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Planning and Managing the Integrated Water System: A Spatial Decision Support System to Analyze the Infrastructure Performances

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Abstract: The demand for water is constantly increasing, while there are factors related to climate change and pollution that make it less and less available. Addressing this problem means being able to face it with a global approach, which takes into account that human beings need water to survive, as well as all the systems on which they rely, namely sanitation, health, education, business, and industry. While human behavior is influenced by the growing awareness on this topic promoted by organizations specifically targeting this mission, the need to protect water resources in operational terms has led mainly to the need for smart urban infrastructure planning, consistent with the objective of promoting sustainable development. To this aim, the authorities in charge of monitoring the implementation of the investment plans by operators need to perform accurate evaluations of the technical quality of the services provided. The present paper introduces a framework to design a Multi-criteria Spatial Decision Support System, conceived to help decision-makers define and analyze the investment priorities of the individual service operators. By building a knowledge model of the network under investigation, decision-makers are aware of physical components of the whole system and are provided with an intervention priority index related to the network objects that could be affected by the planning action to be implemented.

Keywords: integrated water service; Spatial Decision Support Systems; data-model; National Federated Infrastructure Information Service—SINFI; Regulation of the Technical Quality indicators—RQTI; Technique for Order Performance by Similarity to Ideal Solution—TOPSIS

1. Introduction

The water resource is an essential component in our daily life and an irreplaceable resource for all activities connected to urban development. Hence, the need to protect water resources and, at the same time, the duty to pursue a sustainable settlement development bring out the demand for the smart planning of water infrastructures.

In general, the planning system of urban infrastructures, at the regional and sub-regional scales, has an important spatial implication [1]. Moreover, the infrastructures require strategic and long-term investments as they are designed for many years of service, thus involving large capital expenditure. The water infrastructure system, in particular, as a complex sociotechnical system, is very difficult to address at its full extension. Indeed, the involved public values are many when dealing with the management of such a precious resource. Some of the most important that are used as references when dealing with planning and development of water infrastructures, are:

- Accessibility—Everybody needs fresh water;
- Affordability—Reasonable price for water;
- Environmental sustainability—Reasonable use of water;
- Efficiency of the infrastructure—Good service for a reasonable price of drinking water;
- Environmental Protection—Wastewater treatment mandatory for the protection of the ecosystems;
- Public health—Disposal and treatment of sewage for all urbanized areas.

When estimating these values, many issues can arise, due to critical conditions of water systems, detected both from an infrastructural and managerial point of view. There can be significant infrastructural deficits of sewage systems and water treatments. They refer to both the quantity and quality of infrastructures necessary to guarantee all citizens the service in an efficient manner. Moreover, the management efficiency assumes a significant level of criticality in terms of measurement and control. Hence, investments are needed to combine safety, quality and service continuity, environmental protection, and sustainable use of the resource [2]. However, due to the high level of criticality of the Integrated Water Service (IWS) infrastructures and the limited economic resources available, it is necessary to plan the investments by identifying the action priorities based on a system of adequate Key Performance Indicators (KPIs) developed to support decision-making.

1.1. Evaluating Performances of IWS Planning Actions

The planning actions are defined as the result of all anthropization processes that give rise to a geometric or a qualitative change of the water infrastructure (and components) state. Such actions can be grouped into three different classes according to their impact on the system, namely actions that create new objects, actions that can change existing objects, and actions that are meant to completely remove objects.

The resulting set of relationships among actions' effects is indeed very complex. Just imagine that individual actions can embed other actions, all sharing a common goal but discriminating among objects and components. The problem becomes more complex when the spatial component of objects composing the IWS is added. Then, the need to formalize these relationships emerges as they could contribute in choosing the set of specific actions by decision-makers.

The need of an evaluation system of the planning actions' impact on the IWS efficiency is satisfied by identifying a proper set of indicators for measuring the resulting IWS performances. However, the choice of such indicators is a complex and delicate operation. It depends on a set of requirements, such as precision, measurability, statistically documented accessibility and availability, regular updating, transparency and sensitiveness to changes in the monitored phenomena, relevance and potential use, representativeness of the scope to be analyzed, communicative immediacy, and comparability with a reference value that testifies its relevance.

Moreover, when pursuing a goal through planning actions, some KPIs can influence each other, independently of the nature and motivation of the objective [3]. Consequently, it is necessary to select and reduce them to a set of indicators that are controllable and significant and, then, to construct a composite index, which describes and synthesizes multidimensional concepts of different areas that cannot be captured by a single indicator [4].

Once the set of indicators has been identified, it is necessary to define the standardization procedure, the weighting system, and the aggregation function to obtain the composite index. Thus, the construction of such a conceptual framework is essentially a negotiation process in which several stakeholders express their sets of values and objectives [5]. As for the aggregation function, a recent study claims that the additive aggregation represents the most frequently used procedure with respect to the multi-criteria aggregation [6].

In order to monitor the impact of the actions proposed by the IWS operators (Water Companies—WaCo), ARERA, the Italian Authority responsible for the IWS regulation and control, has introduced a system of six macro indicators, addressed to measure the IWS technical quality [7]. For each Mi

macro-indicator, a threshold/target value is defined to reach an incremental improvement of the service quality, which must be progressively guaranteed by WaCo.

In addition to the set of macro-indicators, two ARERA directives specify two sets of indicators (KPIs) to identify the actions to be planned and programmed. The former is named KPI and can be used to measure the system performances. The latter is named C and can be used to determine the IWS critical points.

Each Mi macro-indicator cannot be considered a composite index as the aggregation function that links it to performance and criticality indicators is not made explicit. Moreover, each Mi macro-indicator allows formulating only a synthetic judgment about the whole set of actions that an investment plan puts in place, thus losing the distinctive spatial feature that instead plays a key role in defining and analyzing the investment priorities. The red double-headed arrow in Figure 1 represents the missing relationship among macro-indicators and IWS objects according to the current ARERA evaluation system. This lack makes it impossible to verify the effectiveness of the specific actions that spatially affect the individual IWS objects, nor to predict their effects on the value of the macro-indicators.

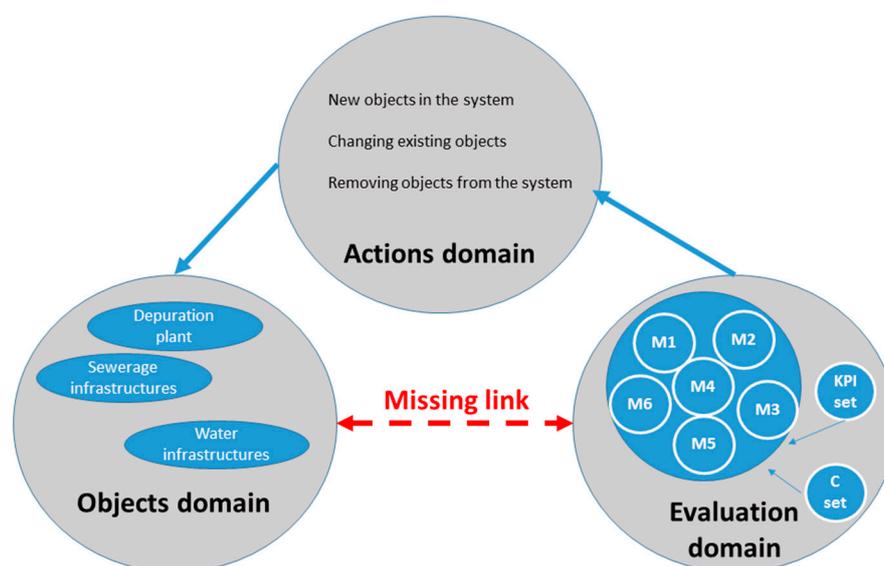


Figure 1. The Integrated Water System and the goal of this study: creating a link between the objects domain and the evaluation domain.

1.2. Aims and Scope

To meet the need to identify intervention actions priorities, this paper introduces a framework to build a Multi-criteria Spatial Decision Support System (MC-SDSS) addressed to derive a composite spatial index, which takes into account the evaluation domain proposed by the Italian legislation. This index specifies the intervention priority related to the network objects that are affected by the planning action.

The methodology is first based on the construction of a knowledge model of the network, according to the specification of the National Federated Infrastructure Information Service (Sistema Informativo Nazionale Federato delle Infrastrutture—SINFI). Then, it selects the spatialized parameters that affect the intervention priority and establishes the link between the evaluation domain and the domain of IWS objects (Figure 1). The resulting index supports decision-makers in planning interventions and, at the same time, controls the IWS performances in terms of technical quality.

