AquiferLevel_PredicT: Predictability of Groundwater Level Dynamics in Aquifers Through Causal Reasoning Modelling

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Abstract

The analysis of causal relationships of hydrological processes is a very unexplored field. It is even less investigated the usage of Causal Reasoning modelling for the study of groundwater hydrodynamic processes. This paper is aimed to analyse and model the relationship of the binomial Rainfall-Piezometry. For that, the inherent causality contained in temporal data records has been captured, analysed and interpreted. This has been done through Bayesian Causal Reasoning (BCR) which is technique belonging to Artificial Intelligence (AI) based on Bayesian Theorem. The data for Rainfall and Groundwater levels (piezometry) has been taken in hourly data records. 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 become 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). This system has been in the spotlight worldwide due to major environmental problems, closely related to the lack of groundwater management.

1. Introduction

Meteorological and hydrological patterns are being considerably perturbed because of anthropogenic climate global warming (O'Gorman 2015; Pfahl et al. 2017). Therefore, water resources systems and are being rapidly transformed (Allan and Soden 2008; Chang et al. 2015; Kalra et al. 2013; Trenberth 2011; Al-Rawas et al., 2019). In this sense, stationarity in traditional stationary hydrological time series (rainfall-runoff-aquifer recharge) is not prevalent anymore (Back, 2011; Donat et al. 2016; Huff, 1990; Wasko and Sharma 2015). In this sense, extreme events such as floods (Vogel et al., 2018) or droughts (Marcos-Garcia, 2017) and their impacts, are increasingly recurrent (Jyrkama and Sykes 2007). Consequently, there is a strong demand of developing potent and reliable analytical methods to build accurate models that simulate and predict/forecast the hydrodynamics of a water system (Hao and Singh 2016; 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 minutal, hourly or daily data and time steps are required for this.

Marotzke et al. (2017) define "weather" as the result of the "interplay of thermodynamic and dynamic processes which determine circulation and rainfall patterns". Furthermore, Nobre et al. (2017) define Climatic variability as "the natural fluctuations of the climate system around the long-term trend". However, those variations are being increasingly altered due to the impact of Climate Change (CC). Currently, CC drives several hydrological processes: a) larger-scale climate structures such as El Niño–Southern Oscillation (ENSO), anti-ENSO called La Niña, North Atlantic Oscillation (NAO) mainly, b) extreme hydrologic events, c) sea level rise, d) melting of mountain glaciers and polar ice, e) thermal

expansion of sea water and f) decrease of general water availability and increase of groundwater extraction (Chang et al. 2015; Kalra et al. 2013). This worldwide phenomenon is strongly related to the effect of global warming (IPCC 2021), which is highly intensified by anthropogenic actions (Marotzke et al. 2017). Min et al. (2011) and Zhang et al. (2013) O'Gorman (2015), provide evidence for an anthropogenic contribution to observed changes in precipitation extremes. NAO is the major cause of seasonal and interdecadal variability of atmospheric circulation on the European continent (Qian et al. 2000). Rodrigo et al. (2000) determined that NAO is the most likely cause of alterations on the precipitation in the south of Spain. Rodriguez-Puebla et al. (2001) show that NAO is main source of interannual variability over Iberian Peninsula.

Uncertainty, randomness, and variability are own features of hydrological time series. Regarding local meteorological processes, their recurrency is also being altered showing greater picks and frequency of massive rainfall-runoff processes in reduced territories. 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 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 Guadalentín, 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 (CHS, 2018; 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 hours (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., 2020; Donat et al., 2016), which are not exempt from great uncertainty and low confidence when it comes to intense events (Stocker, 2014). The maximum annual 24-hour precipitation is a variable considered as unlikely and has traditionally been used as an index to assess risk by using its series to determine return periods of certain thresholds after adjustment to a distribution function of extreme values of a general type, Gumbell, SQRT-ET max (Ministerio de Fomento, 1999), etc. Knowing the possible existence of trends in this variable

could be an indication that it maybe the risk is changing and therefore needs to be re-evaluated. Several studies have been analyzed within this research aimed to evaluate possible trends of maximum annual precipitation in the different sub-basins of the DHS and the analysis of possible changes in the return periods associated with this variable (CHS, 2018; García-Valero, 2021).

