frac{(\mathbf{ORG} + \mathbf{OPM} + \mathbf{ECO} + \mathbf{ENV})}{\mathbf{4}}$ ORG – Organization management OPM – Operation & maintenance management ECO – Economic management ENV – Environmental management

Table A3. Variables distributions detailed numerically.

	NICARAGUA				HONDURAS			
	States (%)				States (%)			
Variables	**A**	**B**	**C**	**D**	**A**	**B**	**C**	**D**
Accessibility	23.1	41.5	21.4	14.0	42.1	44.2	10.2	3.5
Continuity	56.9	14.5	11.7	16.9	79.5	4.4	10.8	5.3
Seasonality	64.7	19.1	4.7	11.5	62.4	25.8	4.5	7.3
Quality	63.3	6.9	1.2	28.6	12.8	6.8	0.2	80.2
Sanitation service level	36.7	23.1	14.9	25.3	42.8	29.0	13.8	14.4
Personal hygiene	30.4	---	66.9	2.7	55.3	---	43.2	1.5
Household hygiene	39.2	---	47.1	13.7	28.2	---	46.3	25.5
Community hygiene	10.1	30.0	36.7	23.2	20.8	30.1	37.2	11.9
System autonomy	25.4	15.6	20.2	38.8	54.6	18.0	11.5	15.9
Production infrastructure	54.5	32.6	7.8	5.1	61.9	29.2	4.2	4.7
Water catchment protection	45.1	36.9	15.9	2.1	48.7	39.2	9.8	2.3
Treatment system	53.7	6.5	9.9	29.9	23.7	1.0	30.5	44.8
Organizational management	12.0	24.3	26.4	37.3	15.9	42.0	31.1	11.0
O&M management	23.1	24.0	25.7	27.2	10.7	52.5	30.6	6.2
Economic management	19.4	19.6	18.5	42.5	59.0	24.6	9.7	6.7
Environmental management	55.0	26.8	11.5	6.7	56.4	35.8	6.0	1.8
Mean	38.3	23.0	21.3	20.3	42.2	27.3	18.7	15.2
Max	64.7	41.5	66.9	42.5	79.5	52.5	46.3	80.2
Min	10.1	6.5	1.2	2.1	10.7	1.0	0.2	1.5
Water service level	44.0	36.9	16.1	3.0	15.1	63.1	20.2	1.6
Sanitation and hygiene service level	17.1	32.4	41.1	9.4	20.7	40.3	34.2	4.8
Water system infrastructure	35.9	39.1	22.4	2.6	31.3	51.6	14.7	2.4
Service provision	12.4	36.6	40.4	10.6	24.5	60.2	13.2	2.1
WaSH service level	14.8	51.9	31.2	2.1	12.1	59.7	27.3	0.9
Water services sustainability index	14.5	45.0	33.8	6.7	21.3	63.2	14.1	1.4
Wat. & San. service performance index	8.0	54.4	34.7	2.9	10.6	70.6	18.2	0.6
Mean	21.0	42.3	31.4	5.3	19.4	58.4	20.3	2.0
Max	44.0	54.4	41.1	10.6	31.3	70.6	34.2	4.8
Min	8.0	32.4	16.1	2.1	10.6	40.3	13.2	0.6

Table A4. Mean, median and interquartile range (IQR) values for the cases of Nicaragua (left) and Honduras (right).

NICARAGUA			
	mean	**median**	**IQR**
ACC	0.57	0.60	0.30
CON	0.70	1.00	0.67
SEA	0.79	1.00	0.33
QUA	0.68	1.00	1.00
SSL	0.55	0.61	0.62
PER	0.53	0.33	0.67
WAT	0.55	0.33	0.67
COM	0.44	0.33	0.33
AUT	0.43	0.38	0.71
INF	0.77	0.82	0.33
PRO	0.75	0.67	0.33
TRE	0.62	1.00	1.00
ORG	0.38	0.37	0.50
OPM	0.45	0.38	0.45
ECO	0.38	0.33	0.67
ENV	0.76	1.00	0.33

HONDURAS			
	mean	**median**	**IQR**
ACC	0.72	0.67	0.41
CON	0.75	0.83	0.00
SEA	0.81	1.00	0.33
QUA	0.17	0.00	0.00
SSL	0.63	0.70	0.41
PER	0.70	1.00	0.67
WAT	0.44	0.33	1.00
COM	0.51	0.50	0.33
AUT	0.68	0.79	0.54
INF	0.79	0.83	0.33
PRO	0.78	0.67	0.33
TRE	0.35	0.33	0.33
ORG	0.51	0.50	0.29
OPM	0.47	0.50	0.17
ECO	0.76	0.88	0.36
ENV	0.82	1.00	0.33

Table A5. Result bias against objective node "WSP" for the three scenarios considered and for the case of Nicaragua.

