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A coupled hydrologic-machine learning modelling framework to support hydrologic modelling in river basins under Interbasin Water Transfer regimes

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ABSTRACT

Interbasin Water Transfer (IWT) is often a complex decision-making process that depends on factors ranging from hydro-meteorological conditions to socio-economic pressures. Hydrologic modelling is particularly challenging under these circumstances, requiring accurate quantitative information which may not always be available. This study proposes a methodological framework to simulate IWT flow contributions in the absence of observational data by introducing a coupled machine learning–hydrologic modelling approach. The proposed methodology employs a hydrologic model to simulate the rainfall-runoff process of a watershed, while a machine learning algorithm is used to simulate the decision-making process of IWTs. Methods are illustrated by simulating the hydrologic balance of the Dese-Zero River Basin (DZRB), a highly artificially modified catchment located in North-East Italy. Results suggest the proposed methodological framework can successfully simulate the complex water flow dynamics of the studied watershed and be a useful instrument to support complex scenario analysis under IWTs data scarce conditions.

1. Introduction

A watershed can be understood as the land area which drains water to a specific point in space by a stream network system. It can also be seen as a control system, where the water stored in the river basin is the result of the interaction between inputs (e.g. precipitation, incoming groundwater, etc.) and outputs (e.g. surface runoff, evapotranspiration, outgoing groundwater, etc.). As a consequence, a watershed is spatially defined according to its natural hydrology, representing the most logical basis for the management of water resources. The overall water movement in a watershed can, however, be rather complex. For instance, boundaries may not necessarily be hard borders, and water may move between watersheds by means of processes such as Interbasin Groundwater Flow (IGF) and Interbasin Water Transfers (IWT). Hydrological modelling under these circumstances is particularly challenging, requiring not only detailed quantified information about the external hydraulic loadings entering or leaving the watershed (Nyeko, 2014), but also a holistic perspective of the issues involved (Giupponi et al., 2012).

IWTs are a subject growing relevance both in science and for economic reasons due to expanding infrastructure base that allows for IWTs trading (Gomez et al., 2015; Marston and Cai, 2016) and water reallocation potential (Pérez-blanco et al., 2020; Rey et al., 2019). Even though an expanding literature on IWTs and water reallocation exists, the rationale behind the decision-making process that results in the complex management of IWTs hydraulic devices is a topic that requires further research (Pande and Sivapalan, 2017), particularly in the case of lack of information. Indeed, as the connections in human–water systems become increasingly stronger, the endogenisation of human agency becomes fundamental for describing the complex water movement of highly modified watersheds (Sivapalan et al., 2014). An example of a watershed that is subject to complex water flow dynamics resulting from complex artificial hydraulic management mechanisms (e.g. IWT) is the Dese-Zero River Basin (DZRB), in Italy.

To the best of our knowledge, no study has previously attempted to simulate the decision-making process of managing IWTs by using hydrologic modelling and machine learning techniques, and under conditions of data scarcity. This is the case of the DZRB, where no time-series data is available that specifies the quantities and timing of how IWTs are managed; however, factors that drive this processes are known, such as the accumulated precipitation during the past days, streamflow conditions downstream to IWTs, and baseflow contributions (Bixio et al., 2009c; Essenfelder et al., 2016; Essenfelder, 2017).

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This paper proposes an innovative methodological framework to simulate the decision-making process behind the management of IWTs in the DZRB under a situation of data scarcity. To do so, this paper identifies the main actors driving this decision-making process and makes use of a coupled machine learning–hydrologic modelling approach to quantify the estimated IWT flows. Under the proposed methodological framework, the hydrologic model takes the role of simulating the rainfall-runoff process, while the machine learning model accounts for the estimation of the IWT loadings entering the DZRB. The proposed methodological framework is designed to be flexible enough so to be used for different case study areas and under different time periods. The hydrologic model selected for this study is the Soil & Water Assessment Tool (SWAT) model (Arnold et al., 1998), an eco-hydrologic model that has already been used to simulate the hydrologic balance in the DZRB in previous studies (Salvetti et al., 2007, 2008; Azzellino et al., 2013; Essenfelder et al., 2016; Pesce et al., 2017), hence providing a reliable starting point and solid foundation for comparison basis. The machine learning technique selected for this study is a non-linear Artificial Neural Networks (ANN) model, given its robustness in simulating hydrologic and decision-making processes (Matsuda, 2005; Demuth, 2006; Çevirgen et al., 2015; Noori and Kalin, 2016; Essenfelder et al., 2018). The capabilities of the coupled SWAT-ANN model are illustrated with an application to the Dese-Zero River Basin (DZRB), in north-eastern Italy.