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 Sykes, 2007; Kovalevskii (2007); Yusoff et al., 2002). Furthermore, other contributions cast doubt about it (Molina et al., 2013; Pulido-Velázquez, 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.

Mathematical groundwater flow models are needed to simulate and predict future groundwater dynamic variability under different management scenarios. There are many developments of numerical simulation models worldwide. Of course, there are different type of numerical models, but they all have something in common which is the power and ability to physically represent the high spatio-temporal variability of aquifer properties and inherent conditions (Coppola et al. 2005; Molina et al 2009). However, the way the uncertainty is analyzed, quantified and integrated to those models is still a non-resolve topic and challenge, especially for predicting developments. Furthermore, mathematical physical codes and developments are often limited by the data volume required and to the anisotropy and intermixture of physical features that need to be represented by too many parameters to which the data is scarce. Consequently, the cost for developing these physical models is a challenge in many contexts The unavoidable and inherent significant error and uncertainty generated within the different iterations of those models´ development make, in many cases, these models not to be as effective and useful as desired (Szidarovszky et al. 2007).

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 Cermak 2000), characterizing and predicting illnesses (Khan et al. 2001), predicting electricity demand (Kandananond 2011), assessing civil aviation safety (Zhou et al., 2017), modeling 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. In this sense, many studies have used ANNs to resolve hydrogeological research problems at different temporal scales (Banadkooki et al. (2020); Chitsazan et al. (2015); Coppola et al. (2005); Feng et al. (2008); 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 et al. 2015) or Machine Learning techniques (Lima et al. 2016), drought predictions (Kousari et al. 2017), and reservoir operations through data mining and artificial intelligence (Hejazi and Cai 2011; Yang et al. 2017b, 2016), 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. This organization comprises a set of trivial and non-trivial (induced and diffused) dependence relationships that explain its general temporal behavior (Hao and Singh 2016; Wang et al. 2009). Furthermore, dependence structures among different random variables should be quantified and considered for the analysis, modeling and prediction of hydrological events. (Hao and Singh 2016). 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; Dutfoy et al. 2014; Vogel, 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 et al. 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 2008). 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 2013), 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 (Wu et al. 2015) and Markov Random Field (MRF; Lee et al. 2012). 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 MRF´s 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 Martínez 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.

Common approaches do not incorporate any causality in their computations. Classic return period approaches just comprise an average value that represents the inverse of the probability of a certain temporal period, generally called recurrence interval. To better perceive the differences and the accuracy of results, this study is applied to a monitored system that comprises a pluviometry station and a piezometric level station in real time. The proposed methodology may be applicable to any other aquifer system as a suitable alternative and appropriate complement to traditional approaches.

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 a state of the art that comprises the main existing approaches and techniques in which this study is based on. Next section comprises the description of the case study. Later on, the applied methodology is described. Next section shows the main results drawn from the research. Final section is devoted to the discussion and 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 km^2 located in southeastern 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. 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 18º mean annual temperature and about 300 mm average annual precipitation (Hunink et al., 2015), unevenly distributed into a ew 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 32366 ha in 2011 to 41065 ha currently, but it fluctuates based on annual water alloca-tions (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 (Garcia-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 desalinization plants. From one side, seawater desalinization 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; Martin-Gorriz et al., 2014). Most of them are under their maximum desalination capacity (March et al., 2015). On the other side, farmers have installed small desalination equipment to reduce the salinity of the low-quality pumped 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 (Jimenez-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 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(X1, X2,. . ., Xn) 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 behavior 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).

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.

Bayesian Causal Modelling (BCM)

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 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 called “AquiferLevel_PredicT” 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. This 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.

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

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).

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. Figure 4 shows the representation of rainfall versus piezometry for the data and the period used in this research.

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. In order 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)

1. Learning And Training

Learning was done automatically through a learning wizard implemented in 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 hours) and then compared to the graphical adjustment developed in phase 1 and the expertise of the aquifer from experts.

