



Water table prediction through causal reasoning modelling

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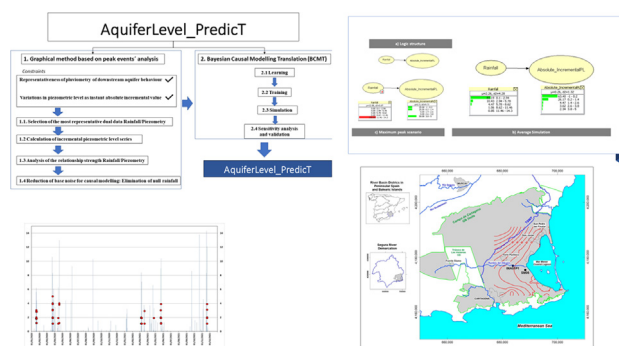
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HIGHLIGHTS

- Causal Reasoning modelling for the study of groundwater hydrodynamic processes
- Analyze and model the relationship of the binomial Rainfall-Piezometry
- Bayesian Causal Reasoning (BCR) to capture the inherent causality in data records
- Hourly Rainfall and Piezometry data were used to capture the sudden aquifer response.
- Applied to the Quaternary aquifer of the Campo de Cartagena groundwater body

GRAPHICAL ABSTRACT



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ABSTRACT

This research is mainly aimed to analyze and model the relationship of the binomial Rainfall-Piezometry. In this sense, the inherent causality contained in temporal hourly Rainfall and Groundwater levels (piezometry) data records has been taken. This has been done through Bayesian Causal Reasoning (BCR) which is technique belonging to Artificial Intelligence (AI) based on Bayesian Theorem. The methodology comprises two main stages, first an analytical method from classic regression analysis, and second, a Bayesian Causal Modelling Translation (BCMT) that itself comprises several iterative steps. This research ultimately becomes a tool for aquifers management that comprises a bivariate function made of two variables Rainfall and Piezometry (Temporal Groundwater level evolution). This innovative methodology has been successfully applied in the Quaternary aquifer of the Campo de Cartagena groundwater body, which is an aquifer system that directly is connected to Mar Menor coastal lagoon (Murcia region, SE Spain).

1. Introduction

Meteorological and hydrological patterns are being considerably perturbed because of anthropogenic climate global warming (O'Gorman, 2015; Pfahl et al., 2017). In this sense, extreme events such as floods (Vogel et al., 2018) or droughts (Marcos-Garcia et al., 2017) and their impacts, are increasingly recurrent (Jyrkama and Sykesa, 2007). Consequently, there is a strong demand of developing potent and reliable analytical methods based on Data Knowledge (DK) to build accurate

models that simulate and predict/forecast the hydrodynamics of a water system (Al-Jamimi et al., 2022; Hao and Singh, 2016; Saleh, 2020; Saleh, 2021; Saleh, 2022; Xu et al., 2015). Accuracy in predictive modelling comprises, first, dealing with the inherent hydrological time series randomness and variability and, second, to incorporate uncertainty (Kong et al., 2017). There is also a strong need to build predictive models considering the sudden behaviour of hydrological systems. In this sense, methods/models based on minimal, hourly or daily data and time steps are required for this.

The occurrence of heavy rainfall often leads to flooding episodes that may have a greater or lesser socio-economic impact depending on the degree of vulnerability of societies. Better infrastructure planning in general will make it possible to reduce the degree of vulnerability to these extreme

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events determining their probability of occurrence and, therefore the greater or lesser risk of exposure to the phenomenon. The case study where this research has been developed is in the Segura Hydrographic Demarcation (DHS), located in SE Spain. This DHS with a relatively small area, presents a complex orographic configuration marked fundamentally by two extensive plains or depressions, that of the Segura and the Guadalestín, as well as by important mountain chains belonging to the foothills of the subbetic system and other pre-coastal mountain ranges. The morphology of the basin and the intense rainfall that tends to occur in the region (Melgarejo-Moreno et al., 2021) increase its risk level in the event of flooding episodes. Over the last 70 years, the average annual precipitation for the entire DHS has not undergone any significant change, although there has been a decrease in the annual number of rainy days and, therefore, in the number of days of rainfall and therefore of the average daily intensity of precipitation, as well as a greater frequency of events greater than 40 mm in 24 h (Lizondo-Osset and García Valero, 2020). This last change is in line with the increase in the frequency and intensity of the most intense precipitation events in the on the Mediterranean basin of the Iberian Peninsula obtained at Oria (2021), as well as in the southeastern peninsular observed in Acero et al. (2011). Both results are compatible with the increase in the occurrence of Isolated High-Level Depressions observed in Muñoz et al. (2020). Attributing these changes to anthropogenic climate change is not straightforward mainly due to the high interannual variability of precipitation observed over the region (Lizondo-Osset and García Valero, 2020), which is indicative of high internal variability, and much more so if it is referred to intense precipitation events. However, some of these changes are in line with climate change projections (Cardoso et al., 2021; Donat et al., 2016), which are not exempt from great uncertainty and low confidence when it comes to intense events (García-Valero, 2018; Stocker and Plattner, 2014).

Predicted changes on meteorological variables such as temperature or rainfall can provoke significant variations on aquifer hydrodynamics such as recharge rates (Jyrkama and Sykesa, 2007), or piezometric levels. There is not a clear consensus on the Climate Change impact on aquifers' behaviour. In this sense, several studies forecast decreases in aquifer recharge (Herrera-Pantoja and Hiscock, 2008; Merritt et al., 2006; Molina et al., 2013; Molina et al., 2021;), whilst others predict increases (Döll, 2009; Green et al., 2007; Gurdak and Roe, 2010; Jyrkama and Sykesa, 2007; Kovalevskii (2007); Yusoff et al., 2002). Furthermore, other contributions cast doubt about it (Molina et al., 2013; Pulido-Velázquez et al., 2015). Especially in arid and semiarid regions, water resource availability can be reduced, modifying stream-aquifer interaction, pumping cost rates and, eventually, leading to aquifers contamination.