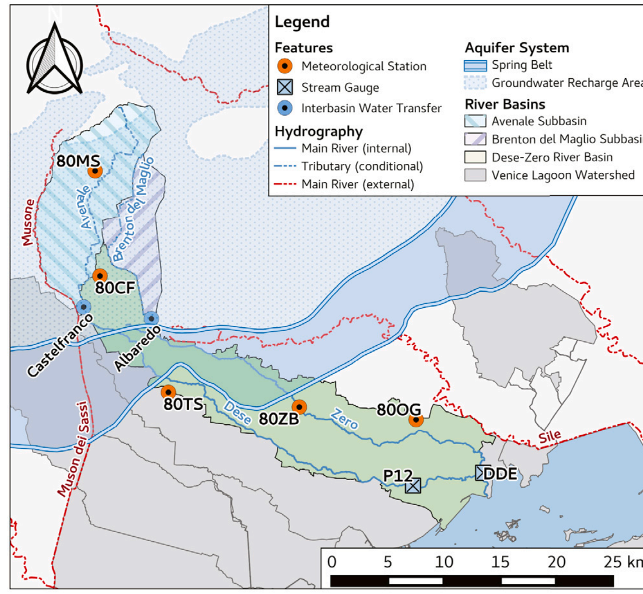

Fig. 1. The case study area and its main hydro-meteorological and hydraulic features.

2. Methodology

2.1. The study area

2.1.1. The dese-zero river basin

The DZRB is a highly artificially modified catchment that is part of the Venice Lagoon Watershed (VLW). In its most northern/north-western region, the DZRB receives significant amounts of spring waters coming mainly from outside the watershed's land area. This IGF contribution originates in an open aquifer located in the Venetian high plains, playing an important role in the overall water budget and nutrient balance of the DZRB (RegioneVeneto, 2000; Salvetti et al., 2007, 2008; Azzellino et al., 2013). Being highly variable throughout a year (Boscolo and Mion, 2008), the influence of the IGF on the DZRB is one of the reasons why this watershed hosts such remarkably modified environment. The DZRB and its main features are shown in Fig. 1.

Throughout the past centuries, several hydraulic works (e.g. water pumping systems and IWTs) have been implemented in the VLW (ADBVE and ADBAdige, 2010). These interventions have been implemented mainly for land reclamations and/or to regulate the amount of water flowing into the Lagoon of Venice (Bixio et al., 2009b). Currently, the general hydraulic management of the DZRB (and of the VLW in general) can be divided in two distinct phases: under low-flow conditions, and; under high-flow conditions. The low-flow phase is understood as the ordinary streamflow condition of the VLW, while high-flow conditions are the situations when streamflow level are abnormally high (Bixio et al., 2009a).

This complex artificial management scheme of the DZRB depends mainly on two factors: i. the amount of water flowing downstream of the hydraulic nodes, and; ii. the amount of water entering the watershed from external sources (Boscolo and Mion, 2008). The contrast between the two hydraulic management phases in the VLW is significant to the point that, during the high-flow phase, the totality of some sub-basins' streamflow is diverted to neighbour river basins which do not discharge in the Lagoon of Venice (Bixio et al., 2009b). As a consequence, the DZRB is a dynamic watershed in extension, ranging in area from a minimum of 250.6 km^2 to a maximum of 394.7 km^2, depending on specific hydraulic management conditions (Bixio et al., 2009b) (Fig. 1).

Two main IWTs are under operation in the upper-basin of the DZRB, namely Castelfranco Veneto hydraulic node and Albaredo di Vedelago hydraulic node. Hydrologically, the Castelfranco Veneto hydraulic node is the most important one (ADBVE and ADBAdige, 2010). This hydraulic node is responsible for managing a IWT from the Avenale sub-basin to either the VLW or to the Muson dei Sassi river, the latter not discharging into the Venice Lagoon. When water is derived from the Avenale sub-basin to the VLW, it may either flow to the Dese river or to the Marzenego river, the latter not part of the DZRB but part of the VLW. The complex Avenale's IWT is operated at the hydraulic junction of Castelfranco Veneto, as shown in Fig. 1. Similarly, the Zero river receives hydraulic contributions from the Brenton del Maglio sub-basin, by means of a hydraulic junction located near the city of Albaredo di Vedelago (Bixio et al., 2009b). Water that is deviated from the Brenton del Maglio sub-basin may either flow to the Zero or to the Sile rivers, the latter not discharging into the Lagoon of Venice.