2. Simulation

The simulated event comprised 17544 hours of data representing the maximum rainfall of the year with 9 mm (l/m^2/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).

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):

$$H(X) = -\sum_{x \notin X} P(x) log P(x)$$

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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:

$I(Y.X) = H(Y) - H(Y|X)$ (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 behavior 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.

Discussion

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 a 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. 6b,c) shows a very high similarity with the behaviour observed at Piezometric 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 hydrodinamic 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, it is an analytical way that allows to reproduce the natural relationship between rainfall and the associated variation in the piezometric level.

Conclusions

AquiferLevel_PredicT is a method that predict in a robust and simple way the piezometry of an aquifer associated with daily 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 (Daily rainfall and aquifer level). In order to anticipate the aquifer level value, the only information needed would be the probability distribution of the rainfall at the controlled pluviometric 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.

Declarations

-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

-Authors Contributions:

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.

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-Competing Interests:

The authors have no competing interests to declare that are relevant to the content of this article.

-Availability of data and materials:

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

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Figures

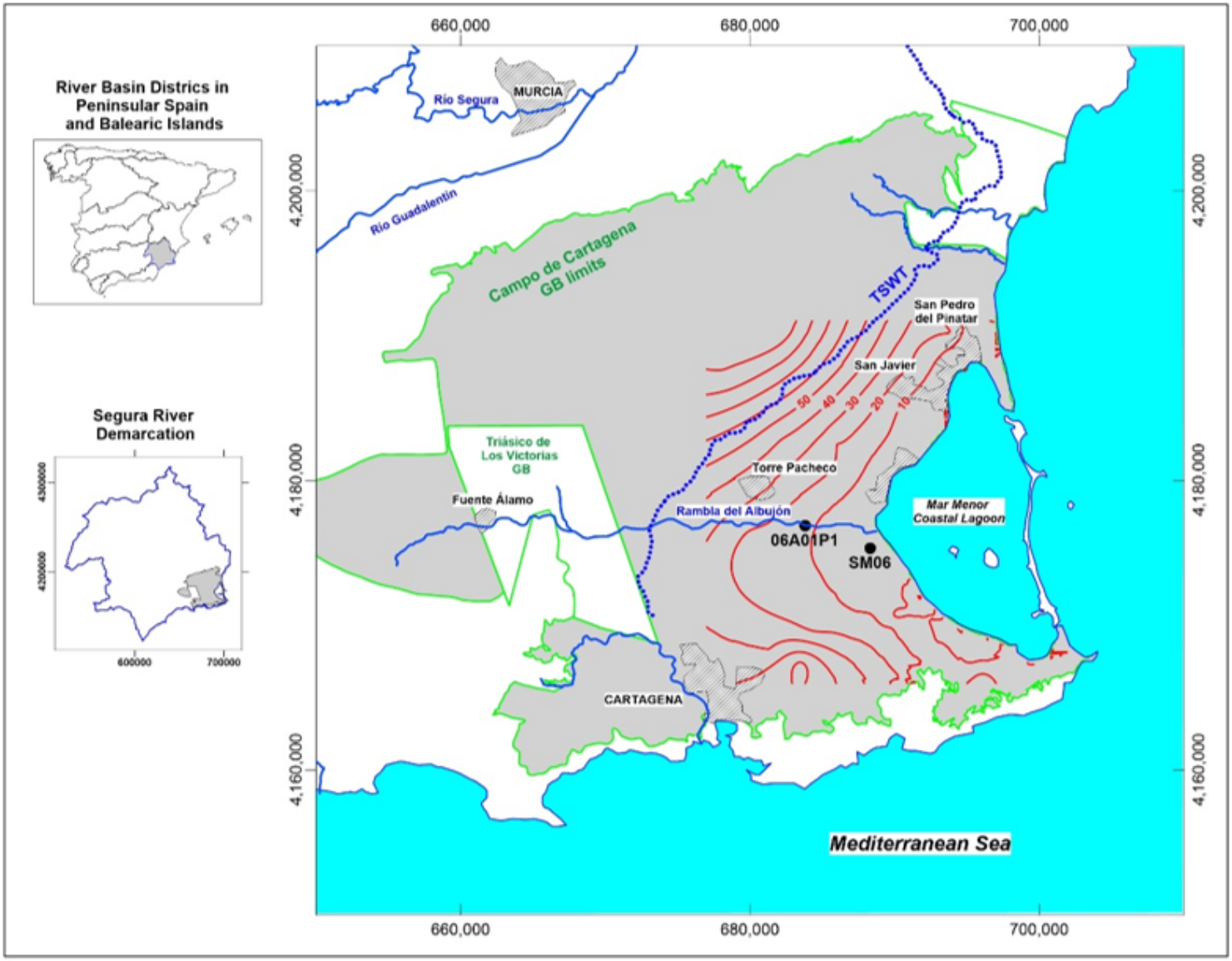

Figure 1

Case study location, isopiezometric countour (may 2018) and monitoring points used.