Today, Artificial Intelligence (AI) techniques, due to the progress in computer science, is the most popular paradigm of techniques for implementing massive data analysis. In this sense, Artificial Neural Networks (ANNs) are one of AI techniques (Derbela and Nouiri, 2020; Yang et al., 2017a). ANNs that has been used for many purposes such as forecasting drinking water demand (Ghiassi et al., 2008), predicting extremal precipitation (Bodri and Cermák, 2000), characterizing and predicting illnesses (Khan et al., 2001), predicting electricity demand (Kandanand, 2011), assessing civil aviation safety (Zhou et al., 2017), modelling river flow (Aichouri et al., 2015), predicting reference evapotranspiration (Mosavi and Edalatifar, 2019), estimating dam capacity (Üneş et al., 2019), or for hydrodynamic prediction of groundwater level (Chitsazan et al., 2015a, b; Khatibi and Nadiri, 2021; Nadiri et al., 2014; Nadiri et al., 2021; Nourani et al., 2008). Also, many studies have used ANNs to resolve hydrogeological research problems at different temporal scales (Chitsazan et al., 2015a, b; Coppola et al. 2005; Sun et al. 2016. Üneş et al. 2017; Üneş et al. 2019). The greatest limitation of ANN is that does not incorporate uncertainty in its analysis because it is a deterministic technique. Consequently, stochastic processes cannot be analyzed or modelled in a realistic and accurate way.

Furthermore, recently, a large amount of data sources is available and a rapid emergence of new techniques in hydrology based on Information Theory and Artificial Intelligence have emerged. In this sense, other

important techniques and applications may comprise the study of dependence relationships through Entropy Theory (Singh, 2011), or forecasts improving by Bayesian approach (Zhao and Sarkar, 2015) or Machine Learning techniques (Lima et al. 2017), drought predictions (Kousari et al. 2017), and reservoir operations through data mining and artificial intelligence (Yang et al., 2017b), among others. The relationship between hydrological variables and their time series can be captured through many ways from the main basic analysis (Pearson Coefficient) to much more rigorous based on AI techniques such as probabilistic conditional dependence. Relationship between variables can be also analyzed through dependence. This has been analyzed for hydrologic studies through many methods (Hao and Singh, 2016). The most conventional measure of dependence is the Pearson's correlation coefficient based on the normal distribution hypothesis to measure the linear dependence. However, in many cases the normal behaviour is not valid, and the linear dependence is too simplistic to characterize much more complex dependence configurations (Hao and Singh, 2016). Another common technique is the Spearman and Kendall correlations. It has also been traditionally implemented as complementary dependence indicator to characterize the nonlinear dependence of hydrological variables, as demonstrated recently with copula models (Nelsen, 2006). In Hydrology, copula applications started after the work (De Michele and Salvadori, 2003), where Frank copulas were tested for a joint study of the negatively associated storm intensity and duration. Other research works such as (Zhang and Singh, 2006, 2007) incorporated copulas for an extreme analysis of rainfall and drought events. Dependences' modelling for and between extremes events is currently strongly studied (Davison and Huser, 2015; Dufloy et al., 2014; Vogel et al., 2018). Dependence in extreme events should be evaluated through techniques designed as extreme distribution like the tail dependence coefficient. This has been commonly used in investigating hydroclimatic extremes, such as precipitation and temperature (Serinaldi and Kilsby, 2014). These extreme events drive the aquifers recharge main processes and they must be considered as a major source of aquifers' income in water budgets.

Another important and recent area of research is the construction of a multivariate distribution in modelling different dependence structures (Sarabia-Alzaga and Gómez-Déniz, 2011). This is applied to hydrology and in the form of frequency analysis, downscaling, streamflow or rainfall simulation, geo-statistical interpolation, bias correction, etc. Other methods, such as multivariate parametric distribution (Balakrishnan and Lai, 2009), entropy (Molina et al., 2016; Singh, 2011), copula (Nelsen, 2006), have been developed to model various dependence structures of multivariate variables through the construction of joint or conditioned distribution.

Bayes' rule implemented through Bayesian Inference and Bayesian Networks (BNs) or Dynamic Bayesian Networks (DBNs) can be considered as popular AI technique (Molina et al., 2013, 2016, 2020). Other techniques related to the previous one is the multinomial logistic regression and Markov Random Field (MRF), (Lee et al., 2000). MRF or undirected graphical model is a set of random variables having a Markov property described by an undirected graph. BNs are directed and acyclic (Not possible close feedback loops), whereas MRFs are undirected and may be cyclic (possibility of close feedback loops). Thus, a Markov network can represent certain dependencies that a Bayesian network cannot (such as cyclic dependencies); on the other hand, it cannot represent certain dependencies that a Bayesian network is able to, such as induced and diffused dependencies (Del Sagrado and Moral, 2003). The identification and quantification of these dependences is not a minor issue and causal analysis is a very good method for capturing these relations (Molina and Zazo, 2017). The demand of skills for working with complex relations and building probability distributions make these new approaches appropriate. Those skills can be summarized as follows: The ability of using field raw-data (Zounemat-Kermani and Teshnehlab, 2008) that can be calibrated within the same analysis; then, "a priori" information of the process is not needed (Nourani et al., 2011); then, they are able to process a great amount of data. Consequently, they are useful for identifying physical relationships

which are not completely either identified or understood. In this sense, BNs have been largely used for groundwater management as Decision Support System for the Integrated Water Resources Management. BNs are being used to model diverse problems of high complexity for water management applications (Molina et al., 2010). However, BNs, Bayesian Inference (BI) or Bayesian Causal Reasoning (BCR) have not been exclusively used so far to reproduce physical hydrodynamic behaviour in groundwater hydrology. In this sense, being able to develop technical tools based on BCR implemented by BNs is an unexplored field that this research aims to cover for the groundwater hydrology field.