As for the selection of the aggregation method for the composite spatial index, the choice depends on the issue to be investigated [8,9], and suitable motivations are required [10]. In the present research, the Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) method has been adopted

according to the ARERA directive, which selects it as the evaluation method to be applied for the WaCo performances.

The paper is organized as follows. Section 2 describes materials and methods applied during the design of the MC-SDSS. In particular, Sections 2.1 and 2.2 briefly describe the Regulation of the Technical Quality for IWS (RQTI) and for each service within it, and the SINFI specifications. Section 2.3 gives an overview of the existing methods and technologies for managing big data that has found their natural integration in Spatial Decision Support Systems. Section 2.4 describes the TOPSIS method. The methodology adopted for MC-SDSS construction is described in Section 3. Section 4 illustrates how TOPSIS-SDSS works when applied to the domain of the water infrastructures. In Section 5, the obtained results are discussed. Conclusions are drawn in Section 6.

2. Materials and Methods

The goal of this section is to briefly recall concepts and methods that have been used in the present research. In particular, besides the current regulation concerning the IWS technical quality as defined by ARERA [7], the SINFI specifications and the multi-criteria method are described.

2.1. Regulation of the IWS Technical Quality

The ARERA regulation model expresses selectivity, correlation, effectiveness, reward, progression, and stability in order to identify correct and effective incentives to promote benefits for users of different services in specific contexts. This model results from an extensive consultation [11,12] and is based on the following indicators:

- prerequisites—the necessary conditions for the admission to the incentive mechanism associated with the general standards;
- specific standards—performance parameters to be guaranteed for services provided to individual users where the noncompliance requires automatic indemnities;
- general standards—these parameters are broken down into macro-indicators and simple indicators, both describing technical conditions to provide a service by an incentive mechanism.

The macro indicators are listed in Table 1 along with a brief description.

Table 1. The list of the macro-indicators and their description.

Macro-Indicator	Description
M1	“Water losses” (to minimize losses, with effective monitoring of water infrastructure), taking into account both actual and percentage water losses;
M2	“Service interruptions” (to maintain service continuity, also through a suitable configuration of supply sources). It represents the ratio between the total length of interruptions in a year and the number of end users served by the supplier;
M3	“Quality of water supplied” (to ensure adequate quality of the resource for human consumption). It uses multi-stage logic, considering: (i) the incidence of non-potability orders; (ii) the rate of noncompliant internal samples; (iii) the level of parameters from noncompliant internal controls;
M4	“Adequacy of the sewage system” (to minimize environmental impact from wastewater). It uses multi-stage logic—considering: (i) the frequency of flooding and/or spills from sewers; (ii) the legal adequacy of flood drains; (iii) the control of flood drains;
M5	“Landfill sludge disposal” (to minimize the environmental impact of wastewater treatment, for sludge). It represents the ratio between the amount of sewage sludge measured dry that is disposed of in landfills and the total quantity of sewage sludge measured dry;
M6	“Quality of purified water” (to minimize the environmental impact of wastewater treatment, for the water line). This represents the rate of wastewater discharge samples exceeding the limits.

ARERA attributes each macro-indicator a weight in its reward/penalty assessment system in which all service operators are evaluated on a national scale. The Authority assigns the highest weight to the M1 macro-indicator, thus affirming that the efficiency improvement governance that it intends to pursue has the efficiency of the water sector of IWS as its priority [13].

These macro-indicators follow Annex 1 of the Directive presented in [14], which identifies the performance indices. Subsequently, based on Annex 4 of the Directive described in [15], it re-elaborates a new scheme of categories and criticality indicators.

2.2. National Federated Infrastructure Information Service

In order to increase knowledge about the infrastructures located on the Italian territory, specific investigations have been carried out, whose goal was both to define methodologies capable of supporting data modelling, and stimulate new actions to put them into practice.

At the international level, the recent Underground Infrastructure Concept Development Study (UICDS) Engineering Report examines the level of knowledge on the American underground infrastructure, and recognizes the importance of acquiring information about it to plan future opportunities for its improvement. Among a set of candidate models, the report recommends to develop the “Model for Underground Data Definition and Integration” (MUDDI), that is, an integration model prototype for information related to the underground infrastructures [16,17].

The study also highlights the relevance of data standardization as extremely important to support a series of primary business processes for the economy and society. Nonetheless, several obstacles still slow the creation of this data. Among others, the lack of standardized models useful for guiding the storage and development of existing databases and the opinion of the public and private sectors that the costs are too high represent an obstacle to achieving the benefits that could be brought to the system.

A similar scenario has occurred in Italy since 2016, when the SINFI implementation began, sponsored and supported by the Ministry of Infrastructures and Transport (Ministero delle Infrastrutture e dei Trasporti) [18–21]. SINFI was conceived as an instrument to coordinate the new broadband and ultra-broadband strategy, by sharing information about infrastructures and underground utilities [22]. SINFI provides users with a unique dashboard, which allows them to efficiently manage and monitor all interventions, although the underlying data model is not fully responsive to the needs of current companies managing IWS. The SINFI case studies represent best practices of coordination actions carried out by the Agenda per l’Italia Digitale (AgID), whose goal is to promote the use and sharing of thematic data models compliant with the national Database Geotopografici (DBGT—Topographic geodatabases) specifications [23]. Starting from the content of the “07—underground networks” layer of the DBGT specifications, the SINFI technical specifications represent a customized extension of them (Figure 2).



Figure 2. Contents of the Topographic geodatabases (DBGT) specific to the National Federated Infrastructure Information Service—SINFI.

2.3. Spatial Decision Support Systems

The growing usage of advanced data sources, such as GPS signal, smartphones, Internet of Things (IoT) [24], Web 2.0 [25], and the Copernicus program [26], is producing large amounts of data that contain spatial and temporal components, and semantic interrelations among them. The capability of translating such volumes of data into insights represents the current challenge that researchers have set to create knowledge from them by appropriate algorithms. In particular, research in the (geospatial) big data domain offers several and multipurpose methods and techniques, known as Advanced Analytics (e.g., predictive analysis, data/text mining, machine learning, sentiment analysis, neural networks), aimed at better understanding trends and getting insights from large amounts of data to finally perform decision-making tasks and obtain value from territorial knowledge.

A Spatial Decision Support System (SDSS) represents a solution towards the achievement of this goal. By combining conventional data, spatially referenced data and information, and decision logic, an SDSS supports decision-makers in analyzing data and presenting processed information in a friendly form [15]. SDSSs evolved and integrated models have been proposed in which new functionalities have been added from different disciplines, such as Business Intelligence processes available to identify a problem or an opportunity among those detected by the SDSS [27]. Two disciplines evolve from this approach, namely Spatial Data Science and Geospatial Business Intelligence. Spatial Data Science [28,29], also known as data-driven science, applies an exploratory approach focused on insight about current activities and foresight about future events. Its goal is to pose questions about spatial phenomena and scenarios and identify potentially new lines of research, that is, it focuses more on asking questions than finding specific answers. Spatial Data Science incorporates tools from multiple disciplines, such as mining, statistics, machine learning, analytics, and programming. In particular, machine learning plays a paramount role in this field as it finalizes the decision model derived from predictive analytics by matching the likelihood that an event occurs to what actually happened at a predicted time.

Geospatial Business Intelligence (GeoBI) aims to explain current or past behavior by aggregating and grouping historical data. It is business intelligence that makes use of geospatial information. In particular, it combines GIS and Business Intelligence technologies to better support data analysis processes and help users make more efficient decisions [30]. GeoBI offers solutions to identify schemas underlying relevant trends and correlations among spatial parameters within a complex (un)structured, historical/current dataset. It focuses on specific questions that need to be answered. When applied to sets of data derived from a territory, GeoBI, known as Territorial Intelligence (TI), integrates computer intelligence with human collective intelligence to achieve a sustainable development for any territory through its local administrations and local politicians [31]. In particular, it supports users to create connections among apparently different fields by exploiting territorial peculiarities [32,33], to produce innovation and create cross-fertilization.

2.4. The GeoTOPSIS Multi-Criteria Technique

TOPSIS is a multi-criteria technique, developed in 1981 by Hwang and Yoon [34], that introduces a ranking index based on the distances from the ideal and anti-ideal point [35].