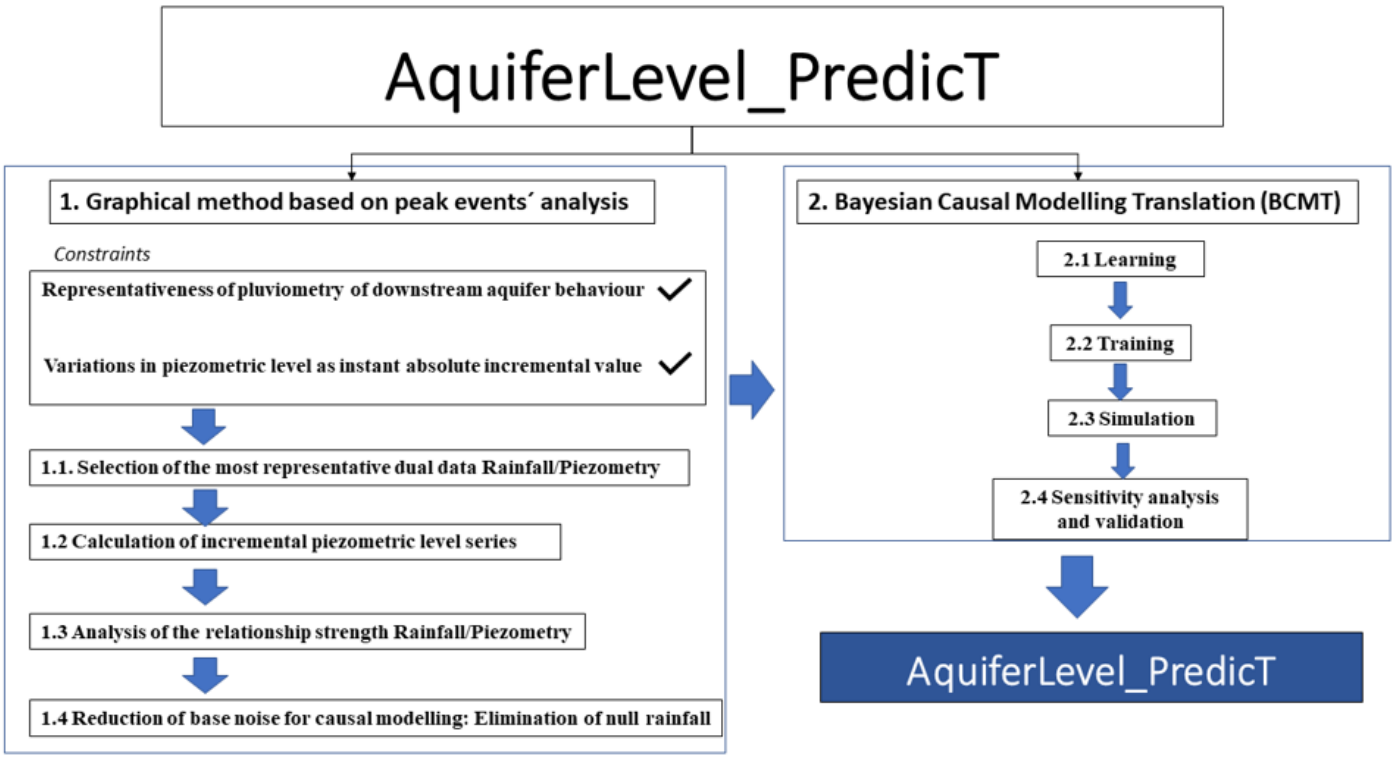

Figure 2

General methodology