The artificially controlled water dynamics observed in the DZRB is fundamental for maintaining an optimal streamflow (RegioneVeneto, 2000). This is especially true during the spring and summer seasons, when the amount of water withdrawals increases mainly due to increased evapotranspiration as a result of the increased irrigation water demand (Bixio et al., 2009b). As a consequence, an irrigation schedule scheme is currently in place in the DZRB (Bixio et al., 2009c). This irrigation schedule is set-up considering water availability and irrigation water demand, which, in turn, depends on soil characteristics and water availability. As a consequence, water may be imported from external sources when water demand for irrigation is greater than the amount of water available (Piave, 2011). Similarly, when water supply is greater than the demand, this same intricate hydraulic control system enables the administration of flood related risks, as the controlled hydraulic devices can be operated as a flood control system (Bixio et al., 2009b).

2.2. The SWAT model

SWAT (Arnold et al., 1998) is a conceptual, eco-hydrologic river basin scale model which allows a number of different physical processes to be simulated in a watershed while also enabling the evaluation of the impacts of different land management practices on the surface runoff, water quality, sediment transport, and agricultural chemical yields processes. SWAT offers the capability of assessing different land and water management processes, such as irrigation scheduling and water transfer between sub-basins, while, at the same time, providing the means to support the assessment of their impacts on a river basin scale (Neitsch et al., 2011).

For hydrologic modelling purposes, SWAT considers a river basin as a mosaic of smaller spatially-defined units, known as sub-basins, which are, in turn, further subdivided into smaller land units called Hydrological Response Units (HRUs) (Neitsch et al., 2011; Winchell et al., 2013). HRUs are defined as lumped land areas within a sub-basin that are comprised of unique land cover, soil, slope and management combinations (Arnold et al., 2012b). The consideration of spatially-distributed elements (i.e. sub-basins) and its subdivision into HRUs enables the model to reflect consequences on eco-hydrologic processes for a variety of land-use and soil classification, both temporally and spatially.

With regards to the simulation of external complex water flow contributions, SWAT allows water to be transferred and applied on an HRU from any water source within (e.g. between reservoirs, reaches, and sub-basins) or outside (e.g. IWT) a watershed (Neitsch et al., 2011). SWAT accounts for these processes by reading input information pertaining to the type of water source, the location of the source, the type of water body receiving the transfer, the location of the receiving water body, and the amount of water transferred for every day of the simulation (Neitsch et al., 2011). As a consequence, detailed quantified information is required to accurately reproduce water transfers in a watershed, something that can become a serious issue in cases of lack or insufficient availability of data.

The most basic information required by SWAT in order to simulate the hydrologic balance of a watershed are: i. Digital Elevation Model (DEM); ii. Soil spatial distribution and characteristics; iii. Land-use spatial distribution and respective land management operations, and; iv. Hydro-meteorological data (Arnold et al., 2012a). In this study, a DEM of resolution 5×5 m is utilised (RegioneVeneto, 2014). The soil and land-use vector maps (RegioneVeneto, 2014) were converted to raster format at a 5×5 m resolution grid by using the resample majority method so to maintain spatial integrity with the DEM. The original soil map classes were combined into 8 representative classes according to their soil textures, soil depth, soil layer profiles, and total coverage area. Missing soil parameters required by SWAT (e.g. saturated hydraulic conductivity) were derived from pedotransfer functions (Sun et al., 2016). The original land-use classes were combined and converted to SWAT-compatible land-use classes according to their representativeness in terms of total coverage area, resulting in a final number of 13 land-use classes. As a result, the DZRB was sub-divided into 14 sub-basins, for a final number of 476 HRUs.

Groundwater flow contributions coming from the shared aquifer system depicted in Fig. 1 were considered as additional inlet elements (Azzellino et al., 2013; Essenfelder et al., 2016). In order to define an upper boundary for the external hydraulic loadings (IWT) from the dynamic areas of the DZRB, the Avenale and Brenton del Maglio sub-basins were set-up as single SWAT projects. Hence, the Avenale sub-basin was sub-divided into 79 HRUs, while the Brenton del Maglio sub-basin has been partitioned into 16 HRUs. Meteorological data available for the case study area has been processed using the SWAT Weather Database Tool (Essenfelder, 2016), and temporally ranges from Jan/1993 to Dec/2014, on a daily basis, for the meteorological stations shown in Fig. 1. Streamflow data was available as measured by two distinct stream gauges, with data ranging from 1997 to 2005. For calibration purposes, observed streamflow data was arranged into the calibration and validation datasets, aiming at a validation:calibration ratio of around 1:4. Table 1 shows more details about the data used for the calibration and validation of the SWAT model.