Relevant and sudden changes in groundwater levels in unconfined aquifers are often produced by intense pulses of rainfall/recharge processes. It is necessary to capture the relationship and dependence between rainfall extreme events and water table variation for improving the understanding and achieving proper aquifers' management. This study is mainly aimed to provide a quantitative assessment through BCM of the hourly dependence relationship between temporal evolution of rainfall and groundwater level and its implications on aquifers' hydrodynamics. Using those time series, a causal analysis (Bayes Theorem) that computes, shows and define the probabilistic interaction of two variables is developed. This analysis provides the knowledge of the level of dependence relationship among those variables at an hourly time step. This approach differs over traditional approaches such as Pearson correlation coefficients or Spearman rank correlation coefficient that measures the dependence in the main data body without fully considering Uncertainty (Hao and Singh, 2016).

This manuscript is organized as follows. Following section is dedicated to show the materials and methods comprising the description of case study and main existing approaches and techniques in which this study is based on. Later, the third section describes the applied methodology. Next section shows the main results drawn from the research. Fifth section is devoted to the discussion, and final section comprises the main conclusions generated from the study.

2. Materials and methods

2.1. Case study and data set

The Campo de Cartagena groundwater body comprises a sub-horizontal region of around 1236 km² located in south-eastern Spain. It is surrounded by small mountain ranges such as Sierra de los Victorias and Sierra Cartagena-La Unión on all borders except in the East, where it is open to the Mediterranean Sea. "In general, it comprises a multilayer aquifer system where the surface layer is a Quaternary and unconfined aquifer formation. This system is formed by a mix of detrital sediments (sand, gravel, silt and clay), and around 1400 wells where 25 % are under control related to pumping. This shallow aquifer has a thickness from 25 to more than 100 m. The water balance of the multilayer system has been a subject of controversy (Jimenez et al. 2016 and Alcolea et al., 2019), mainly due to the amount of the groundwater discharge to the Mar Menor coastal lagoon. The official data of the local Hydrological Plan 2022–2027 indicate a negative water balance (−0.9 hm³/year), with inputs of 67 hm³/year, where 48.8 hm³/year comes from rainfall infiltration and return of irrigation of 18.2 hm³/year. On the other hand, pumping outputs are around 58.8 hm³/year where 9.1 hm³/year correspond to groundwater discharge to the sea. There are no official data regarding the water balance or the exploitation corresponding to the Quaternary aquifer. Regarding the hydraulic parameters, recent data are available from the Quaternary aquifer in the 3 km coastal strip, with transmissivity values obtained with pumping test ranging between 5 and 10^{−3} m²/day, and a storage coefficient of 0.02 selected for groundwater modelling (MITECO, 2020).

A hypersaline coastal lagoon, Mar Menor, highlights in the landscape located between the plain and the Mediterranean Sea (Fig. 1). The region is characterized by a semi-arid climate, with 18° mean annual temperature and about 300 mm average annual precipitation (Hunink et al., 2015), unevenly distributed into a new intensive events that is highly variable in space and time, although mainly occurring in spring and autumn. Potential

evapotranspiration averages 1275 mm/year. Agriculture comprises the main economic activity. The total area under irrigation increased from 32,366 ha in 2011 to 41,065 ha currently, but it fluctuates based on annual water allocations (Hunink et al., 2015). The most representative rainfed crops are almond, winter cereals and olive, while the main irrigated crops are horticultural row crops (lettuce, broccoli, melon and others), and citrus trees (oranges and lemons). In plots dominated by row crops, rotation of autumn-winter (i.e., lettuce, artichoke) and spring-summer (i.e., melon) crops is a common practice. Drip is the primary irrigation method (96 %) due to water scarcity and the requirement of water conservation (Hunink et al., 2015). Non-cultivated soils have a low permeability, low organic carbon content and are poorly developed (García-Pintado et al., 2009). The Tajo-Segura Water Transfer (TSWT) provides more than one third of the total water demand for irrigation. However, during the last decades, the unmet water demand for irrigated agriculture and tourism development led to the construction of several desalination plants. From one side, seawater desalination plants have their maximum production during summer and drought periods, to cover water demand peaks; however, the relatively high operational costs and quality issues limit its widespread use for irrigation (Lapuente, 2012; Martín-Gorrioz et al., 2014). Most of them are under their maximum desalination capacity (March, 2015). On the other side, farmers have installed small desalination equipment to reduce the salinity of the low-quality groundwater (brackish groundwater) and mix them with better quality surface water (i.e., Tajo-Segura Water Transfer) resources to get adequate water for irrigation; the groundwater pumping in some cases, and the management of the reject brine have not had neither sufficient administrative support nor adequate infrastructure, which has led to legal proceedings with significant repercussions. Finally, reclaimed water constitutes the last source of available water for meeting agricultural water demand.

The hydrosystem is heavily anthropized and the role of groundwater has been revealed to be very significant in mitigating the impacts on associated ecosystems (Jiménez-Martínez et al., 2016). Important steps have been taken in hydrogeological modelling (Alcolea et al., 2019), and the necessary data must be improved to make the models more reliable and useful for management decision making.

Two datasets of hourly records have been used for this research covering the period 01/01/2020 until 31/12/2021. First, pluviometry data was taken from the pluviometry station with the code 06A01P01 (Fig. 1); then, piezometric data was taken from the piezometer borehole (observation wells) encoded SM006 (Fig. 1); both are official station of the Segura Basin Water Authority. <https://www.chsegura.es/es/cuenca/redes-de-control/saih/ivisor/>.