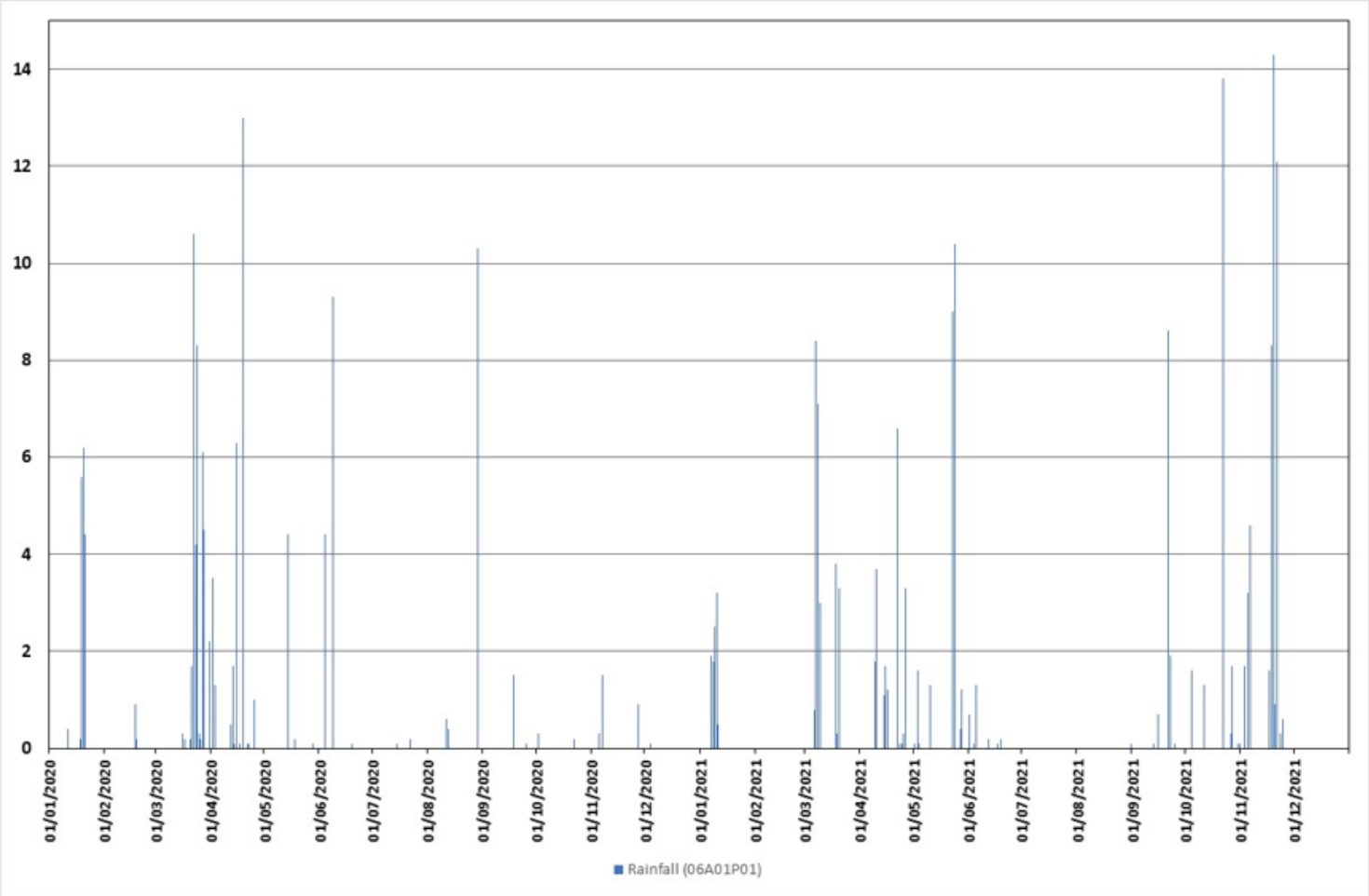

Figure 3

Rainfall temporal evolution (STATION: 06A01P01)