2.3. The ANN model

Artificial neural networks (ANNs) are mathematical constructs that can be configured as linear or non-linear models, being defined as massively parallel distributed processors constituted of single process units, having the ability to store experiential knowledge and make it available for later use (Haykin, 2001). ANNs have been applied with relatively success in several fields of research, such as hydrologic modelling, image classification, remote sensing, human behaviour analysis, and decision-making simulation (Wu et al., 2005; Giacinto and Roli, 2001; Hsieh, 2009; Strnad et al., 2015).

Neural networks were born taking inspiration from the attempt to translate the knowledge on how the human brain works into a quantitative model, being capable of acquiring and storing knowledge from the surrounding environment, ultimately being capable of learning (through training) from this interaction (Wilamowski and Irwin, 2011). Together with the notion of learning comes the idea of adaptability, as ANNs have the capability of adapting their synaptic weights according to their perception of the surrounding environment. These capabilities of ANN models make this kind of machine learning technique an interesting option to simulate intellectual activity processes (Matsuda, 2005), such as the decision-making processes behind the management of IWTs.

The ANN model used in this study has been developed by the authors (Essenfelder, 2017) and is structured as a Multilayer Perceptron (MLP) neural network, using back-propagation as the supervised training algorithm and Levenberg–Marquardt as the optimisation algorithm (Hagan and Menhaj, 1994; Yu and Wilamowski, 2011). The model is capable of running in a multi-core configuration, either as a simple input–output model, as a time-delayed input–output model, or as either Non-Linear Autoregressive (NAR) or Non-Linear Autoregressive with eXogenous inputs (NARX) variants. For this study, a NARX ANN model variant is used, consisting of two hidden-layers and using a Swish activation function (Ramachandran et al., 2017) between hidden-layer nodes. The activation function at the output layer is a rectified linear activation unit (ReLU) function, hence allowing simulated values to be greater than the maximum observed valued in the target dataset. Regarding the training process, the ANN model evaluates the evolution of the Mean Squared Error (MSE) of the simulated results with regards to the targets (i.e. observations) as a metric system to assess whether generalisation has been achieved and to avoid the overfitting of the resulting trained model (Maier and Dandy, 2000; Hsieh and Tang, 1998).

The target variable considered in this study is the daily amount of water that is transferred in IWTs systems. As described in Section 2.2, the basins that contribute to the two simulated IWTs are modelled separately (i.e. Avenale and Brenton del Maglio sub-basins). Hence, the target variable describes the amount of water that is transferred from each of the individual sub-basins the DZRB by means of IWTs. Similarly, the difference between the total amount of streamflow as simulated by the individual SWAT projects for each subbasin and the amount of water that is transferred to the DZRB represents the water flow that is not discharging in the VLW; the latter being an important aspect for managing flood risk in the DZRB, which is, however, out of the scope of analysis of this paper.

The amount of water transferred in IWTs systems is usually variable in time, depending, among other factor, on water availability at the source and water demand at the destination. In this context, the way the IWTs of the DZRB are managed corresponds to a decision-making process, in which decision-makers determine the amount of water to be transferred as a function of hydro-meterological, hydraulic, and water requirement (e.g. irrigation) conditions. Since there is no available data series of observed flow transferred in the IWTs systems, the daily amount of water that is transferred in IWTs systems is estimated by means of hydrologic modelling, as described in Section 2.4.

During the hydrological simulations of the coupled SWAT-ANN model, the neural networks module receives on-line information from and is called iteratively by the SWAT model, for every day of simulation. The IWT results obtained from the ANN model are, then, transmitted to the SWAT model and incorporated into the hydrological simulations, being finally passed to the subsequent routing phase calculation steps. The maximum IWT estimated values should not exceed

Table 1
SWAT model input and related data.
Source: Data source: RegioneVeneto (2014), ARPAV (2015).