The ideal solution allows maximizing the benefit criteria/indicators and minimizing the cost criteria or sub-criteria. On the other hand, the anti-ideal solution maximizes the cost criteria/indicators while minimizing the benefit ones [36,37]. TOPSIS establishes that the alternative with the best performance corresponds to the one having the minimum distance from the ideal alternative and the maximum distance from the anti-ideal alternative [38].

The TOPSIS algorithm involves different stages. The starting point is the definition of the decision matrix D . The performances of m alternatives i with respect to criteria j are collected in the decision matrix:

$D = [x_{i,j}] m \times n$, where $x_{i,j}$ is the original value of the indicators of the i -th alternatives (A_i ; $i = 1, \dots, m$) with respect to the j -th criterion (C_j ; $j = 1, \dots, n$).

The second step concerns the normalization of the decision matrix D . To eliminate the effect of the different units of measure, the performances of the different criteria/indicators are normalized. Literature shows that, by using any linear normalization technique, the final ranking does not undergo significant distortions [39,40]. Therefore, the technique of linear standardization to unitary standard [1] is adopted:

$$v_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m r_{ij}^2}} \quad (1)$$

Once the matrix has been normalized, each column is multiplied by the respective weight w_j . This leads to determining the ideal and the anti-ideal solution. The ideal solution is determined by considering, for each criterion, the best performance offered by the alternatives in play. The anti-ideal solution is obtained by combining the worst performances of the alternatives with respect to each criterion. The term “best” performance means the maximum and the minimum value offered by the alternatives, when referring to a benefit criterion and a cost criterion, respectively. Vice versa, it applies to the definition of “worst performance.”

$$\overline{d}_i^+ = \left[\sum_j (\overline{v}_{ij} - A_j^+) \right]^{\frac{1}{2}} \quad (2)$$

$$\overline{d}_i^- = \left[\sum_j (\overline{v}_{ij} - A_j^-) \right]^{\frac{1}{2}} \quad (3)$$

Each (real) alternative A_i and two (virtual) alternatives can be understood as a point in a m -dimensional space (where m is the number of criteria), where the generic j -th axis measures the normalized and weighted performances (of the type v_{ij}) of the considered alternative with respect to criterion C_j .

Finally, the relative proximity to the solution is calculated by the formula:

$$RS_i = \frac{\overline{d}_i^-}{\overline{d}_i^+ + \overline{d}_i^-} \quad (4)$$

The proximity coefficient (RS) assumes values between 0 and 1, and the more its value tends to 1, the better the position occupied by the alternative in the ranking, as it approaches the ideal point. On the other hand, values tending to 0 indicate that the alternative is closer to the anti-ideal solution. The advantage of the TOPSIS method is twofold. It requires only a limited number of inputs and the results are easy to understand also by decision-makers [39,40].

In the present paper, the research exploits the Geo-TOPSIS method as introduced in [41], where the alternatives are characterized by a geographical component (geo-alternatives).

3. The Methodology for Designing a SDSS

The methodology presented in this paper aims to satisfy the needs of the IWS planning, which translates into the need to identify investment priorities with reference to the different sectors of water services, also in relation to their compliance with the technical quality objectives. The six macro-indicators of Table 1, in fact, identify the performance objectives that IWS is requested to achieve with respect to the threshold values determined by ARERA. In particular, the proposed methodology is aimed at developing an SDSS that supports the analysis and display of large amounts of data to help decision-makers monitor performances [42].

The methodology includes the construction of an MC-SDSS framework by TOPSIS that allows the construction of a map containing the geolocated investment priorities.

It is divided into the following macro-phases:

- macro-phase 1: construction of the knowledge domain;
- macro-phase 2: construction of the evaluation domain through the selection of a set of decision criteria measured by spatialized performances;
- macro-phase 3: construction of the domain of choices by mapping critical issues and selection of investment priorities.

Figure 3. summarizes the basic steps to follow to implement the given methodology.

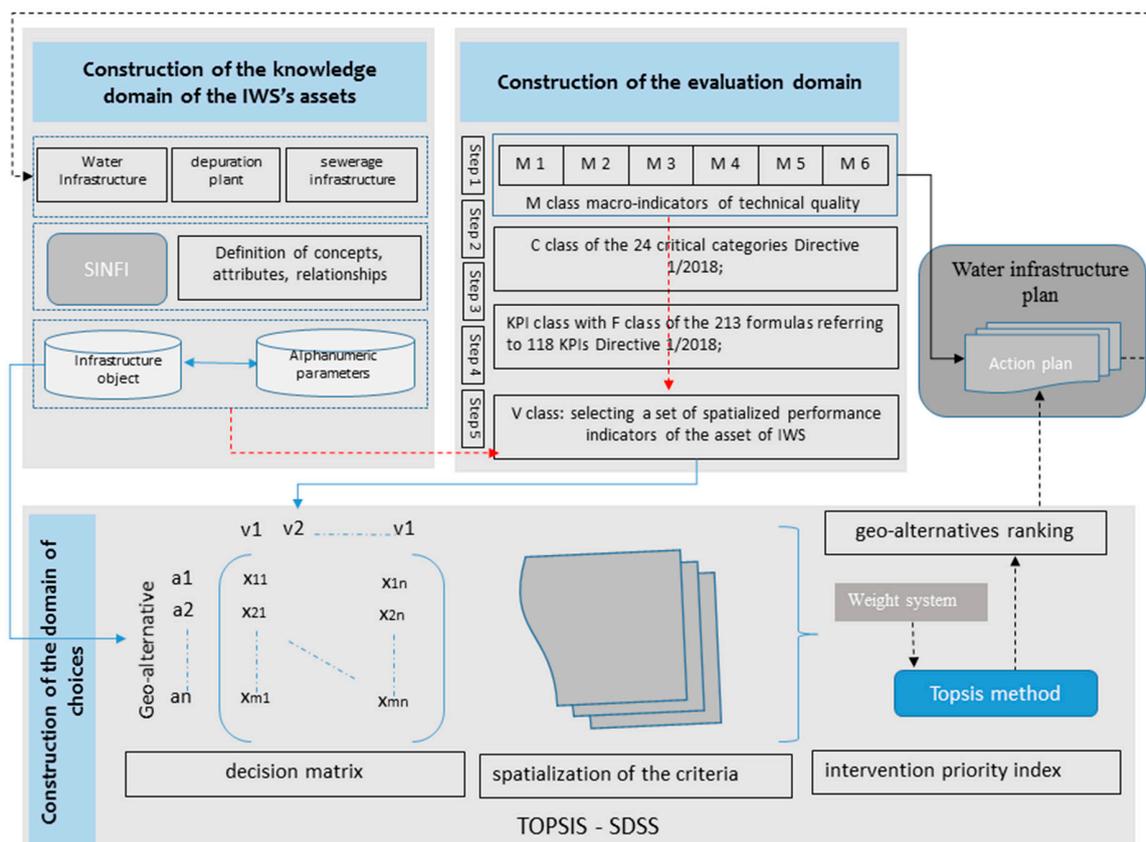


Figure 3. A summarized framework of the methodology.

3.1. Macro-Phase 1

In the first macro-phase, a model is defined to structure knowledge of the IWS assets in line with the SINFI model.

Starting from the content specifications of the information level 07, an ontology-based approach is carried out to create the hierarchy of two macro classes relating to the water supply network and the water disposal network. Subsequently, the membership relations between the IWS's base objects (geometrically represented by arcs and nodes of a graph) and the identified classes with their attributes are built (Figure 4). The goal is to detect the objects and their properties on which planning interventions will act, and make explicit their impact on the performance indicators and their corresponding M_i macro-indicators.

3.2. Macro-Phase 2

The objective of the second macro-phase is the construction of the assessment domain by selecting a set of decision criteria represented by the spatialized performance indicators of the IWS asset status.