2.2. Methods

BNs are probabilistic graphic models (Pearl, 1988) and they provide multivariate probability. The joint distribution $P(X_1, X_2, \dots, X_n)$ contains information about all aspects of the relations among the n random variables. In theory, one can answer any query about relations among the variables based on the joint probability. They are very useful to define logical relationships among variables into complex models by means of the marginal probability assessment through causality. Consequently, a joint probability provides a full image about how random variables are related, while marginalization allows focusing on one aspect of the image.

BNs allow analyzing the temporal behaviour of series for each time step, as it is shown in Molina and Zazo (2017) and Molina et al. (2016). This property allows having a dynamic tool of simulated process. Moreover, BNs allows developing a rigorous analysis and quantification of the conditional dependence between hydrological variables. For the calibration and validation of this analysis, Information Theory is a discipline from which some indicators are specifically designed. These indicators comprise Mutual Information, Total and Conditional Entropy, Mutual Independence, among others (Nourani et al., 2015; Pearl, 1988).

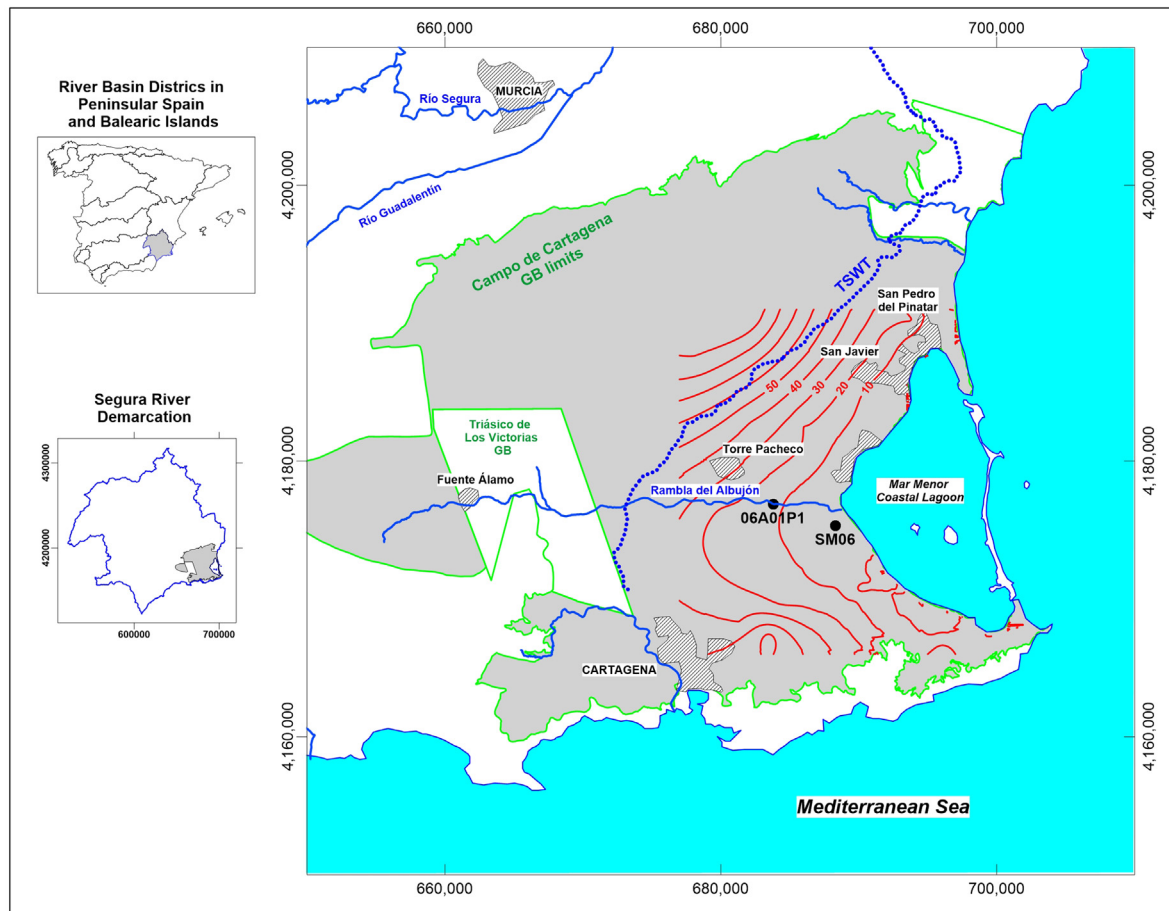


Fig. 1. Case study location, isopiezometric countour (May 2018) and monitoring points used. Source: own elaboration.

Conditional Probability through Bayesian Theorem allows quantifying the variables relationship strength through Bayes’ rule (Molina and Zazo, 2018; Macian-Sorribes et al., 2020). For events A and B:

$$P(A|B) = \frac{P(A, B)}{P(B)} = \frac{P(A \cap B)}{P(B)}$$

where: P(A|B) is probability on event A assuming that event B is true, P(A, B) is the joint probability on events A and B, P(B) is probability on B.

The series are fed into the learning and training process of the Causal Bayesian model. This early BCM stage is crucial since it includes the discovery and characterization of the logical and non-trivial structure of temporal interdependence that underlies the hydrological (rainfall) series.

Calibration: The model has been continuously calibrated with historical extreme rainfall records, and historical piezometric level data.

Sensitivity analysis: predictive rainfall-aquifer level simulator is finally validated through Artificial Intelligence and Information Theory indicators such as: P-Value, Mutual Information, Conditional Entropy and Total Entropy.

The implementation of Bayesian Inference through Bayesian Networks is generally called Causal Reasoning (CR). This is a very active and productive research line in recent years, and it has the possibility of using Bayesian Networks to discover causal dependences in almost unprocessed hydrological data (Molina et al., 2013; Pearl, 2000; Spirtes et al., 2000; Koehrsen, 2018).

The innovative application of this research is aimed to contribute a proper and sustainable aquifer management. In this sense, the accurate assessment of the probabilistic correlation between rainfall and groundwater hydrodynamics for nonstationary series is crucial to reach a deep and robust understanding of aquifers’ behaviour and management.