ID	Data provider	Description	Ref. year
DEM	Regione Veneto	Digital elevation model for the Veneto Region (5 × 5 m cells)	2000
Weather Data	ARPAV	Meteorological data for the Veneto Region	–
Streamflow	ARPAV/Regione Veneto	Measured streamflow data	–
Hydrography	ARPAV	Hydrography of interest to the Directive 2000/60/EC (scale 1:10.000)	2012
Sub-basins	ARPAV	Regional watersheds' limits (scale 1:10.000)	2015
Land-use	Regione Veneto	Land-use map and classes for the Veneto Region (scale 1:10.000)	2000
Soils	ARPAV	Soil map and classification for the VLW (scale 1:50.000)	2000

Table 2
ANN model input variable list.

Spatial scale	Variable	Unit	Symbol
Watershed	Precipitation[a,b]	mm	PCP
	Temperature (max and min)[a]	°C	TMP
	Act. evapotranspiration[c]	mm H_2O/day	AET
	Soil water content[c]	mm H_2O/day	SWC
	Irrigation water demand[c]	mm H_2O/day	IRR
Subbasin	Upstream streamflow[b,c,d]	m^3 s^{-1}	UFLW
	Downstream streamflow[b,c]	m^3 s^{-1}	DFLW
	Maximum IWTs flow[d]	m^3 s^{-1}	MFLW
	Baseflow[c]	mm H_2O/day	GWQ
–	Crop growing season[e]	–	CGS

[a]Values derived directly from daily observations.
[b]Time window of 7 days variable.
[c]Extracted daily from the SWAT model.
[d]Used to limit the maximum output values.
[e]Estimated to start on March 1st and to end on October 31st.

neither the daily simulated streamflow that is reaching an hydraulic node (i.e. upstream basin streamflow in Table 2), neither the technical limitations of the hydraulic node (i.e. maximum IWTs flow in Table 2). The maximum technical flow of the IWTs in the case study area were obtained from ConsiglioVeneto (2009) and Bixio et al. (2009b). In order to account for past hydro-meteorological information, the variables precipitation, upstream streamflow, and downstream streamflow are considered in a temporal window of 7 days. Since two IWTs are being considered in this study, an ANN model is set-up individually for each hydraulic node. Table 2 shows the list of input variables to the ANN models, the spatial scale in which they are considered, their units, and their symbols.

In the case study area, expert local knowledge on irrigation, land reclamation and the hydraulic management of the watershed must be integrated with the understanding of hydro-meteorological parameters for the proper management of the VLW's sub-basins (Bixio et al., 2009c). Hence, the information shown in Table 2 is selected having in mind the complex decision-making process, where the selected input variables are presented to the ANN model in order to transmit the knowledge of when water availability and water demand might need artificial interventions.

2.4. The methodological framework

A schematic representation of the proposed methodological framework to couple the SWAT and ANN models is depicted in Fig. 2. The methodological framework presented here relies on two assumptions: i. the hydrologic model utilised in the first step is capable of reproducing physically-consistent results regarding the rainfall-runoff process for the case study area, and; ii. the difference between observed and simulated streamflow values in any point downstream of IWTs contribution points is a good proxy for the estimation of the quantification of the absolute amount of water transferred by IWTs in the case study area. The second assumption is necessary in the DZRB case study as no quantitative information is available regarding the IWT process; in river basins where the amount of water transferred by IWTs is known, this assumption can be relaxed and this step can be by-passed.

The first step of the proposed methodological framework (i.e. SWAT Model - Reference Calibration in Fig. 2) consists in reference calibrating the SWAT model based on specific information already published in the literature (Salvetti et al., 2007, 2008; Azzellino et al., 2013; Essenfelder et al., 2016). Information from other sources is used as well, in order to get specific information pertaining the hydrologic balance of the case study area, such as technical details about the groundwater dynamics and irrigation schedule schemes (Bixio et al., 2009a,b,c; Boscolo and Mion, 2008; RegioneVeneto, 2000; ADBVE and ADBAdige, 2010). All this information is manually transferred to the parametrisation of the SWAT model.

The second step (i.e. Validation — PBIAS in Fig. 2), the first inside the SWAT-ANN box, consists in evaluating the accuracy in which the SWAT model is capable of reproducing the hydrologic balance of the case study watershed. The PBIAS model efficiency metric is selected as it is capable of expressing the tendency of simulated data to over-or-underestimate the reference data (Moriasi et al., 2007). In case the results are considered non-satisfactory (something that is expected for the DZRB due to the operation of IWTs), and, assuming that the first methodological step is consistent, it is possible to estimate the difference between the observed and simulated values. This information, then, is considered as a proxy for the quantification of the absolute amount of water transferred by IWTs in the case study area.