Scenario "16+1"					
Input nodes	**A (2.9%)**	**B (34.7)**	**C (54.4)**	**D (8%)**	**Method**
Data–driven	10.8	13.0	-21.4	-2.4	mle
	16.4	-29.5	-9.1	22.2	bayes
Lowest IQR	11.3	10.9	-20.1	-2.1	mle
	16.4	-29.4	-8.9	21.9	bayes
Highest IQR	12.0	11.2	-20.9	-2.3	mle
	16.5	29.6	-24.5	-21.6	bayes
Smart	11.0	15.3	-23.6	-2.7	mle
	16.4	-29.2	-9.1	21.9	bayes

All values are express in percentage.
"WSP" node is taking as a reference.

Scenario "16+2+1"					
Input nodes	**A (2.9%)**	**B (34.7)**	**C (54.4)**	**D (8%)**	**Method**
Data–driven	-1.2	14.2	-10.4	-2.6	mle
	0.8	-6.7	3.3	2.6	bayes
Lowest IQR	-1.2	12.6	-8.9	-2.5	mle
	0.9	-8.7	4.5	3.3	bayes
Highest IQR	-2.0	11.7	-7.3	-2.4	mle
	-0.3 (-2.7)	-3.4 (-9.3)	2.1 (17.0)	1.6 (-5.0)	bayes
Smart	-1.5	11.9	-8.0	-2.4	mle
	-0.2 (2.6)	-3.6 (-9.7)	2.1 (2.0)	1.7 (5.1)	bayes

All values are express in percentage.
"WSP" node is taking as a reference.
In brackets, biases obtained when using the test dataset for network validation.

Scenario "16+4+2+1"					
Input nodes	**A**	**B**	**C**	**D**	**Method**
Data–driven	-3.8	7.5	-1.7	-2.0	mle
	-3.7	6.4	-0.9	-1.8	bayes
Lowest IQR	-3.8	6.3	-0.6	-1.9	mle
	-3.7 (-2.5)	5.4 (2.8)	-0.2 (0.8)	-1.5 (-1.1)	bayes
Highest IQR	-4.3	7.4	-1.2	-1.9	mle
	-4.0	6.8	-1.1	-1.7	bayes
Smart	-4.0	6.9	-1.0	-1.9	mle
	-3.9 (-2.9)	5.9 (2.9)	-0.3 (1.1)	-1.7 (-1.1)	bayes

All values are express in percentage.
"WSP" node is taking as a reference.
In brackets, biases obtained when using the test dataset for network validation.

Table A6. Result bias applying Honduras database to Nicaragua final network. General index, partial indices and dimensions are considered for the comparison.

Nodes	A	B	C	D
Wat. & San. service performance index (WSP)	-3.6	-3.2	7.0*	-0.2
WaSH service level (WSHL)	6.6*	-0.7	-5.6*	-0.3
Water services sustainability index (WSSI)	-9.4	-7.1*	15.8*	0.7
Water service level (WSL)	36.0*	-27.0*	-9.1*	0.1
Sanitation and hygiene service level (SHL)	-0.1	-1.8	4.2	-2.3
Water system infrastructure (WSI)	5.5*	-8.1*	3.3	-0.7
Service provision (SEP)	-13.2*	-16.4*	28.8*	0.8

Values are express as percentages, taking as a reference the IS distributions of each node.
* Errors higher than 5% threshold established.

Table A7. Result bias in relation to "WSP" node for the case of Honduras.

Scenario "16+1"					
Input nodes	**A (10.6%)**	**B (70.6%)**	**C (18.2%)**	**D (0.6%)**	**Method**
Data–driven	-0.2	15.7	-14.7	-0.8	mle
	13.6	-42.9	6.2	23.1	bayes
Lowest IQR	-1.6	17.2	-14.8	-0.8	mle
	13.8	-43.4	6.4	23.2	bayes
Highest IQR	-1.5	16.8	-14.5	-0.8	mle
	13.6	-42.5	5.9	23.0	bayes
Smart	0.3	15.8	-15.3	-0.8	mle
	13.4	-42.7	6.3	23.0	bayes

All values are express in percentage.
"WSP" node is taking as a reference.

Scenario "16+2+1"					
Input nodes	**A (10.6%)**	**B (70.6%)**	**C (18.2%)**	**D (0.6%)**	**Method**
Data–driven	-2.2	11.2	-8.2	-0.8	mle
	-1.2	-9.9	8.2	2.9	bayes
Lowest IQR	-3.6	11.0	-6.6	-0.8	mle
	-2.2 (-0.9)	-3.2 (-6.5)	4.2 (4.5)	1.2 (2.9)	bayes
Highest IQR	-2.6	11.7	-8.3	-0.8	mle
	-1.5	-9.3	8.0	2.8	bayes
Smart	-2.9	11.7	-8.0	-0.8	mle
	-1.6	-6.2	5.8	2.0	bayes

All values are express in percentage.
"WSP" node is taking as a reference.
In brackets, biases obtained when using the test dataset for network validation.