3. Methodology

This paper is mainly aimed to show the development of a method that ultimately becomes a tool called “AquiferLevel_PredicT”. This tool is based on Bayesian Casual Modelling (BCM), a technique within Artificial Intelligence (AI). This method may enhance predictive capacity of instant rainfall-piezometry relationship. “AquiferLevel_PredicT” follows a methodology that comprise 2 main stages (Fig. 2). First one comprises a Graphical method based on peak events’ analysis. This stage is conditioned by two initial constraints which are, on one hand, a) pluviometry station is representative of downstream aquifer level of groundwater-flow behaviour so there is a representative rainfall of the aquifer response; on the other hand, b) variations in piezometric level should be considered as an instant absolute incremental value. First stage comprises sub-phases such as: 1.1. Selection of the most representative dual data on Rainfall and Piezometric level, 1.2 Calculation of incremental piezometric level series; 1.3 Analysis of the relationship strength Rainfall-Piezometric Level; 1.4 Elimination of null rainfall data to reduce the base noise of the following causal stage. Second main stage is called Bayesian Causal Modelling Translation (BCMT) that comprises the 2.1 Learning, 2.2 Training, 2.3 Simulation through BCM modelling, 2.4 Sensitivity Analysis and Validation.

Learning phase comprises the automatic data and information scanning that the model uses to recognise the main patterns and features of input information. This phase was done by a Wizard called “Learning Wizard” implemented in the software HUGIN 8.9. Training data was done by letting the model to assimilate the information and explore different data dimensions. Simulation phase is based on the model compilation of Bayes Theorem for different scenarios of the dual rainfall-piezometry. Later, a sensitivity analysis was done by applying some indicators of the Information Theory that comprises the analysis of the most sensitive parameters

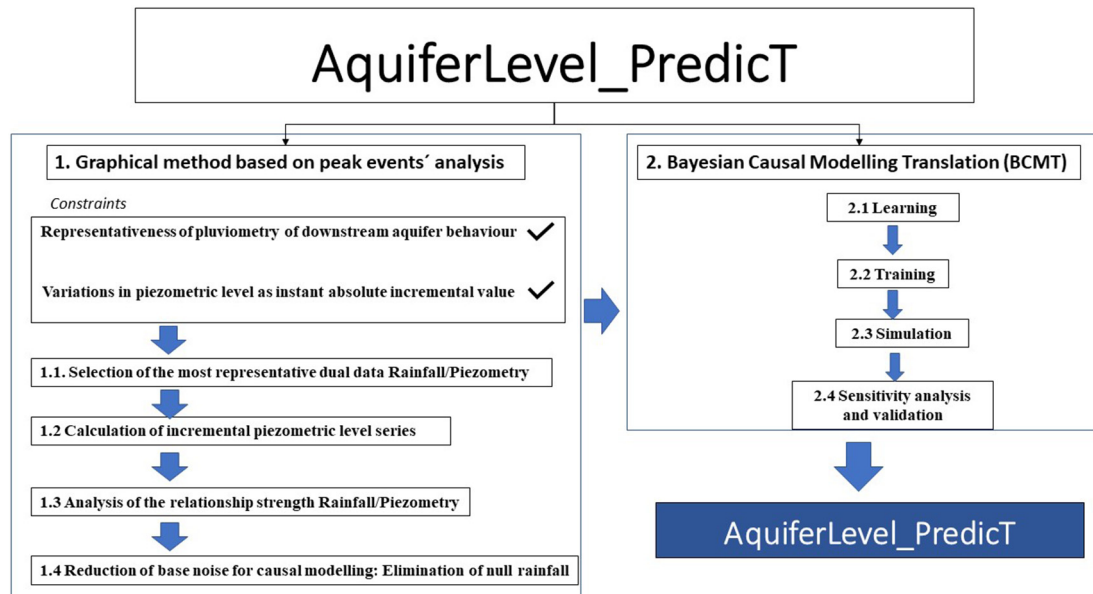


Fig. 2. General methodology. Source: own elaboration.

or scenarios. Finally, a validation of the model was done by comparing the outcome with real field observations.

The final model comprises a joint bivariate system made of one independence (parent node) representing the “Rainfall” and one conditional distribution probability (child node), representing the “Aquifer Level or piezometry”.

4. Results

4.1. Graphical method based on peak events' analysis

4.1.1. Rainfall characterization

A dataset of hourly rainfall data was selected and represented for a period covering the period 01/01/2020 until 31/12/2021 (Fig. 3). Then, null values were eliminated aimed to reduce the base noise of the causal stage (3.4).

4.1.2. Temporal piezometric evolution analysis

A data record on Piezometric level data was used for this research (Fig. 4). Once the data was analyzed, an incremental piezometric level series was created. This was done aimed to objectivize this research. Therefore, an absolute value of incremental temporal series on piezometric level was calculated to become the continuous and sudden response of aquifers to variations in rainfall. Fig. 4 shows the representation of rainfall versus piezometry for the data and the period used in this research.

4.1.3. Representativeness of the relationship between pluviometry and piezometry

This phase was developed through a pure graphical peak assessment (Fig. 5). The crucial issue is to pay special attention at the rainfall picks and the effect on the positive increment events of piezometric level. The response of the aquifer to sudden pulses of rainfall is key here (Figs. 4 and 5).