The third methodological step (i.e. ANN Model — Training & Validation, inside SWAT-ANN box in Fig. 2) consists in two different phases. First, the ANN model is trained under varying structures (i.e. number of neurons per layer) so to obtain an optimal ANN model configuration. Second, the model is validated by means of k-fold cross validation. For training and validation of the ANN model, the inputs-target dataset is randomly split into calibration (70%), validation (15%) and test (15%) datasets. The test dataset is used during the training phase of the ANN model in order to avoid the over-fitting of the model, not being used, however, for the calibration of the ANN model itself. The validation dataset, instead, is used only after the completion of the ANN training to evaluate its performance, thereby not being presented to the model during the training phase. The training process of the ANN model is repeated 1000 times, where each training attempt is initialised by restarting the initial weight connection values, adjusting the neural network structure, and k-folding the data samples. The 10 best ANN models (i.e. the ANN models with the 10 lowest MSE) are stored as

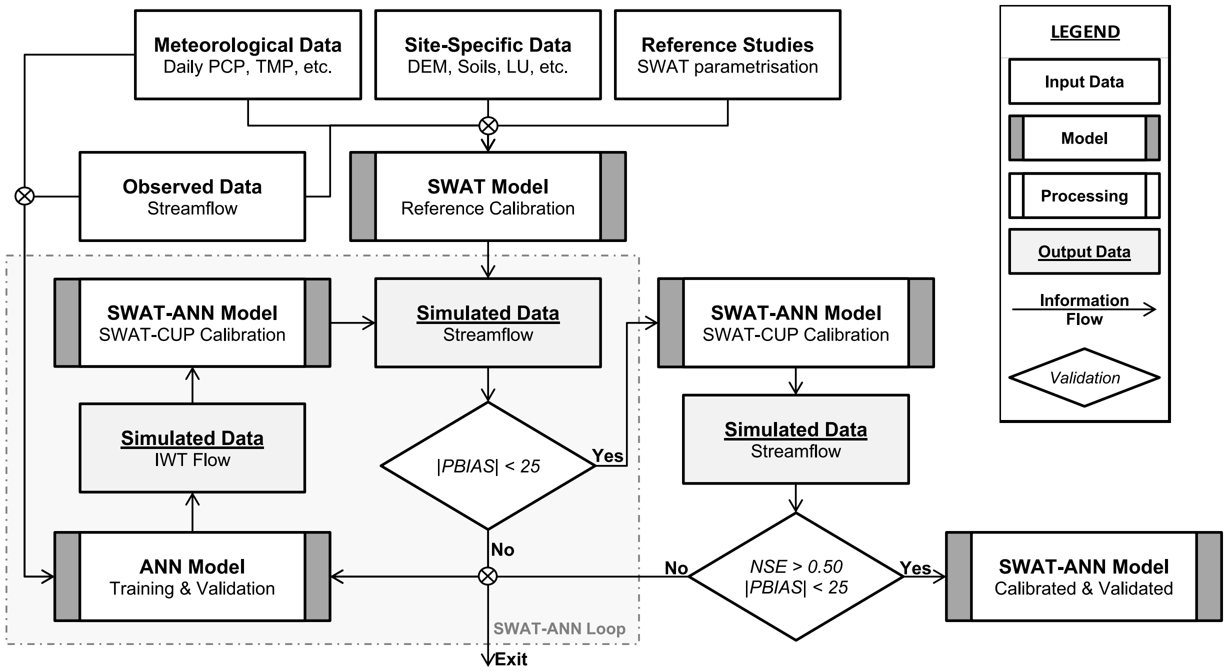

Fig. 2. Flowchart depicting the proposed methodological framework.

an ensemble of valid models, considered to be the best candidates for fitted models (Demuth, 2006). The simulated IWTs values are estimated as the median of the 10 models. Step three is done separately for each IWT (i.e. one for the Castelfranco Veneto and another for the Albaredo di Vedelago hydraulic nodes).