Scenario "16+4+2+1"					
Input nodes	**A**	**B**	**C**	**D**	**Method**
Data–driven	-3.6	7.4	-3.1	-0.7	mle
	-3.5	6.1	-2.1	-0.5	bayes
Lowest IQR	-3.5	7.3	-3.1	-0.7	mle
	-3.6 (-3.4)	6.5 (5.9)	-2.3 (-2.6)	-0.6 (0.1)	bayes
Highest IQR	-3.7	7.6	-3.2	-0.7	mle
	-3.7 (-3.5)	6.7 (6.2)	-2.4 (-2.8)	-0.6 (0.1)	bayes
Smart	-3.4	7.2	-3.1	-0.7	mle
	-3.5 (-3.4)	6.1 (5.5)	-2.1 (-2.2)	-0.5 (0.1)	bayes

All values are express in percentage.
"WSP" node is taking as a reference.
In brackets, biases obtained when using the test dataset for network validation.

Table A8. Evolution of the identification of strong links within the different country samples generated.

Links		**Repetitiveness (%)**						
		n=175	**n=160**	**n=145**	**n=130**	**n=115**	**n=100**	**n=85**
3.1.1	**3.9.2**	100	97	80	63	55	53	40
3.2.1	**3.9.2**	100	100	99	97	83	63	38
5.5.2	**6.4.2**	99	65	51	38	22	17	8
6.1.1	**7.1.1**	97	73	57	41	39	29	31
6.4.2	**15.1.1**	100	81	58	34	23	23	8
6.a.1	**6.4.1**	100	83	72	58	38	40	22
6.a.1	**10.1.1**	70	42	44	22	16	11	9
7.1.1	1.1.1	100	100	98	92	78	70	50
7.1.2	3.9.1	100	100	100	100	100	100	100
7.1.2	7.2.1	82	44	40	33	18	10	15
9.4.1	7.2.1	96	77	55	38	25	18	10
9.4.1	9.1.2	100	100	100	100	100	100	99
11.6.2	5.5.2	100	96	85	58	50	39	23
12.2.2	9.1.2	100	100	100	100	100	100	100
14.4.1	15.1.2.2	100	100	93	75	51	54	31
15.1.1	15.4.2	98	79	57	35	25	16	14
15.1.2.2	15.1.2.1	100	100	100	100	100	100	98
15.1.2.2	15.4.1	100	100	100	100	100	100	100

In bold, those interlinkages associated with SDG–6 indicators.

Table A9. Disaggregated identification of all strong links identified for the different country samples.

from	to	n=175		n=160		n=145		n=130		n=115		n=100		n=85	
3.9.2	**3.1.1**	58	**100**	46	**97**	45	**80**	44	**63**	40	**55**	32	**43**	38	**40**
3.1.1	**3.9.2**	42		51		35		19		15		11		2	
3.2.1	**3.9.2**	100	**100**	96	**100**	81	**99**	56	**97**	45	**83**	23	**63**	4	**38**
3.9.2	**3.2.1**	0		4		18		41		38		40		34	
5.5.2	**6.4.2**	90	**99**	56	**65**	35	**51**	33	**38**	16	**22**	13	**17**	6	**8**
6.4.2	**5.5.2**	9		9		16		5		6		4		2	
6.1.1	**7.1.1**	87	**97**	47	**73**	29	**57**	16	**41**	12	**39**	9	**29**	11	**31**
7.1.1	**6.1.1**	10		26		28		25		27		20		20	
6.4.2	**15.1.1**	100	**100**	81	**81**	58	**58**	34	**34**	22	**23**	23	**23**	6	**8**
15.1.1	**6.4.2**	0		0		0		0		1		0		2	
6.a.1	**6.4.1**	100	**100**	83	**83**	72	**72**	57	**58**	38	**38**	40	**40**	21	**22**
6.4.1	**6.a.1**	0		0		0		1		0		0		1	
6.a.1	**10.1.1**	70	**70**	42	**42**	43	**44**	20	**22**	15	**16**	10	**11**	8	**9**
10.1.1	**6.a.1**	0		0		1		2		1		1		1	
7.1.1	**1.1.1**	100	**100**	100	**100**	98	**98**	92	**92**	78	**78**	69	**70**	48	**50**
1.1.1	**7.1.1**	0		0		0		0		0		1		2	
7.1.2	**3.9.1**	100	**100**	100	**100**	100	**100**	98	**100**	100	**100**	97	**100**	97	**100**
3.9.1	**7.1.2**	0		0		0		2		0		3		3	
7.2.1	**7.1.2**	32	**82**	12	**44**	9	**40**	9	**33**	7	**18**	0	**10**	2	**15**
7.1.2	**7.2.1**	50		32		31		24		11		10		13	
9.4.1	**7.2.1**	94	**96**	60	**77**	34	**55**	18	**38**	8	**25**	4	**18**	2	**10**
7.2.1	**9.4.1**	2		17		21		20		17		14		8	
9.4.1	**9.1.2**	97	**100**	95	**100**	92	**100**	90	**100**	89	**100**	85	**100**	81	**99**
9.1.2	**9.4.1**	3		5		8		10		11		15		18	
11.6.2	**5.5.2**	100	**100**	95	**96**	85	**85**	56	**58**	49	**50**	35	**39**	20	**23**
5.5.2	**11.6.2**	0		1		0		2		1		4		3	
12.2.2	**9.1.2**	100	**100**	97	**100**	95	**100**	88	**100**	83	**100**	77	**100**	70	**100**
9.1.2	**12.2.2**	0		3		5		12		17		23		30	
14.4.1	**15.1.2.2**	72	**100**	50	**100**	38	**93**	23	**75**	19	**51**	12	**54**	10	**31**
15.1.2.2	**14.4.1**	28		50		55		52		32		42		21	
15.1.1	**15.4.2**	66	**98**	51	**79**	36	**57**	25	**35**	17	**25**	9	**16**	9	**14**
15.4.2	**15.1.1**	32		28		21		10		8		7		5	
15.1.2.2	**15.1.2.1**	99	**100**	94	**100**	91	**100**	93	**100**	94	**100**	88	**100**	80	**98**
15.1.2.1	**15.1.2.2**	1		6		9		7		6		12		18	
15.1.2.2	**15.4.1**	100	**100**	100	**100**	100	**100**	100	**100**	100	**100**	97	**100**	94	**100**
15.4.1	**15.1.2.2**	0		0		0		0		0		3		6	