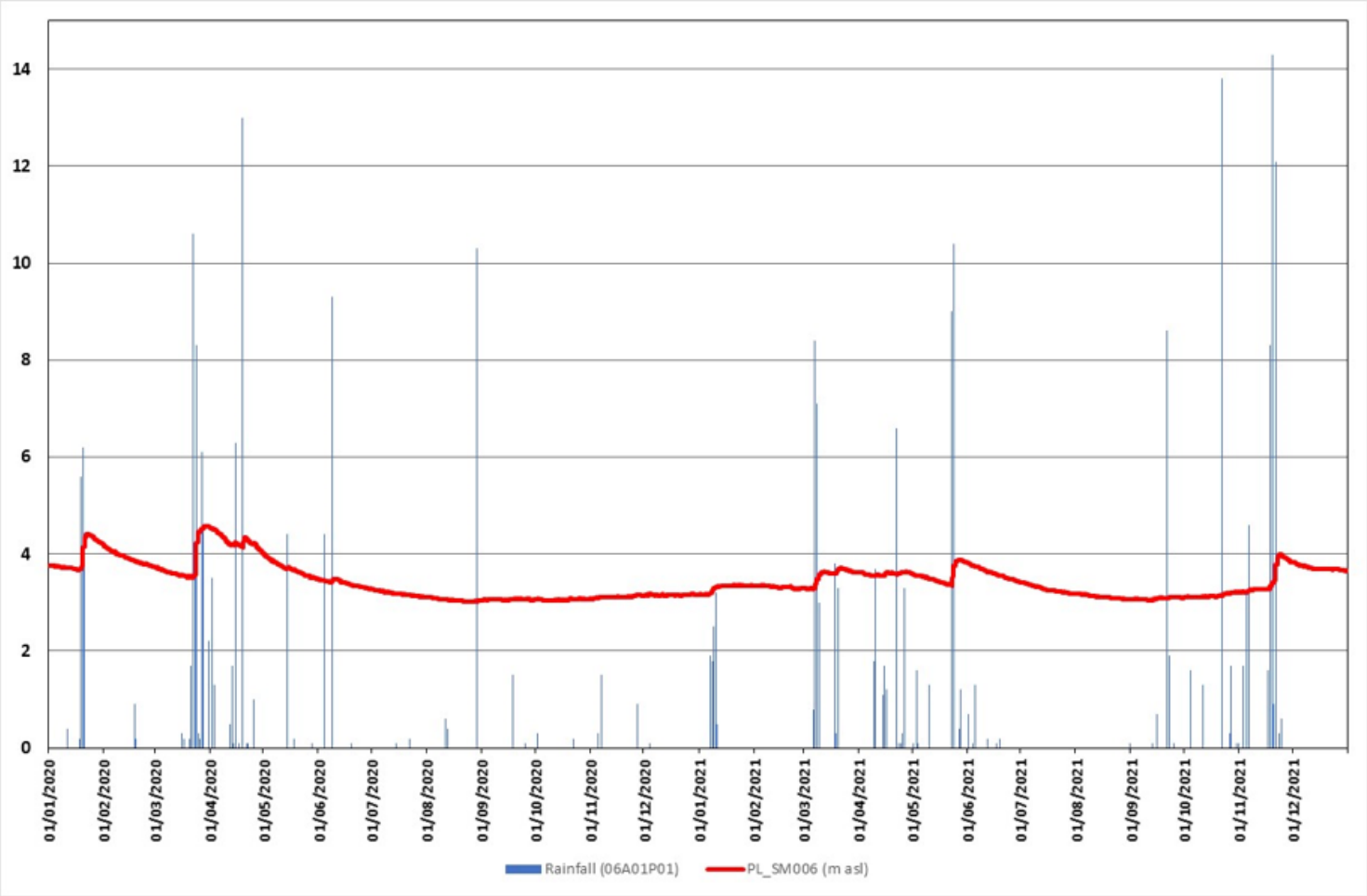

Figure 4

Relationship Rainfall-Piezometry. Hourly Rainfall data taken at (06A01P01) and piezometric level taken from SM006