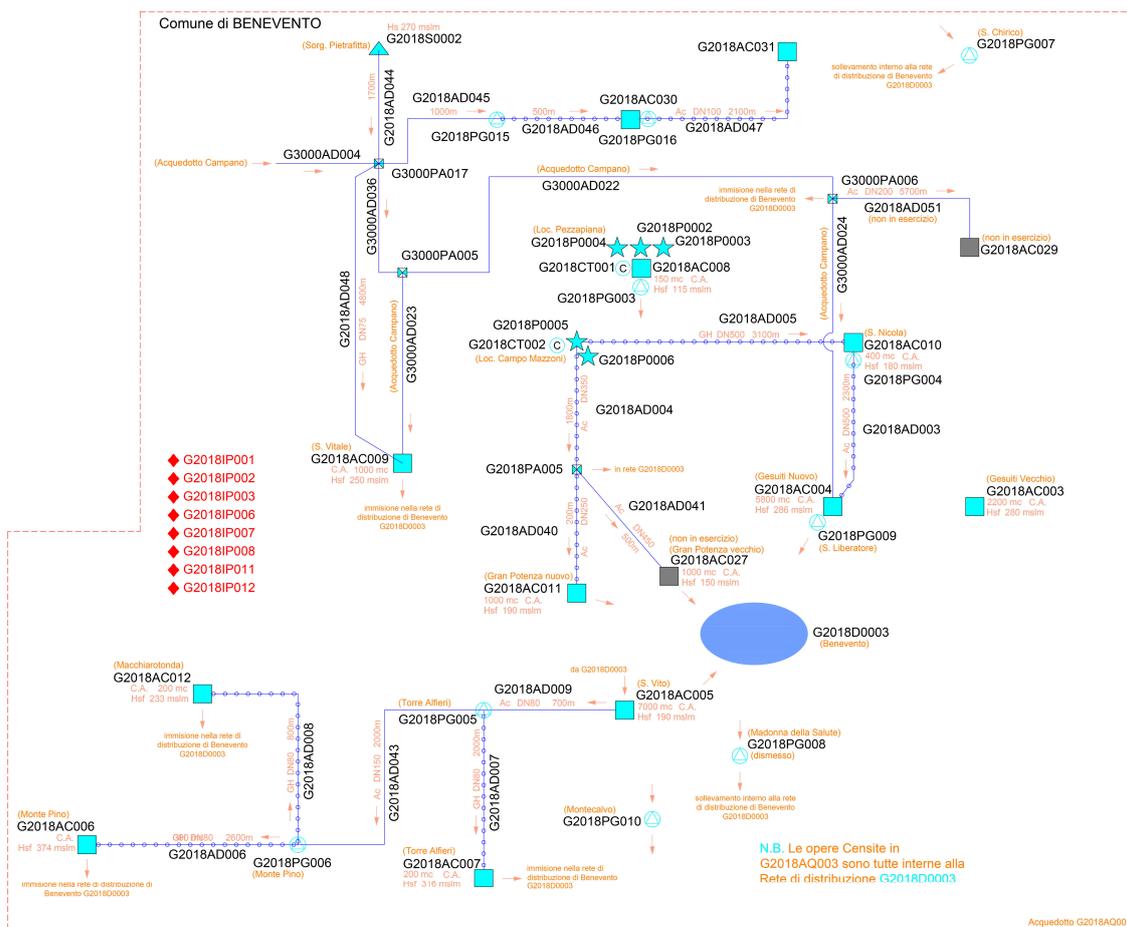


Figure 4. The objects of the IWS asset.

To select these indicators, the steps to be followed are meant to derive:

1. the representation of the relations between the M class of the technical quality macro-indicators and the C class of the critical categories catalogued in Annex 4 of Directive 1/2018 [15];
2. the representation of the relations between the previous C class and the KPIs detailed in Directive 2/2016 [14];
3. the representation of the relations between the KPI class and the F class of the n-formulas referring to the same KPIs;
4. the representation of the relations between the F class and the V class of the variables belonging to the same formulas;
5. the representation of the relations between the M and V classes. The frequency of each variable describes the weight that each of them expresses with respect to the variation of each Mi macro-indicator. Afterwards, the V variables are correlated at the spatial type attributes of the object class of the network data model, thus identifying the performance indicators.

3.3. Macro-Phase 3

The third macro-phase is made up of three steps. Based on the results of the previous macro-phase, the first step is addressed to the construction of the decision tree for the definition of the priority classification of the geo-alternatives on which to apply the actions. Here, a geo-alternative corresponds to an object of the IWS infrastructure. The second step performs the criteria spatialization [43,44], by using spatial analysis techniques in the underlying GIS environment. Through a multi-criteria approach based on the Geo-TOPSIS method, the third step involves the construction of the intervention priority index [45] as the proximity coefficient associated with each geo-alternative.

The TOPSIS method has been chosen for two reasons. First, it is included in the Directive established by ARERA to program and evaluate the performances of an operator starting from the M macro-indicators. Then, it helps users with different expertise understand results.

4. Analyzing the Water System of a Municipality: A Case Study

The goal of this Section is to show how the methodology previously described works. To this aim, it was applied to a specific case study, namely the IWS of the Municipality of Solofra (Southern Italy) (Figure 5). The water network of this town was characterized by a 60% level of water losses. This implied the need to identify actions for network restructuring to be included in the Investment Program (2019–2023).

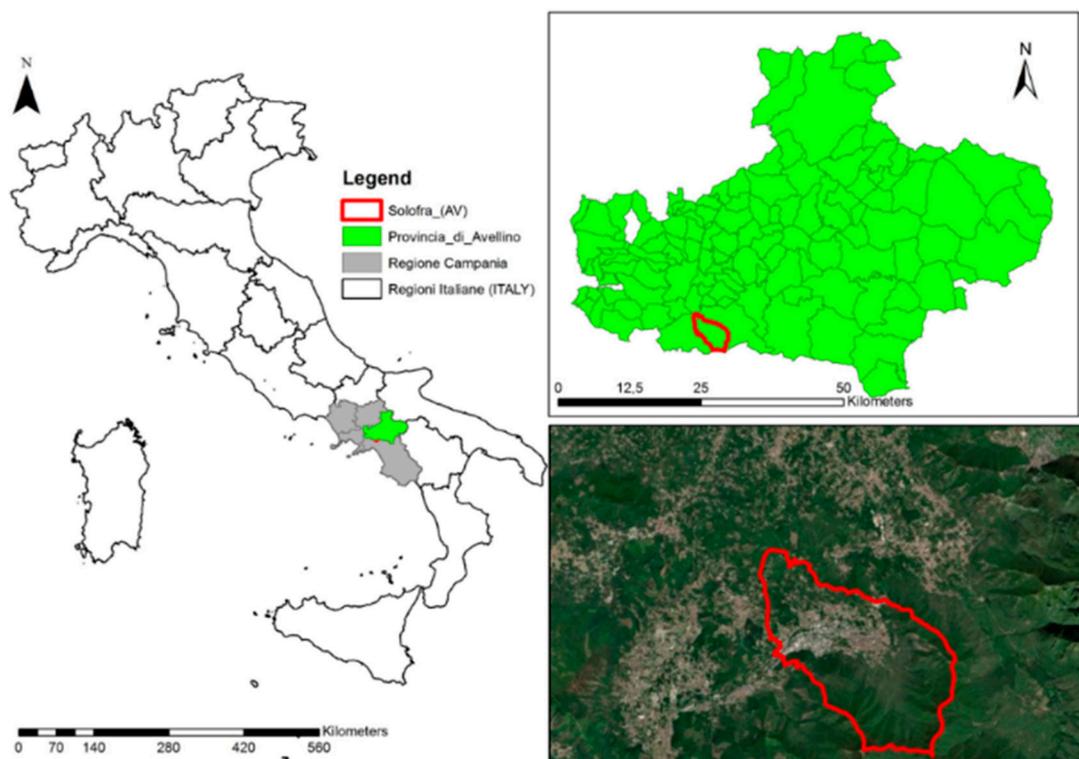


Figure 5. The Municipality of Solofra (Southern Italy).

The application of the first macro-phase took into account all IWS objects; the application of the second macro-phase took into account all Mi macro-indicators, while the application of the third macro-phase was focused on the intervention priorities concerning the water loss M1 macro-indicator.

4.1. Macro-Phase 1

To define the standard data storage model, an ontology-based architecture was used according to a Semantic Web approach [46–54].