Table A10. Values related to the strength of the links (*arc strength*) and their direction.

from	to	arc strength (*direction*)						
		n=175	**n=160**	**n=145**	**n=130**	**n=115**	**n=100**	**n=85**
3.9.2	**3.1.1**	0.93 (*0.52*)	0.91 (*0.53*)	0.90 (*0.54*)	0.91 (*0.55*)	0.91 (*0.56*)	0.89 (*0.57*)	0.90 (*0.59*)
3.1.1	**3.9.2**	0.92 (*0.51*)	0.90 (*0.52*)	0.90 (*0.52*)	0.89 (*0.53*)	0.89 (*0.54*)	0.91 (*0.53*)	0.89 (*0.54*)
3.2.1	**3.9.2**	0.99 (*0.56*)	0.97 (*0.56*)	0.94 (*0.55*)	0.92 (*0.54*)	0.90 (*0.54*)	0.88 (*0.53*)	0.88 (*0.52*)
3.9.2	**3.2.1**	—	0.99 (*0.51*)	0.96 (*0.52*)	0.94 (*0.52*)	0.93 (*0.54*)	0.91 (*0.56*)	0.88 (*0.57*)
5.5.2	**6.4.2**	0.86 (*0.54*)	0.87 (*0.56*)	0.86 (*0.56*)	0.87 (*0.56*)	0.89 (*0.55*)	0.88 (*0.55*)	0.91 (*0.54*)
6.4.2	**5.5.2**	0.85 (*0.51*)	0.87 (*0.52*)	0.87 (*0.53*)	0.87 (*0.54*)	0.88 (*0.53*)	0.84 (*0.53*)	0.87 (*0.52*)
6.1.1	**7.1.1**	0.86 (*0.53*)	0.86 (*0.53*)	0.91 (*0.53*)	0.88 (*0.53*)	0.88 (*0.53*)	0.90 (*0.53*)	0.87 (*0.54*)
7.1.1	**6.1.1**	0.87 (*0.52*)	0.86 (*0.53*)	0.88 (*0.54*)	0.89 (*0.55*)	0.91 (*0.55*)	0.89 (*0.55*)	0.90 (*0.55*)
6.4.2	**15.1.1**	0.88 (*0.66*)	0.87 (*0.66*)	0.87 (*0.65*)	0.86 (*0.63*)	0.87 (*0.63*)	0.87 (*0.61*)	0.84 (*0.55*)
15.1.1	**6.4.2**	—	—	—	—	0.83 (*0.55*)	—	0.86 (*0.52*)
6.a.1	**6.4.1**	0.90 (*0.70*)	0.89 (*0.69*)	0.89 (*0.68*)	0.89 (*0.67*)	0.87 (*0.67*)	0.88 (*0.65*)	0.87 (*0.66*)
6.4.1	**6.a.1**	—	—	—	0.81 (*0.51*)	—	—	0.88 (*0.51*)
6.a.1	**10.1.1**	0.84 (*0.69*)	0.85 (*0.66*)	0.85 (*0.66*)	0.86 (*0.64*)	0.86 (*0.64*)	0.84 (*0.61*)	0.86 (*0.57*)
10.1.1	**6.a.1**	—	—	0.80 (*0.51*)	0.91 (*0.55*)	0.97 (*0.56*)	0.82 (*0.52*)	0.85 (*0.51*)
7.1.1	**1.1.1**	0.98 (*0.62*)	0.97 (*0.61*)	0.95 (*0.61*)	0.94 (*0.61*)	0.93 (*0.61*)	0.91 (*0.59*)	0.91 (*0.62*)
1.1.1	**7.1.1**	—	—	—	—	—	1.00 (*0.51*)	0.93 (*0.53*)
7.1.2	**3.9.1**	1.00 (*0.60*)	1.00 (*0.61*)	0.99 (*0.62*)	0.99 (*0.62*)	0.99 (*0.62*)	1.00 (*0.62*)	0.99 (*0.62*)
3.9.1	**7.1.2**	—	—	—	0.99 (*0.54*)	—	1.00 (*0.53*)	0.99 (*0.54*)