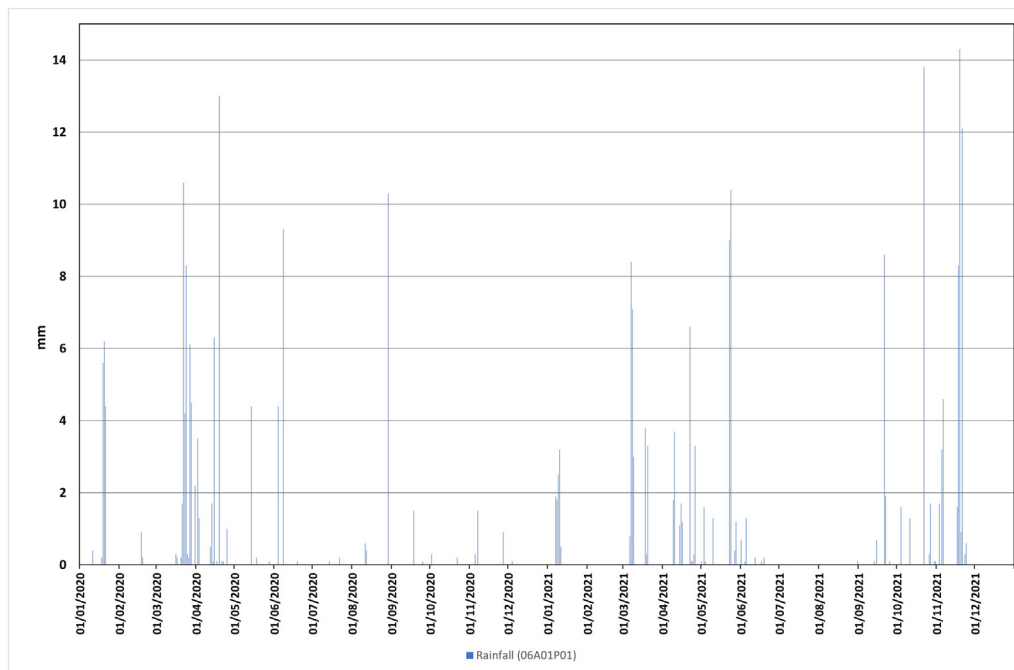


Fig. 3. Rainfall temporal evolution (STATION: 06A01P01). Control period: 01/01/2020–31/12/2021. Hourly rainfall data records. Source: own elaboration.

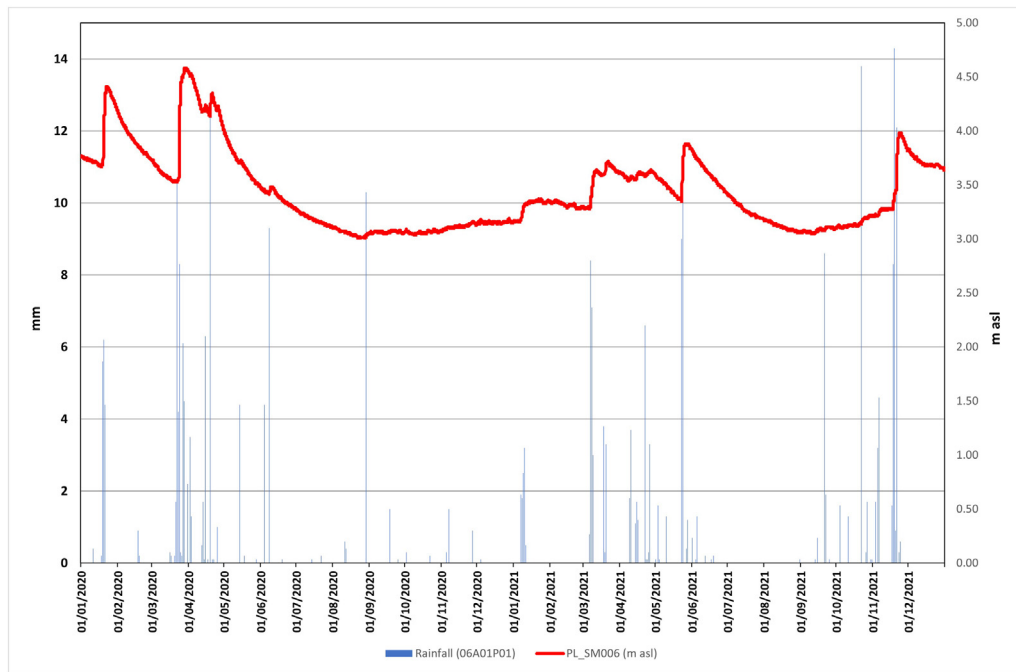


Fig. 4. Relationship Rainfall-Piezometry. Hourly Rainfall data taken at (06A01P01) and piezometric level taken from SM006 (Location showed at Fig. 1). Source: own elaboration.

To reduce the base noise for the following CRM phase, and increment the causality between both processes (rainfall and piezometry), null rainfall data were eliminated. Then, the Learning and Training sub-phases proved this good data correlation of both phenomena (Rainfall vs Piezometry).

4.2. Bayesian Causal Modelling Translation (BCMT)

4.2.1. Learning and training

Learning was done automatically through a learning wizard implemented in HUGIN® Expert version 8.9 (HUGIN, 2021). Learning comprised two series of data “Rainfall” and “Absolute_IncrementalPL”, one series per variable involved in this model. Both series were discretized into five intervals and then, in the structure constraint phase, connect from “rainfall” node (parent) to “runoff” node which is the child (Fig. 5). Training phase was developed with the initial part of the series (720 h) and then compared to the graphical adjustment developed in phase 1 and the expertise of the aquifer from experts.

4.2.2. Simulation

The simulated event comprised 17,544 h of data representing the maximum rainfall of the year with 9 mm (l/m²/h). As aforementioned, “Rainfall” node was discretized into five equal range intervals: 0.1–2.94 mm/h; 2.94–5.78 mm/h; 5.78–8.62 mm/h; 8.62–11.46 mm/h; 11.46–14.3 mm/h. Results show a very similar behaviour with the graphical and mathematical adjustment. In this sense, the average probability of incremental piezometric level is 0.26 cm/h (Fig. 6b) while in the maximum peak is 2.3 cm/h (Fig. 6c).