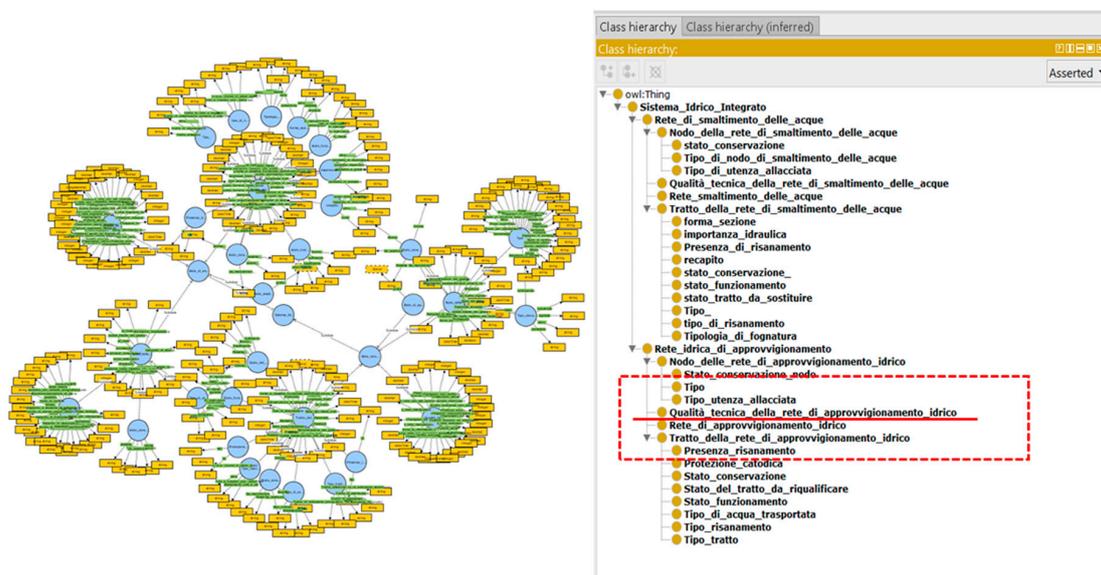
The first step of the adopted methodology consisted of identifying the objects. IWS was associated to the information layer “07,” which is divided into two themes (macro-classes), namely water supply network and water disposal network. Each theme embeds three classes, namely line, node, and network, as shown in Table 2. While the network class includes concepts referring to the network as a whole, the first two themes are associated to the geographic elementary units that outline the network.

Table 2. Classes: line, node, and network.

Theme	Classes
theme 01: Water supply network (0701)	class 01: Section of the water supply network (TR_AAC-070101) class 02: Node of the water supply network (TR_AAC-070102) class 03: Water supply network (TR_AAC-070103)
theme 02: Water disposal network (0702)	class 01: Section of the water disposal network (TR_AAC-070201) class 02: Node of the water disposal network (TR_AAC-070202) class 03: Water disposal network (TR_AAC-070203)

Then, the reference manuals of the water infrastructure engineering led to identifying the attributes able to characterize the IWS structure. Although it is not possible to examine details, Figure 6 is useful to show the complexity of the domain in terms of resources and properties. Along with geometric features, specific attributes were added according to both the performance indexes and the six technical quality macro indicators, as follows:

- responsible for the operation of the network;
- position and localization;
- typology and function of nodes and traits;
- environmental conditions;
- year of construction;
- operating status and physical conditions;
- survey date;
- type of user connected to the network;
- state of the elements to be maintained or replaced;
- length and working pressure of the pipes.

**Figure 6.** Data model visualization, Class hierarchy and RQTI class (in red) [46].

The cognitive map shown in Figure 6 was used to verify the consistency of concepts. The result was translated into a SINFI-compliant catalog organized as a data storage model. Each attribute had an alphanumeric coding representing its unique and distinctive semantic number, such as ND_AAC_TY that indicates the type of water supply network node, and TR_SAC_TY indicating the type of section of the disposal network of water (Figure 7).

07010106	TR_AAC_MAT	Materiale [1..n]	Enum (Materiale)	aTratti su	Tracciato
		Tipologia di materiale			
07010108	TR_AAC_PRO	Profondità [0..1]	Enum (Range di profondità)	aTratti su	Tracciato
		Range di profondità cui è posato l'oggetto			
07010104	TR_AAC_DIA	Diametro	Integer	aTratti su	Tracciato
		Diametro nominale/diagonale della sezione [mm]			
07010131	TR_AAC_LUN	Lunghezza tratto	Real		
		Indica la lunghezza del tratto in km			
07010132	TR_AAC_ABI	N°abitanti	String(50)		
		Indica il numero di abitanti servito dal tratto			

Figure 7. Example of attributes and their SINFI-compliant alphanumeric coding [35].

4.2. Macro-Phase 2

The second macro-phase was addressed to construct the assessment domain. For the indicators selection, the PoWer Business Intelligence (PWBI) environment was used [43], which is a BI software that allows generating information from large amounts of data. To explain the individual steps of this macro-phase, a particular technique was adopted for representing related data, namely a “sankey” graph, where the thickness of a relationship represents its frequency between the elements of the corresponding classes. In this case, it was possible to highlight the link between the M class and the most representative variables of the V class. The analysis followed the steps previously described and the intermediate results are included in Appendix A.

Step 1 consisted of representing the relations between the M class of the technical quality and the C class of the 24 critical categories catalogued in Annex 4 of Directive 1/2018 (Appendix A: Figure A1).

Step 2 consisted of representing the relations between the previous C class and the 118 performance indexes of the KPI class detailed in Directive 2/2016 (Appendix A: Figure A2).

The third step consisted of representing the relations between the KPI class and the F class of the 213 formulas, referring to the same 118 KPI elements (Appendix A: Figure A3).

The fourth step consisted of representing the relations between the F class of the 213 formulas, and the V class of the 279 variables belonging to the same formulas (Appendix A: Figure A4).

The fifth step summarized relationships between the M and V classes (Appendix A: Figure A5). It was also possible to analyze the frequency of each variable, which represented the weight expressed as variation of the Mi macro-indicators.

The V variables were correlated by considering the spatial type attributes of the object class, related to the data model of the water network as described in Figure 6. Their direct contribution to the data management was also taken into account.

Figure 8 summarizes the whole analysis, from which it emerged that some variables were not directly reflected in spatial attributes and/or elements (Group NN), while the recurrent variables were related to the following attributes:

- age of conduct;
- material;
- diameter of the pipe;
- length of the network section;
- the hydraulic load under static conditions on each node and section of the network;
- number of users served by each arc of the network.

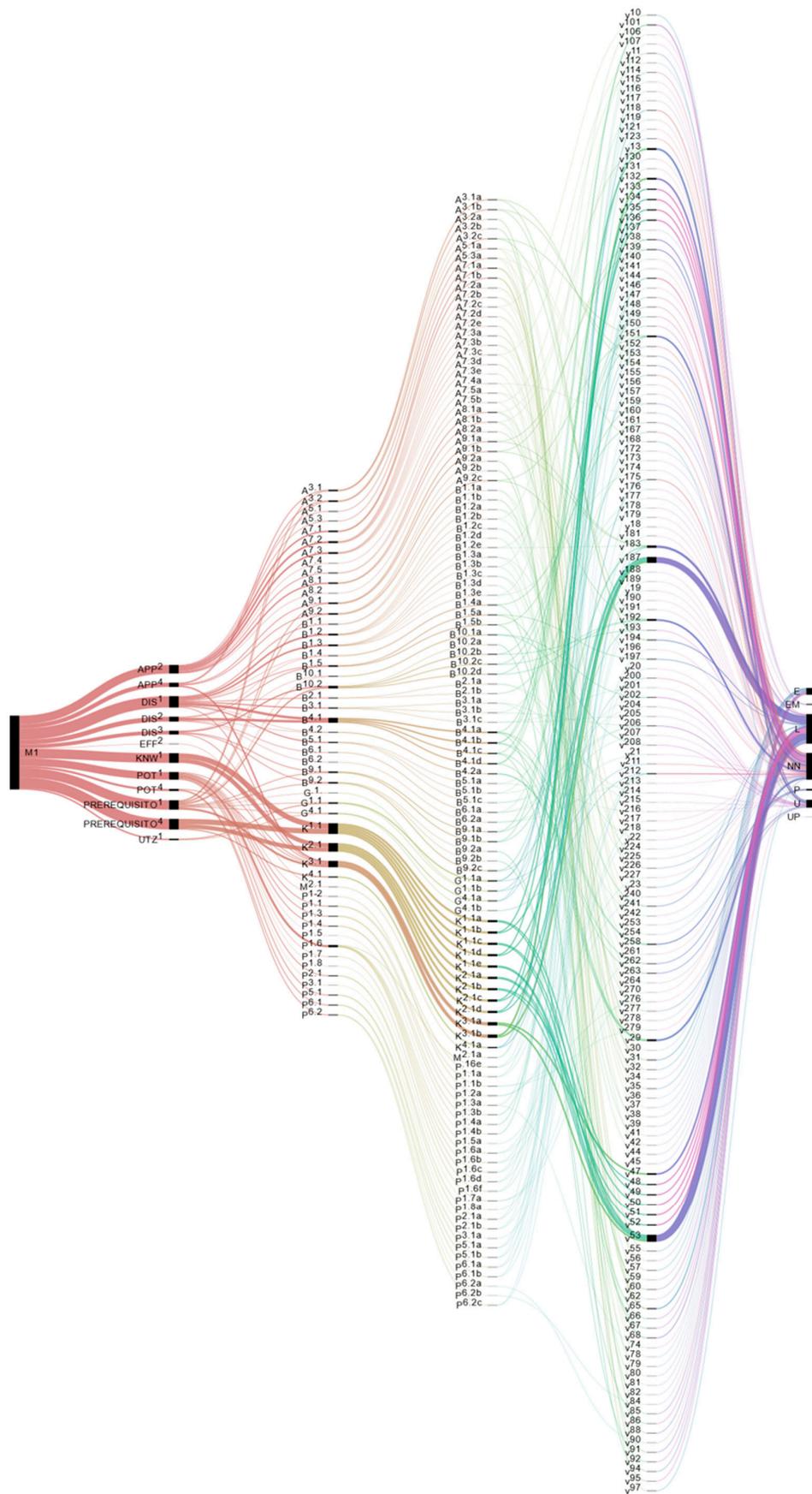


Figure 8. Schematization of all relations between M and V classes.