7.2.1	**7.1.2**	0.84 (*0.52*)	0.83 (*0.52*)	0.89 (*0.55*)	0.87 (*0.54*)	0.88 (*0.54*)	—	0.96 (*0.56*)
7.1.2	**7.2.1**	0.84 (*0.59*)	0.86 (*0.54*)	0.87 (*0.55*)	0.86 (*0.57*)	0.87 (*0.57*)	0.87 (*0.60*)	0.89 (*0.59*)
9.4.1	**7.2.1**	0.88 (*0.58*)	0.86 (*0.60*)	0.85 (*0.60*)	0.85 (*0.61*)	0.86 (*0.57*)	0.91 (*0.59*)	0.84 (*0.59*)
7.2.1	**9.4.1**	0.88 (*0.52*)	0.88 (*0.53*)	0.86 (*0.60*)	0.86 (*0.57*)	0.86 (*0.57*)	0.85 (*0.60*)	0.87 (*0.58*)
9.4.1	**9.1.2**	1.00 (*0.55*)	1.00 (*0.56*)	0.99 (*0.57*)	0.99 (*0.58*)	0.99 (*0.59*)	0.99 (*0.59*)	0.98 (*0.59*)
9.1.2	**9.4.1**	1.00 (*0.51*)	1.00 (*0.51*)	0.99 (*0.52*)	0.99 (*0.52*)	0.99 (*0.52*)	0.99 (*0.52*)	0.97 (*0.53*)
11.6.2	**5.5.2**	0.94 (*0.61*)	0.91 (*0.60*)	0.90 (*0.59*)	0.91 (*0.58*)	0.88 (*0.60*)	0.88 (*0.58*)	0.89 (*0.56*)
5.5.2	**11.6.2**	—	0.89 (*0.51*)	—	0.85 (*0.53*)	0.91 (*0.51*)	0.91 (*0.52*)	0.87 (*0.52*)
12.2.2	**9.1.2**	0.99 (*0.58*)	1.00 (*0.58*)	0.99 (*0.58*)	0.99 (*0.57*)	0.99 (*0.57*)	0.99 (*0.58*)	0.98 (*0.57*)
9.1.2	**12.2.2**	—	1.00 (*0.51*)	0.99 (*0.52*)	0.99 (*0.52*)	0.99 (*0.53*)	0.99 (*0.54*)	0.97 (*0.54*)
14.4.1	**15.1.2.2**	0.95 (*0.53*)	0.92 (*0.52*)	0.91 (*0.53*)	0.89 (*0.54*)	0.88 (*0.53*)	0.89 (*0.55*)	0.87 (*0.53*)
15.1.2.2	**14.4.1**	0.95 (*0.51*)	0.94 (*0.53*)	0.93 (*0.54*)	0.92 (*0.55*)	0.92 (*0.55*)	0.91 (*0.57*)	0.90 (*0.57*)
15.1.1	**15.4.2**	0.88 (*0.53*)	0.87 (*0.54*)	0.88 (*0.55*)	0.87 (*0.56*)	0.87 (*0.57*)	0.85 (*0.54*)	0.88 (*0.56*)
15.4.2	**15.1.1**	0.89 (*0.52*)	0.88 (*0.51*)	0.87 (*0.53*)	0.90 (*0.54*)	0.88 (*0.53*)	0.91 (*0.53*)	0.90 (*0.53*)
15.1.2.2	**15.1.2.1**	1.00 (*0.57*)	1.00 (*0.57*)	1.00 (*0.59*)	1.00 (*0.58*)	0.99 (*0.58*)	0.99 (*0.58*)	0.97 (*0.58*)
15.1.2.1	**15.1.2.2**	1.00 (*0.52*)	1.00 (*0.53*)	1.00 (*0.53*)	1.00 (*0.54*)	0.99 (*0.52*)	0.97 (*0.52*)	0.98 (*0.53*)
15.1.2.2	**15.4.1**	1.00 (*0.73*)	1.00 (*0.71*)	1.00 (*0.69*)	1.00 (*0.67*)	0.99 (*0.66*)	1.00 (*0.65*)	0.99 (*0.62*)
15.4.1	**15.1.2.2**	—	—	—	—	—	1.00 (*0.55*)	0.99 (*0.52*)