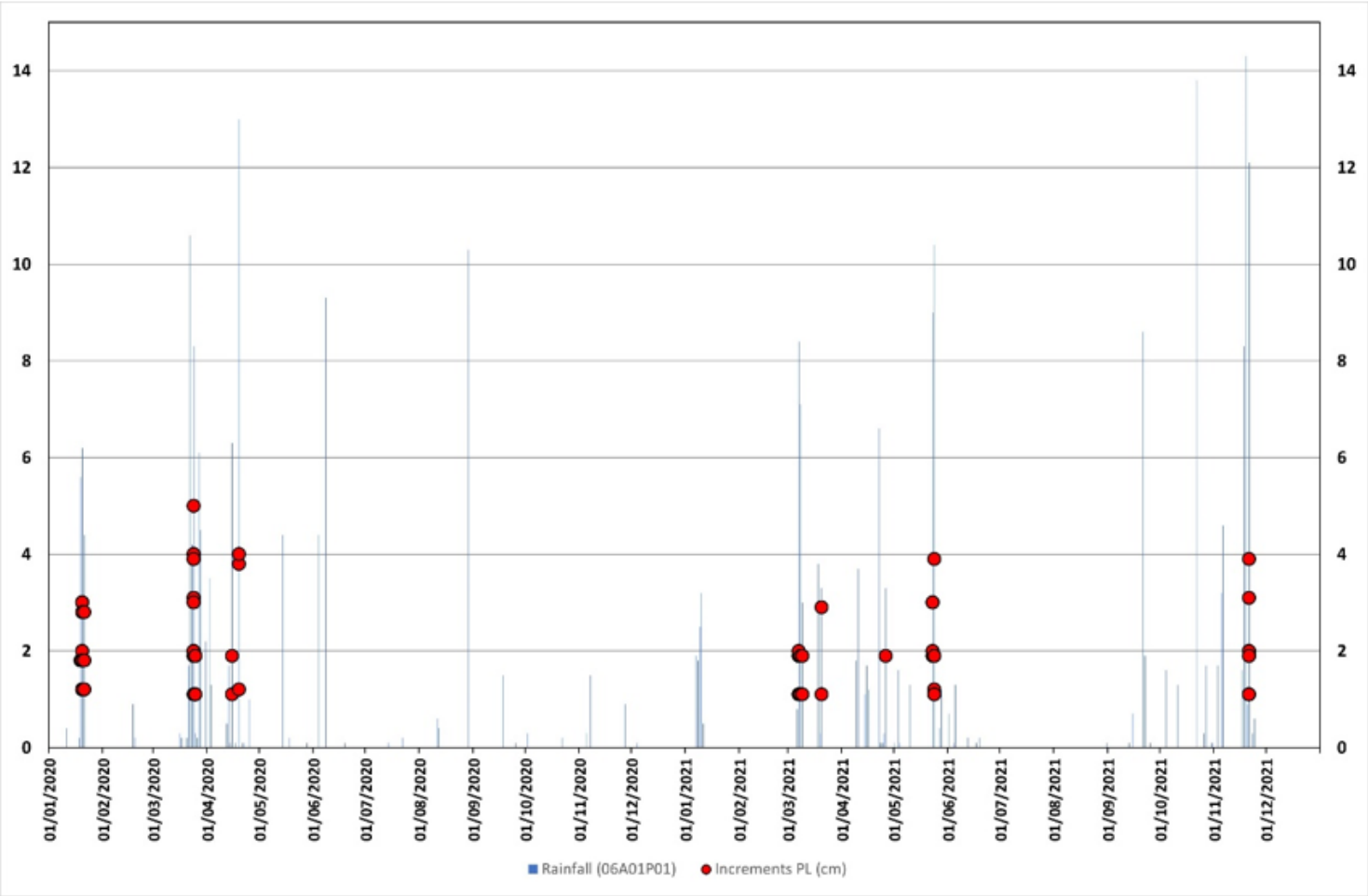

Figure 5

Relationship Rainfall- Increment of Piezometry. Hourly Rainfall data taken at (06A01P01) and increment of level piezometric level taken from SM006