The fourth step (i.e. SWAT-ANN Model — SWAT-CUP Calibration, inside the SWAT-ANN box in Fig. 2) consists in coupling the ANN model obtained at step three with the SWAT model obtained at step one. The two models are coupled and run simultaneously during the SWAT-ANN calibration cycle, exchanging information at a daily level. This is done through a modification in the source code of the SWAT model to call the ANN model during every simulated day. The coupled SWAT-ANN model utilises the SWAT-CUP software and the SUFI2 procedure (Abbaspour, 2015) for calibration purposes. A first initial calibration cycle is performed by running 900 calibration iterations, followed by two sub-sequent fine-tuning calibration cycles of 500 iterations each. At the end of every calibration cycle, results with lowest PBIAS are assumed to be the most fitted model for the calibration cycle, while the model configuration with the lowest PBIAS value at the end of the third calibration cycle is assumed to be the overall most fitted SWAT-ANN model. In case a PBIAS value lower than 25 and greater than −25 is obtained, the model is assumed as valid and the calibration process of the model proceeds successfully to the next methodological step. In case PBIAS results indicate non-satisfactory results, the resulting SWAT-ANN model is considered as a non-valid model and the overall calibration process is terminated (i.e. an impossible estimation of IWT flows is assumed, as shown in Fig. 2).

In case of a positive PBIAS validation check, the fifth methodological step is reached and a new calibration of the coupled SWAT-ANN model is performed (i.e. SWAT-ANN Model - SWAT-CUP Calibration, outside the SWAT-ANN box in Fig. 2) by using the SWAT-CUP software and in a similar fashion to the calibration procedure described in the fourth methodological step. This time, however, two efficiency criteria are simultaneously evaluated, namely the Nash-Sutcliffe model efficiency coefficient — NSE, and, again, the PBIAS. The NSE is employed in this step as it allows for the identification of not only how well the simulated values of the SWAT-ANN model is being reproduced in time but also how well these results fit with the observations, as the calculation of the NSE criterion involves the computation of the squared difference between the observed and predicted values (Krause and Boyle, 2005). The metrics to evaluate the performance of the coupled SWAT-ANN are obtained from the literature (Moriasi et al., 2007). In case the resulting SWAT-ANN model is capable of producing satisfactory results with respect to observations, the model is assumed to be validated.

3. Results and discussion

The results and discussion section are presented following the five methodological steps presented in Section 2.4 and summarised in Fig. 2.

3.1. Steps 1 and 2 – SWAT model – reference calibration

Following the methodological framework described in Section 2.4 and summarised in Fig. 2, the manually calibrated SWAT model is followed by a calibration step using the SWAT-CUP and the SUFI2 procedure to further refinement. Regarding the water balance calibration, this procedure consists in modifying a total of 16 distinct SWAT parameters, focusing on three main hydrological-related processes (i.e. surface runoff, baseflow, and soil hydraulic properties). The list of modified parameters and their final calibrated values for this step is shown in Table 3. In accordance with the proposed methodology, the performance of the pre-calibrated SWAT model is evaluated by means of the R2 — Coefficient of Determination. The results regarding the performance evaluation of the pre-calibrated SWAT model are shown in Table 4.

The results shown in Table 4 indicate an acceptable behaviour if R2 is considered as the sole model efficiency criterion, both under the daily and monthly model configurations for streamflow (with the monthly basis configuration showing slightly better results); however, the results for the NSE and PBIAS are both non-acceptable. These results indicate that the hydrologic simulations are mispredicting the observed streamflow. This behaviour is confirmed by a considerable large underestimation bias for streamflow, in the order of 51% for the DZRB.

The results shown in Table 4 are somehow expected due to the fact that the DZRB is characterised by receiving significant amounts of external water coming from the IWTs, especially during the crop

Table 3
SWAT-CUP/SUFI2 final results for the pre-calibrated SWAT model.

Parameter	Description	Calibrated value (min–max)
CN2	Initial SCS CN II value	80.1 (70.4–89.9)
ESCO	Soil evaporation compensation factor	0.90
EPCO	Plant uptake compensation factor	0.87
SURLAG	Surface runoff lag coefficient	4.45
OV_N	Manning's 'n' - overland flow	0.13 (0.01–0.29)
CH_N1	Manning's 'n' - tributary channels	0.08
CH_N2	Manning's 'n' - main channel	0.23
GW_DELAY	Groundwater delay time	22.95
ALPHA_BF	Baseflow alpha factor	0.8785
GWQMN	Shallow aquifer water depth for return flow to occur	641.11
REVAPMN	Shallow aquifer water depth for "revap" to occur	258.85
GW_REVAP	Groundwater "revap" coefficient	0.1685
RCHRG_DP	Deep aquifer percolation fraction	0.0473
ALPHA_BF_D	Deep aquifer alpha factor	0.0868
SOL_AWC()	Available water capacity of the soil layer	0.13 (0.03–0.18)
SOL_K()	Saturated hydraulic conductivity	15.29 (0.01–92.48)

Table 4
Pre-calibrated SWAT model results (streamflow, calibration dataset).