Table A11. Overall interlinkages identified in relation to SDG–6 indicators for the different country samples generated.

SDG6–related links identified			Repetitiveness (%)						
			n=175	**n=160**	**n=145**	**n=130**	**n=115**	**n=100**	**n=85**
3.9.2 (mortality rate due to unsafe WaSH)	**3.1.1**	**Maternal mortality ratio**	100	100	100	86	91	90	83
	3.2.1	**Infant mortality rate**	100	100	100	100	100	98	88
	3.3.5	People requiring interventions against NTD	100	99	94	89	76	70	65
	6.2.1	Population using AT LEAST BASIC sanitation services	100	98	84	86	65	69	55
	7.2.1	Renewable energy share in total final energy consumption	85	51	42	28	32	28	29
6.1.1 (basic drinking water)	6.2.1	Population using AT LEAST BASIC sanitation services	99	87	70	68	63	60	50
	7.1.1	**Population with access to electricity**	100	100	100	96	95	82	80
6.2.1 (basic sanitation)	3.8.1	Universal health coverage (UHC)	84	80	74	63	60	57	53
	3.9.2	Mortality rate attributed to unsafe WaSH	100	98	84	86	65	69	55
	6.1.1	Population using AT LEAST BASIC drinking water services	99	87	70	68	63	60	50
	7.1.2	Population with primary reliance on clean fuels and tech.	94	64	60	59	51	50	47
6.4.1 (water–use efficiency)	3.8.1	Universal health coverage (UHC)	63	49	27	30	24	29	21
	6.5.1	Degree of IWRM implementation	89	62	52	38	38	32	30
	6.a.1	Total official development assistance (ODA)	100	100	100	99	95	96	87
	8.1.1	Annual growth rate of real GDP per capita	97	78	62	59	44	33	25
6.4.2 (freshwater withdrawal)	**5.5.2**	**Proportion of women in managerial positions**	100	100	99	97	94	84	68
	7.2.1	Renewable energy share in the total final energy consumption	62	49	56	51	46	47	48
	15.1.1	**Forest area as a proportion of total land area**	100	100	97	94	91	91	74
6.5.1 (IWRM)	6.4.1	Water–Use Efficiency	62	52	38	38	32	30	62
	10.1.1	Growth rates of household expenditure (bottom 40% pop.)	63	46	30	27	27	21	63
	15.1.2.2	Average proportion of KBAs covered by protected areas	83	69	62	53	46	37	83
6.a.1 (cooperation and capacity building)	3.1.1	Maternal mortality ratio	83	67	63	52	51	38	83
	3.3.5	People requiring interventions against NTD	66	71	60	58	49	51	66
	6.4.1	**Water–Use Efficiency**	100	100	99	95	96	87	100
	10.1.1	**Growth rates of household expenditure (bottom 40% pop.)**	98	93	88	78	65	57	98
	11.6.1	Municipal Solid Waste collection coverage	47	35	36	32	30	23	47
	12.2.1	Material footprint per capita – raw material –	98	94	82	82	61	55	98

In bold, those interlinkages identified as strong ones.

Table A12. Contingency tables associated with SDG–6 interlinkages identified (3.9.2 indicator is included as well). Results are obtained from the 179 countries considered within this study.

SDG 3.9.2: Mortality rate attributed to unsafe water, unsafe sanitation and lack of hygiene

	3.1.1				
3.9.2	**0-20**	**21-40**	**41-60**	**61-80**	**81-100**
0-20	24	10	0	0	0
21-40	1	23	1	0	0
41-60	0	8	11	5	0
61-80	0	2	19	11	3
81-100	1	0	5	20	35
Σ	26	43	36	36	38

	3.2.1				
3.9.2	**0-20**	**21-40**	**41-60**	**61-80**	**81-100**
0-20	5	10	16	3	0
21-40	0	2	10	13	0
41-60	0	0	2	11	11
61-80	0	0	0	2	33
81-100	0	0	0	0	61
Σ	5	12	28	29	105