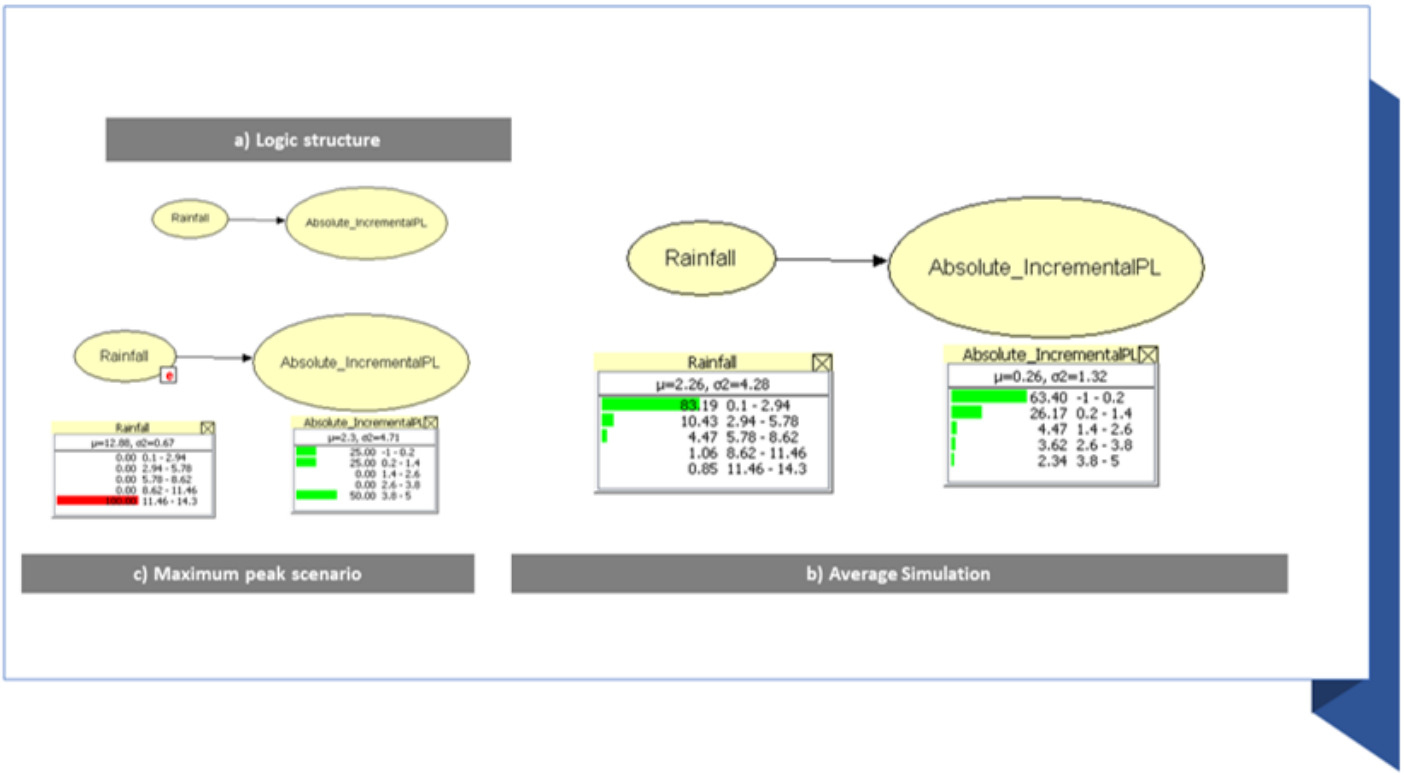

Figure 6

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