4.2.3. Sensitivity analysis and validation

Sensitivity analysis was developed using Entropy and Shannon’s measure of mutual information. The entropy measure assumes that the uncertainty or randomness of a variable X, characterized by probability distribution P(x), can be represented by the entropy function H(X):

$$H(X) = - \sum_{x \in X} P(x) \log P(x) \tag{5}$$

The entropy of a probability distribution can be understood as a value of the related uncertainty to that random process. Consequently, a score of

uncertainty/certainty level of events can be made attending to this entropy, H(X), that can be reduced by collecting information in addition to the current knowledge about variable X. This is understood as lowering the uncertainty on true state of X. The entropy measure therefore enables an assessment of the additional information required to specify a particular alternative.

On the other hand, Shannon’s measure of mutual information is used to assess the effect of collecting information about one variable (Y) in reducing the total uncertainty about variable X using:

$$I(Y.X) = H(Y) - H(Y|X) \tag{6}$$

where I(Y.X) is the mutual information between variables. This measure reports the expected degree to which the joint probability of X and Y diverges from what it would be if X were independent of Y. If I(Y.X) = 0, X and Y are mutually independent (Pearl, 1988).

H(Y|X) is conditional entropy which means the uncertainty that remains about Y when X is known to be x. This has been useful because if two variables have a mutual information ≠ 0 involves that they are dependent. On the contrary in case the mutual information is 0 means that they are independent. This analysis represents another way for characterizing and quantifying the temporal dependence and behaviour of hydrological series.

The values of this analysis for this modelling shoes the following results. P-value of the relation rainfall-runoff is 3*10⁻¹⁰; Mutual Information for “Rainfall” node is 0.07, for “Absolute_IncrementalPL” node is 0.13 and for the causal relationship is 0.08. Furthermore, Total Entropy of Rainfall node is 0.62 and for the “Absolute_IncrementalPL” node has a value of 0.99. Consequently, Conditional Entropy is 0.55 for rainfall and 0.86 for the “Absolute_IncrementalPL” node. The understanding and explanation of these values is shown in the next section.

Model validation is done by means of the observation and comparison of rainfall picks and its correspondence with aquifer response in terms of water table variation expressed as instant absolute incremental value (Fig. 5). Furthermore, regarding model reliability, since the model is based on observations, reliability is assured.

Model reproducibility is assured since it is only necessary to have well identified an observation well that faithfully and rapidly responds exclusively to rainfall changes measured at a nearby pluviometry station.

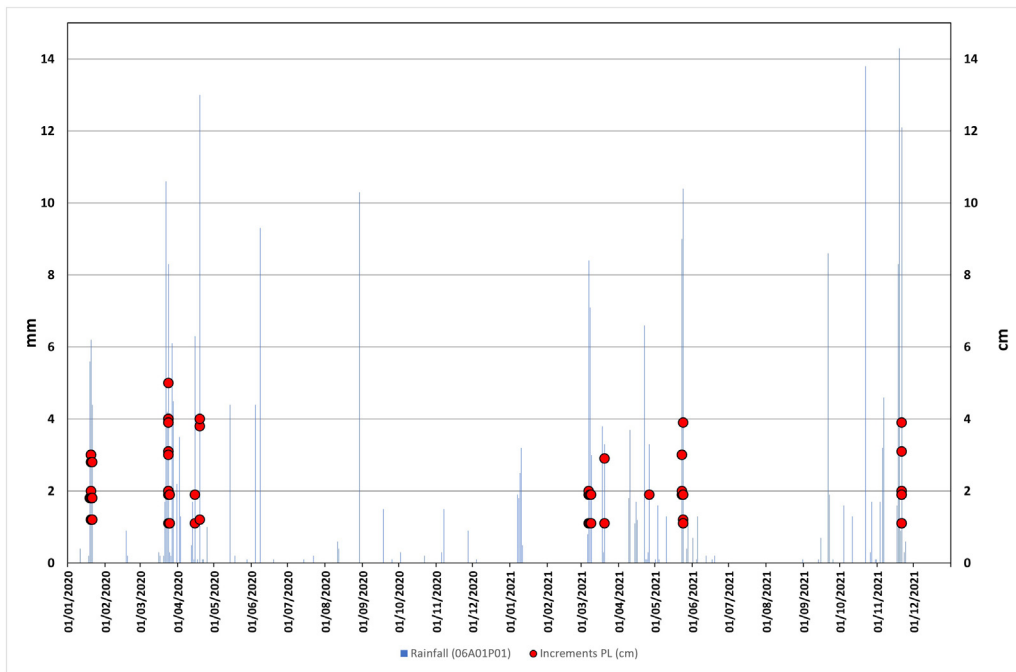


Fig. 5. Relationship Rainfall- Increment of Piezometry. Hourly Rainfall data taken at (06A01P01) and increment of level piezometric level taken from SM006. Source: own elaboration.

5. Discussion

One of the main problems for the good management of the “forgotten resource” which is the groundwater, is the lack of processes understanding because of their complexity and multifactorial nature. Being able to have methods, methodologies, techniques, and tools to separate and simplify the analysis of groundwater hydrodynamic processes is crucial. In this sense, significant sudden changes in groundwater levels in unconfined aquifers are often produced by intense pulses of rainfall and recharge. Being able to capture the relationship and dependence between rainfall extreme events and water table variation is essential for improving the understanding and achieving proper aquifers management.

This paper is mainly aimed to show the development of a method called “AquiferLevel_PredicT” based on Bayesian Casual Modelling (BCM), a technique within Artificial Intelligence (AI). This modelling approach becomes a joint bivariate causal model, generated to predict the piezometry/aquifer level given an hourly rainfall data. The simplicity of the BCM process should not be a weakness of this method because the stronger the pre-process of the data is the simpler the BCM can become. In other words, the detailed analysis of information that feeds the BCM is crucial to develop a simple but robust causal model.