	3.3.5				
3.9.2	**0-20**	**21-40**	**41-60**	**61-80**	**81-100**
0-20	24	10	0	0	0
21-40	15	10	0	0	0
41-60	2	16	2	3	1
61-80	3	11	9	5	7
81-100	0	1	10	20	30
Σ	44	48	21	28	38

	6.2.1				
3.9.2	**0-20**	**21-40**	**41-60**	**61-80**	**81-100**
0-20	13	14	7	0	0
21-40	2	5	12	6	0
41-60	0	1	1	9	13
61-80	0	0	1	2	32
81-100	0	0	0	2	59
Σ	15	20	21	19	104

	7.1.2				
3.9.2	**0-20**	**21-40**	**41-60**	**61-80**	**81-100**
0-20	28	3	3	0	0
21-40	10	6	5	3	1
41-60	1	1	5	6	11
61-80	0	2	3	4	26
81-100	0	0	0	5	56
Σ	39	12	16	18	94

SDG 6.1.1: Proportion of population using AT LEAST BASIC drinking water services

	6.2.1				
6.1.1	**0-20**	**21-40**	**41-60**	**61-80**	**81-100**
0-20	1	0	0	0	0
21-40	3	0	0	0	0
41-60	6	7	1	2	0
61-80	5	12	11	1	1
81-100	0	1	9	16	103
Σ	15	20	21	19	104

	7.1.1				
6.1.1	**0-20**	**21-40**	**41-60**	**61-80**	**81-100**
0-20	0	0	1	0	0
21-40	0	2	1	0	0
41-60	7	6	2	1	0
61-80	3	6	10	9	2
81-100	0	0	2	2	125
Σ	10	14	16	12	127

Continuation of Table A12.

SDG 6.2.1: Proportion of population using AT LEAST BASIC sanitation services

	3.8.1				
6.2.1	**0-20**	**21-40**	**41-60**	**61-80**	**81-100**
0-20	0	10	5	0	0
21-40	0	9	11	0	0
41-60	0	3	17	1	0
61-80	0	0	8	11	0
81-100	0	0	6	80	18
Σ	0	22	47	92	18

	3.9.2				
6.2.1	**0-20**	**21-40**	**41-60**	**61-80**	**81-100**
0-20	13	2	0	0	0
21-40	14	5	1	0	0
41-60	7	12	1	1	0
61-80	0	6	9	2	2
81-100	0	0	13	32	59
Σ	34	25	24	35	61

	6.1.1				
6.2.1	**0-20**	**21-40**	**41-60**	**61-80**	**81-100**
0-20	1	3	6	5	0
21-40	0	0	7	12	1
41-60	0	0	1	11	9
61-80	0	0	2	1	16
81-100	0	0	0	1	103
Σ	1	3	16	30	129

	7.1.2				
6.2.1	**0-20**	**21-40**	**41-60**	**61-80**	**81-100**
0-20	13	2	0	0	0
21-40	14	3	3	0	0
41-60	9	3	5	4	0
61-80	3	1	7	3	5
81-100	0	3	1	11	89
Σ	39	12	16	18	94

SDG 6.4.1: Water–Use Efficiency

	3.8.1				
6.4.1	**0-20**	**21-40**	**41-60**	**61-80**	**81-100**
0-20	0	0	1	2	4
21-40	0	2	2	26	10
41-60	0	7	20	48	4
61-80	0	10	22	12	0
81-100	0	3	2	4	0
Σ	0	22	47	92	18

	6.5.1				
6.4.1	**0-20**	**21-40**	**41-60**	**61-80**	**81-100**
0-20	0	1	0	2	4
21-40	1	10	10	9	10
41-60	3	35	23	17	1
61-80	2	24	14	4	0
81-100	2	5	2	0	0
Σ	8	75	49	32	15

	6.a.1				
6.4.1	**0-20**	**21-40**	**41-60**	**61-80**	**81-100**
0-20	6	0	0	0	1
21-40	30	1	3	6	0
41-60	14	5	5	33	22
61-80	1	0	5	17	21
81-100	0	0	0	4	5
Σ	51	6	13	60	49

	8.1.1				
6.4.1	**0-20**	**21-40**	**41-60**	**61-80**	**81-100**
0-20	1	0	1	5	0
21-40	0	0	11	28	1
41-60	2	1	20	55	1
61-80	0	1	14	26	3
81-100	0	0	0	9	0
Σ	3	2	46	123	5

Continuation of Table A12.