4.3. Macro-Phase 3

The third macro-phase consisted of three steps. The first one was addressed to build the decision tree for the definition of the priority ranking of the geo-alternatives on which the planning actions should have been applied. Specifically, the attributes selected in the previous phase were in turn associated to three clusters. The first cluster (CL1) related to the geometry and the constituent material, the second (CL2) referred to the hydraulic conditions, and the third (CL3) concerned the degree of service coverage.

These clusters allowed deriving the decision tree in relation to the goal, which, in line with M1, turned out to be the identification of the network arcs to which a priority should have been given to minimize network losses. The decision tree included the following three criteria:

- CL1: This criterion allowed establishing that an arc of the water network maximizes losses when its length and diameter increase, age increases. Moreover, it depends on the type of material (cast iron/steel/plastic).
- CL2: This criterion allowed establishing that a stretch of network maximizes losses when the pressure within its individual arcs and nodes increases.
- CL3: This criterion allowed establishing that a section of the network maximizes losses when the number of users served increases.

The second step performed the spatialization of the criteria, by using spatial analysis techniques in the GIS environment.

As for CL1, the age of the pipeline, the material (cast iron/steel/plastic), the diameter of the pipe, and the length of the network section were spatialized for each arc of the network (Figure 9).

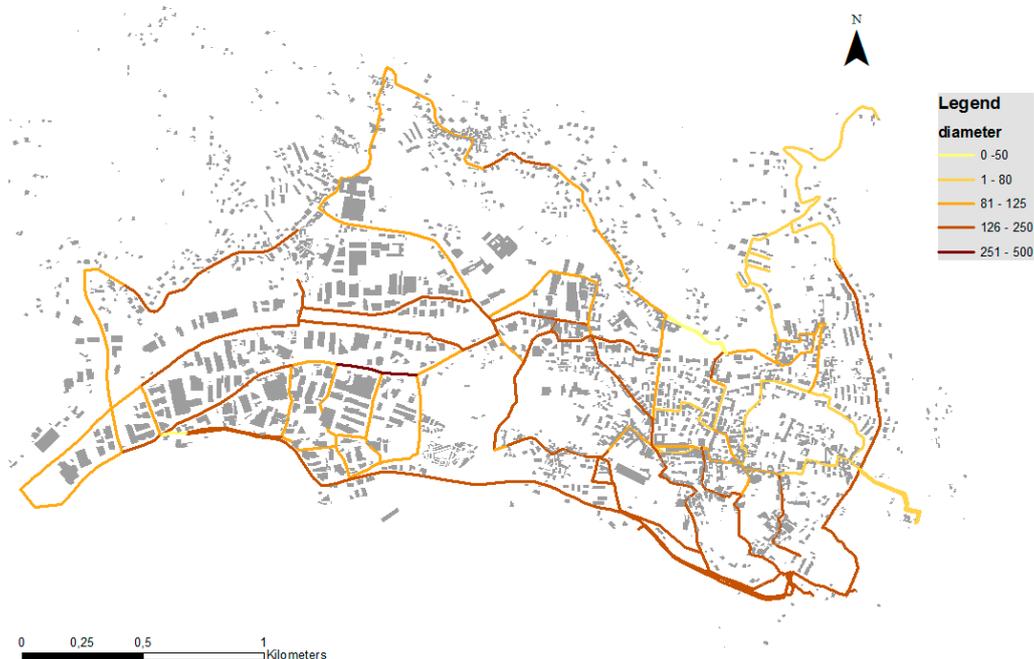


Figure 9. Spatialization of variables related to CL1.

As for CL2, which concerned the hydraulic characterization of the network, a map of the load distribution was built under maximum pressure conditions. In particular, the hypothesis of static load was used, which was assessed with reference to the difference in height between the free surface of the head tank, to which the i -th network arc belongs, and the elevation of the same arc obtained as the average of the elevations at those nodes.

Through the construction of a graphic modeler, a set of spatial functions were implemented that can estimate the area of influence of each tank. Starting from the digital terrain model (DTM), it was

possible to derive the difference between the altitude of the reservoirs and the altitude of the soil, thus estimating the static load on each node of the network (Figure 10).

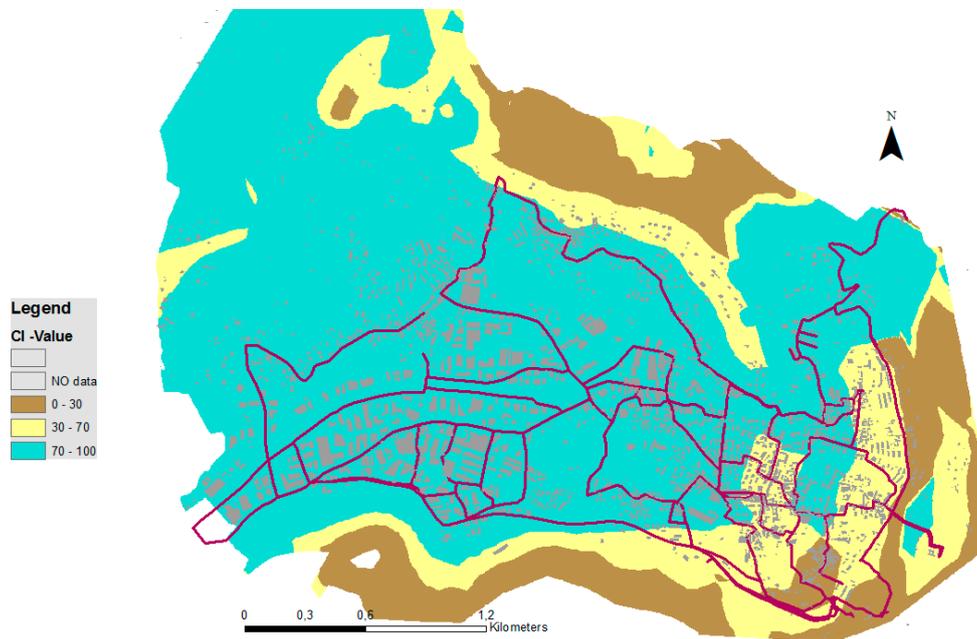


Figure 10. Spatialization of variables related to CL2.

As for CL3, the number of users served by each arc of the network was estimated. By using the QGIS graphic modeler, the area of influence of the network was identified, according to each arc, through a proximity function that identified the buildings covered by the service and hence the inhabitants served (Figure 11).