The values of probabilities for the posterior “AquiferLevel” variable through the average simulation and the peak simulation (Fig. 6 b,c) shows a very high similarity with the behaviour observed at Piezometric

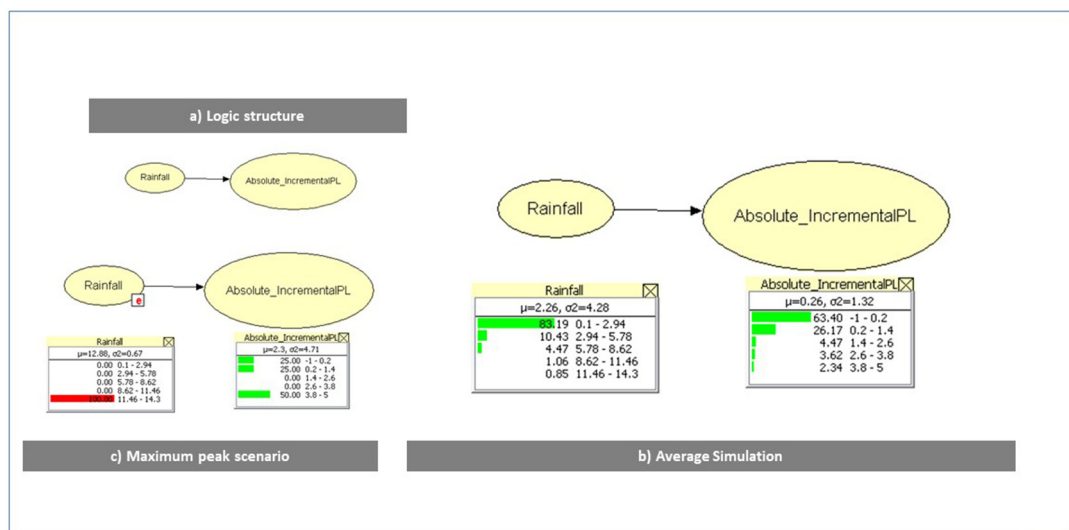


Fig. 6. (a) Logic structure of the bivariate causal model. (b) Average Simulation. (c) Simulation of the maximum event. Source: Hugin Expert. Version 8.9. Source: own elaboration.

Station (SM006). The simulated event comprised hourly rainfall and piezometric data covering a period of 2 years which assures enough data to build a robust and reliable BCM development (Zazo et al., 2022). For the BCM, null rainfall data was deleted because it introduces base noise and uncertainty in the causality. Furthermore, null data does not provide any advantage to the physical modelling. This method and application are the beginning of an innovative research line on the probabilistic prediction of aquifers' hydrodynamics. Next developments will include, among others: to analyze and model with other temporal scales (daily, monthly), to develop a BCM including recharge rate, to enrich the method with the characterization, analysis and modelling of other types of events, or to analyze and model in a probabilistic way, the climatic settings so the main meteorological events that origin the main hydrodynamic events can also be anticipated.

The low values of Mutual Information and the high values of Entropy within the sensibility analysis of the BCM are justified for the great amount of minimum rainfall that do not alter the aquifer level. As rainfall intensity data increases, the effect in the alteration of piezometric level also increases. This is because aquifer recharge is mainly produced in the strongest pulse of rainfall. However, the extremely low rate of P -Value (3×10^{-10}) which is the degree of independency between the causal relationship of two variables, assures a great dependence of the hydrological relationship between rainfall-piezometry.

Piezometry was introduced and computed as an incremental function for the variable "Absolute_IncrementalPL". It has been found this indicator/variable very effective because it directly shows the absolute change (positive or negative) in the aquifer water table. Therefore, this is an analytical way that allows to reproduce the natural relationship between rainfall and the associated variation in the piezometric level.

Regarding limitations of the research, the main problem is acquiring the right data and information for capturing the real aquifer behaviour (Response). For that, it is crucial to select very well studied boreholes (observation wells) that are exclusively affected by rainfall. That may be a handicap for generalizing this research.

6. Conclusions

The understanding of groundwater hydrodynamics natural behaviour is a basic unresolved challenge. This is mainly for the difficulties to capture the natural regime of the aquifer response to processes like rainfall and to others. It is necessary to simplify and synthesized the analysis to really get to understand that aquifers' behaviour.

AquiferLevel_PredicT comprises a method that predict in a robust and simple way the piezometry of an aquifer associated with hourly rainfall. This makes this method very powerful for anticipate future groundwater behaviour as well as negative impacts on the nature and human environment. The fact that values of probabilities are completely aligned with other classical regression analysis validates the method for this hydrological data (hourly rainfall and aquifer level). To anticipate the aquifer level value, the only information needed would be the probability distribution of the rainfall at the controlled rainfall station. That would automatically provide the incremental or decreasing value of aquifer level in a continuous way.

This whole methodology will become a digital and technological package in the form of Digital Application and Software that could be extrapolated to several similar cases studies. This maybe coupled with posterior devices for the prevention of negative consequences, especially related to water quality and contamination issues (if aquifer level rises very rapidly), in the form of Decision Support Systems, MultiHazard-Early Warning System (MH-EWS) or others.

Ethical approval

Not applicable.

Consent to participate

All authors whose names appear on the submission.

1) made substantial contributions to the conception or design of the work; or the acquisition, analysis, or interpretation of data; or the creation of new software used in the work;

2) drafted the work or revised it critically for important intellectual content;

3) approved the version to be published; and.

4) agree to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

Consent to publish

All authors whose names appear on the submission give their consent to publish this paper in case it is accepted.

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Availability of data and materials

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

CRediT authorship contribution statement

José-Luis Molina: Conceptualization, Methodology, Formal analysis, Visualization, and leadership of Investigation. José-Luis García-Aróstegui: Formal analysis. Discussion and Conclusions sections were developed by all authors, and all authors wrote the paper.

Data availability

The authors are unable or have chosen not to specify which data has been used.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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