SDG 6.4.2: Level of water stress

	5.5.2				
6.4.2	**0-20**	**21-40**	**41-60**	**61-80**	**81-100**
0-20	14	6	1	0	0
21-40	1	1	0	0	0
41-60	3	11	0	0	0
61-80	3	15	3	0	0
81-100	9	95	17	0	0
Σ	30	128	21	0	0

	7.2.1				
6.4.2	**0-20**	**21-40**	**41-60**	**61-80**	**81-100**
0-20	19	0	1	1	0
21-40	1	0	1	0	0
41-60	12	2	0	0	0
61-80	15	3	1	1	1
81-100	31	35	19	20	16
Σ	78	40	22	22	17

	15.1.1				
6.4.2	**0-20**	**21-40**	**41-60**	**61-80**	**81-100**
0-20	21	0	0	0	0
21-40	2	0	0	0	0
41-60	6	6	1	1	0
61-80	7	12	1	1	0
81-100	33	32	35	16	5
Σ	69	50	37	18	5

SDG 6.5.1: Degree of integrated water resources management implementation

	6.4.1				
6.5.1	**0-20**	**21-40**	**41-60**	**61-80**	**81-100**
0-20	0	1	3	2	2
21-40	1	10	35	24	5
41-60	0	10	23	14	2
61-80	2	9	17	4	0
81-100	4	10	1	0	0
Σ	7	40	79	44	9

	10.1.1				
6.5.1	**0-20**	**21-40**	**41-60**	**61-80**	**81-100**
0-20	0	0	0	8	0
21-40	0	0	11	53	11
41-60	0	0	15	31	3
61-80	0	2	12	16	2
81-100	1	1	10	3	0
Σ	1	3	48	111	16

	15.1.2.2				
6.5.1	**0-20**	**21-40**	**41-60**	**61-80**	**81-100**
0-20	2	2	2	1	1
21-40	19	28	14	10	4
41-60	9	15	15	6	4
61-80	4	7	4	6	11
81-100	0	2	5	5	3
Σ	34	54	40	28	23

Continuation of Table A12.

SDG 6.a.1: Total official development assistance for water supply and sanitation

3.1.1

6.a.1	0-20	21-40	41-60	61-80	81-100
0-20	0	1	1	14	35
21-40	0	0	4	2	0
41-60	3	2	4	4	0
61-80	13	20	18	6	3
81-100	10	20	9	10	0
Σ	26	43	36	36	38

3.3.5

6.a.1	0-20	21-40	41-60	61-80	81-100
0-20	0	1	6	19	25
21-40	0	2	0	4	0
41-60	0	6	6	0	1
61-80	15	28	6	2	9
81-100	29	11	3	3	3
Σ	44	48	21	28	38

6.4.1

6.a.1	0-20	21-40	41-60	61-80	81-100
0-20	6	30	14	1	0
21-40	0	1	5	0	0
41-60	0	3	5	5	0
61-80	0	6	33	17	4
81-100	1	0	22	21	5
Σ	7	40	79	44	9

10.1.1

6.a.1	0-20	21-40	41-60	61-80	81-100
0-20	1	2	35	13	0
21-40	0	0	0	6	0
41-60	0	0	0	11	2
61-80	0	1	7	43	9
81-100	0	0	6	38	5
Σ	1	3	48	111	16

11.6.1

6.a.1	0-20	21-40	41-60	61-80	81-100
0-20	0	0	1	2	48
21-40	0	0	0	4	2
41-60	0	2	1	9	1
61-80	3	16	4	28	9
81-100	2	13	5	24	5
Σ	5	31	11	67	65

12.2.1

6.a.1	0-20	21-40	41-60	61-80	81-100
0-20	16	34	1	0	0
21-40	0	6	0	0	0
41-60	2	7	4	0	0
61-80	2	30	20	7	1
81-100	0	10	33	6	0
Σ	20	87	58	13	1

Table A13. Further contingency tables associated with SDG–6 indirect interlinkages identified. Results are obtained from the 179 countries considered within this study.

	9.4.1				
6.4.2	**0-20**	**21-40**	**41-60**	**61-80**	**81-100**
0-20	0	3	13	5	0
21-40	0	0	0	2	0
41-60	1	5	4	3	1
61-80	2	6	6	7	0
81-100	1	9	33	64	14
Σ	4	23	56	81	15

	16.5.2				
6.4.2	**0-20**	**21-40**	**41-60**	**61-80**	**81-100**
0-20	0	1	0	6	14
21-40	0	0	0	1	1
41-60	0	0	2	3	9
61-80	0	0	0	3	18
81-100	0	1	9	36	75
Σ	0	2	11	49	117

	14.5.1				
6.4.2	**0-20**	**21-40**	**41-60**	**61-80**	**81-100**
0-20	8	8	2	2	1
21-40	2	0	0	0	0
41-60	2	4	1	2	5
61-80	7	2	4	4	4
81-100	44	22	28	15	12
Σ	63	36	35	23	22

	15.4.2				
6.4.2	**0-20**	**21-40**	**41-60**	**61-80**	**81-100**
0-20	3	5	3	7	3
21-40	0	1	0	0	1
41-60	0	1	1	1	11
61-80	0	0	3	2	16
81-100	3	3	4	16	95
Σ	6	10	11	26	126