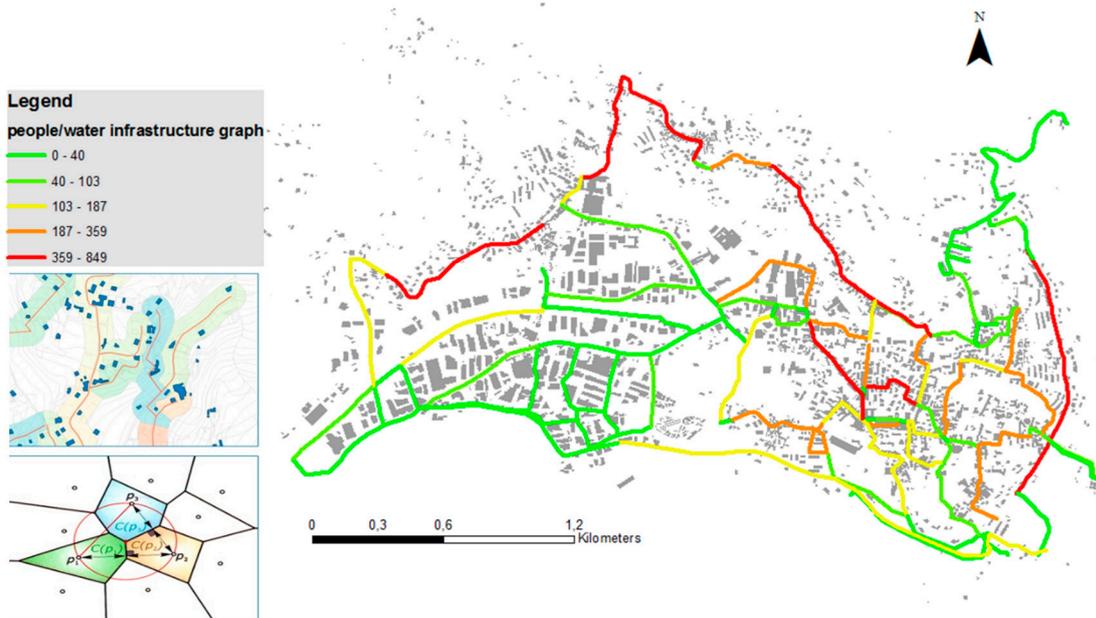


Figure 11. Spatialization of variables related to CL3.

Each geo-alternative, consisting of the *i*-th arc of the network, was described by an alphanumeric record, representative of the selected criteria, containing the related attributes (length of the sections, diameter, hydraulic load, age, material, and population).

Starting from the hypothesis that the lower the value assumed by these attributes the better the condition of the water network arc assessed with respect to the M1 macro-indicator (minimization of water losses), the construction of the decision matrix and its normalization were carried out, by assigning each criterion to the corresponding cluster. Then, a weight was associated, equal to the sum of the frequencies previously calculated for each attribute (Figure 12).

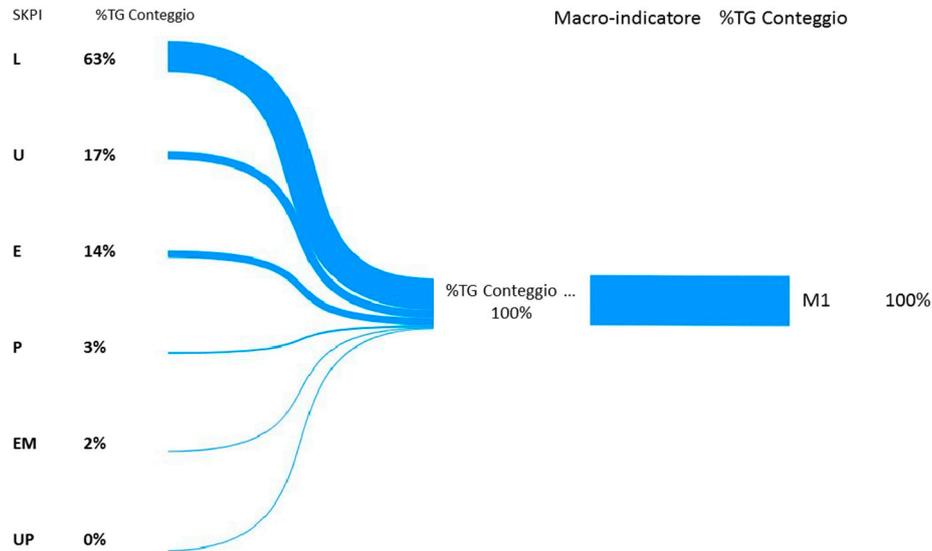


Figure 12. Sum of the frequencies calculated for each attribute.

The ranking obtained between the different geo-alternatives (Figure 13) assigned a greater probability of loss for the network arcs where the distance from the anti-ideal solution was smaller (smaller index). This solution was characterized by longer sections of the water network, with a larger diameter, subjected to a greater hydraulic load and more served areas.



Figure 13. Ranking map of the geo-alternatives.

5. Results and Discussion

Figure 13 shows the SAFE interface that embeds the model proposed in [55]. Built as a decision support tool, SAFE can be used in several domains, from social and institutional to emergency and health [56,57]. It is based on the awareness that the environment and citizens are important “data sources,” which constantly provide relevant information for better urban planning.

The module described in this paper extends the decision support functions to the IWS infrastructure sector. It allows monitoring all critical issues related to the IWS management, optimizing the planning of interventions, and supporting the preparation of the investment plan, thus globally improving the service performances. In fact, according to the criteria/attributes of the identified decision tree, the methodology has made it possible to identify the ranking between the different arcs of the network. Furthermore, for the same ranking class, thanks to the dynamic display of the individual parameters, the system also allows evaluating the types of intervention to implement the selected action.

Finally, the use of a dynamic system for representing critical issues in a PWBI environment also allows both visualizing the information in a way understandable even to non-expert users, and making decisions to intervene in a complex system of actors, such as IWS. Indeed, the evaluation of the intervention priorities on the IWS is a complex and multidimensional problem that requires the integration of multiple indicators to form composite indices.

The main contribution of the present research has been the introduction of a method to build a composite index based on TOPSIS, which is widely used in multi-criteria frameworks, thanks to its ease of implementation and ability to consider an unlimited number of alternatives and criteria.

As for the weighting method, the proposed methodology has overcome the subjectivity of the selection, which is usually based on an ongoing discussion with the decision-makers. In fact, the methodology treats the weights as coefficients of relative importance and quantifies them as a function of the frequency of occurrence of the relations of the spatial variables with respect to the macro-indicators (Figure 12).

As for the aggregation method, TOPSIS represents a compensatory method. It uses linear functions, such as the arithmetic mean that is the most common scheme used in the development of composite indicators [58,59]. The main advantage is that it can be easily replicated, but at the same time, it neglects the imbalances between the sub-indicators and the composite index, which could lead to changes in the identified priority ranking [60]. To limit this problem, a Constant Elasticity of Substitution [61] can be introduced to generate the distances to ideal and anti-ideal solutions. In this way, different levels of compensation can be obtained between the individual indicators of the scoreboard, thus mitigating the effect of the spatial correlation. Moreover, by deriving the composite index also for evaluating the sewer and purification assets, the strengths and weaknesses of the performances of the entire IWS can be estimated.

Finally, in the described case study, the identification of the intervention priorities to renew the network and reduce water losses in favor of the environment allows for guiding the investment plan, which should be compliant with the regional water infrastructure plan. To implement such a plan, different approaches can be followed: among others, promoting higher political grants for this investment, providing direct financial support for the investment, and pushing ARERA to distribute the investment on the water tariff collected by WaCo. These different approaches depend on the actors of the system, who deal with those issues differently and with different solutions [62–65]. Indeed, although the public value of the water resource is shared by all subjects, they try to maintain their position and responsibility by letting others solve the problem.

The proposed system supports the formulation of the problems from different points of view (actor), allowing to better understand the gap between the existing perceived situation and the desired situation by including ideas on causes and possible solutions.

6. Conclusions and Future Work

Within the recent regulation of the IWS technical quality, the commitment to contain water losses, with effective control of the aqueduct infrastructure, is associated to the M1 macro-indicator. This indicator jointly takes into account both linear water losses (identified by M1a) and percentage losses (identified by M1b). However, this characterization does not allow making the issues analyzed by the ARERA control model explicit, as this latter is based on the measurement of the variation of macro indicators between the planning of investments and the verification of their implementation. In the planning phase, it is necessary to identify a set of investments that allow the achievement of the objectives in terms of M_i variation. Since the current structure of the method does not allow taking into account the measure of the effects that the i -th investment, related to the j -th IWS object, brings to the macro-indicators, the investment plan is elaborated by noncodified methodologies for evaluating their variation. Furthermore, during the control phase, the reward/penalty mechanism, in verifying the achievement of the objectives, does not allow, for the above reasons, to make explicit the greater or smaller contribution (relative efficiency) made by individual investments. This implies a strong limitation on the introduction of corrective actions on investment planning, and therefore on the effectiveness and efficiency of the IWS.

In the proposed SDSS, all the connections that the variables of the macro-indicators develop on the KPIs and on the physical objects have been made explicit. In fact, the interconnection between the Physical and the Evaluation domains with the link explanation allows a more effective forecast of the possible effects of the investment already in the planning phase. It will be then possible, *ex post*, to trace back to the overall investments made to contribute to improving performances in terms of technical quality. Moreover, it will be possible to identify IWS individual objects on which the investments have had a positive impact. In this way, the model allows the identification of the assets, which, if affected by an appropriate investment, allow maximizing, with the minimum expense, the effects on the macro-indicators, and therefore the achievement of the planning objectives set by ARERA.

The proposed data model, developed through a SINFI-based approach, makes explicit the interoperability logic foreseen for spatial data by the INSPIRE directive [66]. This allows IWS operators to reduce the time and costs of updating, producing significant effects to face various critical problems related to the management of the system itself. In fact, in the following phases, the proposed data model could represent the ARERA coding for the assessment/forecast methodologies of the indirect effects that the variation of the variables of the individual KPIs determines on the macro-indicators. However, the biggest concern lies in the limited capacity by IWS operators to invest in knowledge of networks. This limit is reflected in the lack of data necessary for the macro indicators processing, thus making the RQTI a scarcely effective tool to direct the planned investments towards efficient and effective solutions. The methodology presented in this paper represents an initial proposal to support modeling of planning actions.

As future work, the goal is to extend the proposed methodology to other IWS sectors, *i.e.*, the sewage and water treatment sectors, also by experimenting different methods to build the composite index, such as AHP [67]. Moreover, further developments require more sophisticated considerations on the assumptions of planning actions. These actions must be modeled as prototypes by specialists, so that planners can perform them on virtual models of water infrastructures and can estimate the real impact on macro-indicators, as well as on KPIs. By analyzing the resulting impacts, the prototypes of actions can be validated and transformed into specific actions to be incorporated in the Investment Plan.

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Appendix A

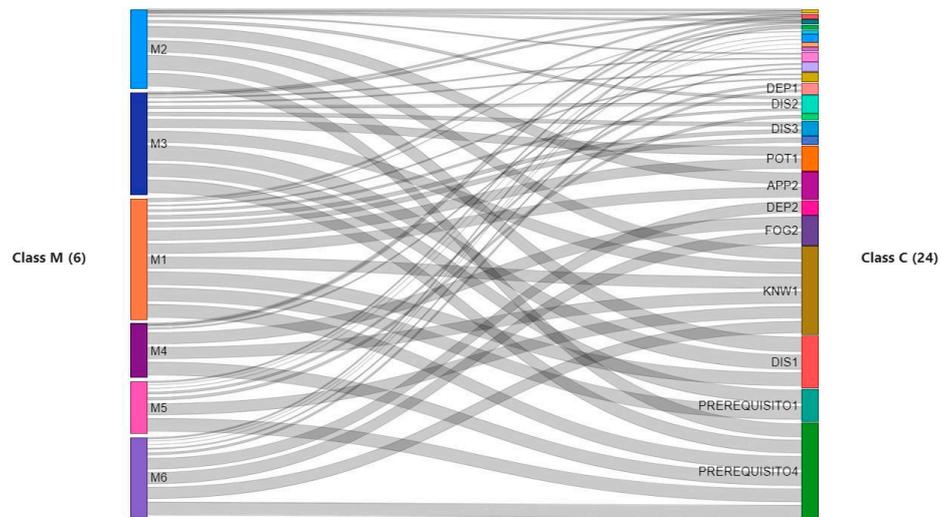


Figure A1. Relations between the M class and C class.

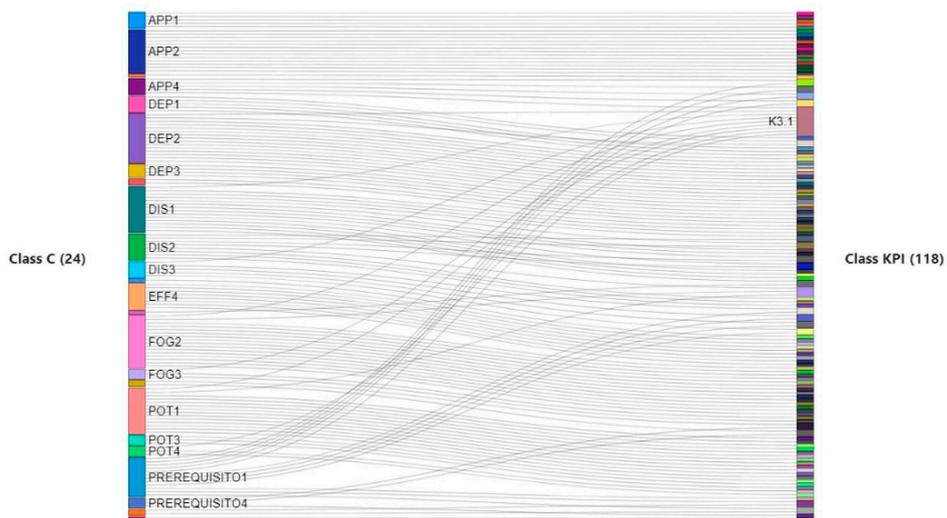


Figure A2. Relations between the C class and KPI class.

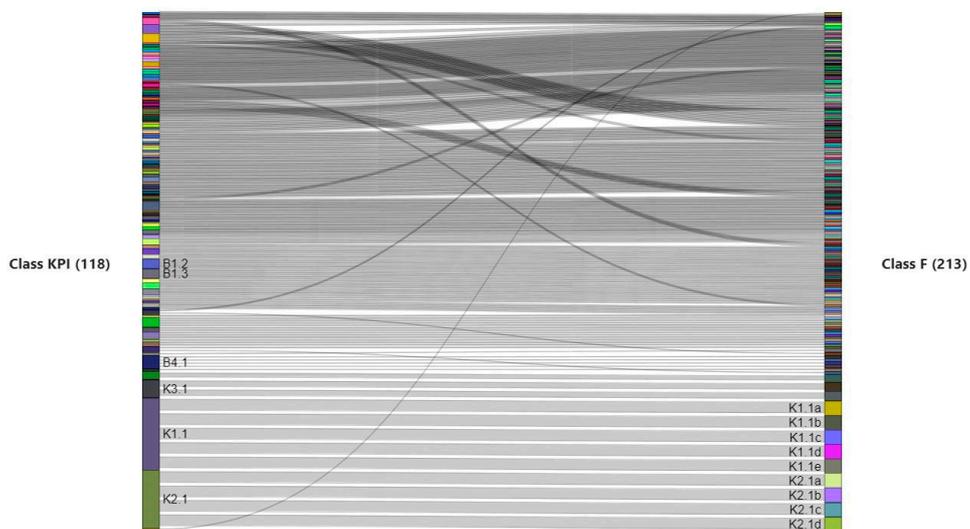


Figure A3. Relations between the KPI class and F class.



Figure A4. Relations between the F class and V class.

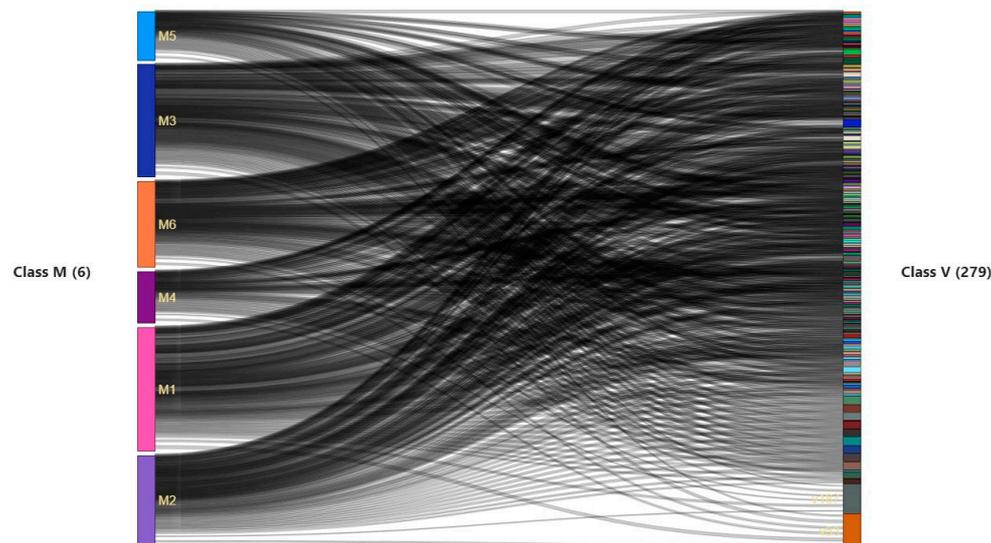


Figure A5. Relations between the M class and V class.

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