Scenario	R2	NSE	PBIAS
Daily basis	0.542	0.222	51.243
Monthly basis	0.595	−0.134	51.263

Table 5
ANN model results, for IWTs water flow estimates.

Temporal Scale	Sub-basin	Dataset	R2	NSE	PBIAS	MSE
Daily	Dese	Training	0.654	0.652	0.233	0.320
		Validation	0.617	0.609	0.389	0.373
		Test	0.531	0.519	−0.465	0.423
	Zero	Training	0.678	0.675	1.098	0.159
		Validation	0.660	0.649	0.827	0.171
		Test	0.568	0.554	−0.130	0.198
Monthly	Dese	Training	0.837	0.834	0.748	0.160
		Validation	0.802	0.800	1.438	0.208
		Test	0.735	0.731	1.015	0.247
	Zero	Training	0.892	0.891	−0.349	0.112
		Validation	0.890	0.889	0.823	0.117
		Test	0.865	0.865	−0.668	0.129

growing season. In general, under the assumed configuration and due to the complexity of the studied watershed, the SWAT model alone is not capable of reproducing the overall water balance of the DZRB. However, it is interesting to notice that even if the IWTs components of the system are missing, the proposed pre-calibrated SWAT model is capable of producing simulations somewhat linearly correlated to the observed data, as evidenced by the coefficient of determination results. In fact, on a daily basis, the linear correlation between the observed streamflow and the simulated streamflow is as high as 0.736 for the DZRB.

In summary, the results for the pre-calibrated SWAT model suggest that, although the proposed model configuration is not capable of accurately simulating the hydrology of the studied watersheds, it is capable of linearly reproducing its behaviour in time, even if it systematically underestimate the streamflow observed values.

3.2. Step 3 – ANN model – training & validation

Recognising the fact that IWTs are missing to fully describe the hydrologic system of the case study area (see Fig. 2), the next proposed methodological step consists in estimating the hydrologic influences resulting from the complex management of the IWTs hydraulic nodes. As described in the Section 2.4, an ANN model is used for such a purpose. Moreover, for modelling purposes, the DZRB is split into Dese and Zero subbasins, allowing for the training of specific ANN models for each system. The modelling results of this operation are summarised in Table 5, while Fig. 3 depicts the information regarding the training progress and model performance.

The results shown in Table 5 and Fig. 3 indicate that the ANN model is capable of satisfactory reproducing the estimated total IWTs water flows to the studied watershed. In fact, both the NSE and PBIAS results shown in Table 5 suggest a very good skill of the ANN model to reproduce the desired hydraulic influences, particularly when aggregated at the monthly scale. Spatially, the skill of the ANN model is slightly lower when attempting to simulate the estimated total hydraulic influences from IWTs to the Dese subbasin. Even so, the results are considered to be satisfactory, as shown by a value of approximately 0.73 for NSE and of approximately 1.0 for PBIAS, both for the test dataset. The positive PBIAS results indicate, however, a slightly tendency of the ANN model to underestimate the target values. The strong modelling skill of the ANN model is graphically presented by the scatter plot of the target vs simulated values, as shown at the second row of Fig. 3.

The third row of Fig. 3 depicts some useful statistics regarding the simulation results of the ensemble of ANN models, such as the range of the simulated values and their respective first and third quartiles for each month, together with the median value of the target values for comparison purposes. In general, these results indicate that the ANN model has a very good skill in reproducing the monthly median IWTs flow contributions. Interestingly, it is possible to draw an interesting parallel with the water demand for irrigation during the crop growing season in the DZRB, as can be observed during the increased water inflow during the months between March and September. In summary, the results shown here indicate that the employed ANN model is capable of computing, both at the daily and monthly scales, the estimated hydraulic influences not taken into account when running the SWAT model alone.

3.3. Steps 4 and 5 – SWAT-ANN model – SWAT-CUP calibration & validation

Following the calibration and validation of the neural networks model, the next proposed methodological step consists on coupling the SWAT and the ANN models, on re-running the calibration process for the new model, and on the re-evaluation of the new simulation results. The outcomes of this operation are summarised in Tables 6 and 7. Fig. 4, instead, depicts a comparison between the results of the SWAT and SWAT-ANN models when performing the simulation of streamflow extreme values on a daily basis.

Confronting the results shown in Tables 3 and 7, it is possible to verify that the mean calibrated values for the majority of the calibrated parameters have not change significantly from the pre-calibrated SWAT model configuration, indicating a satisfactory SWAT pre-calibration

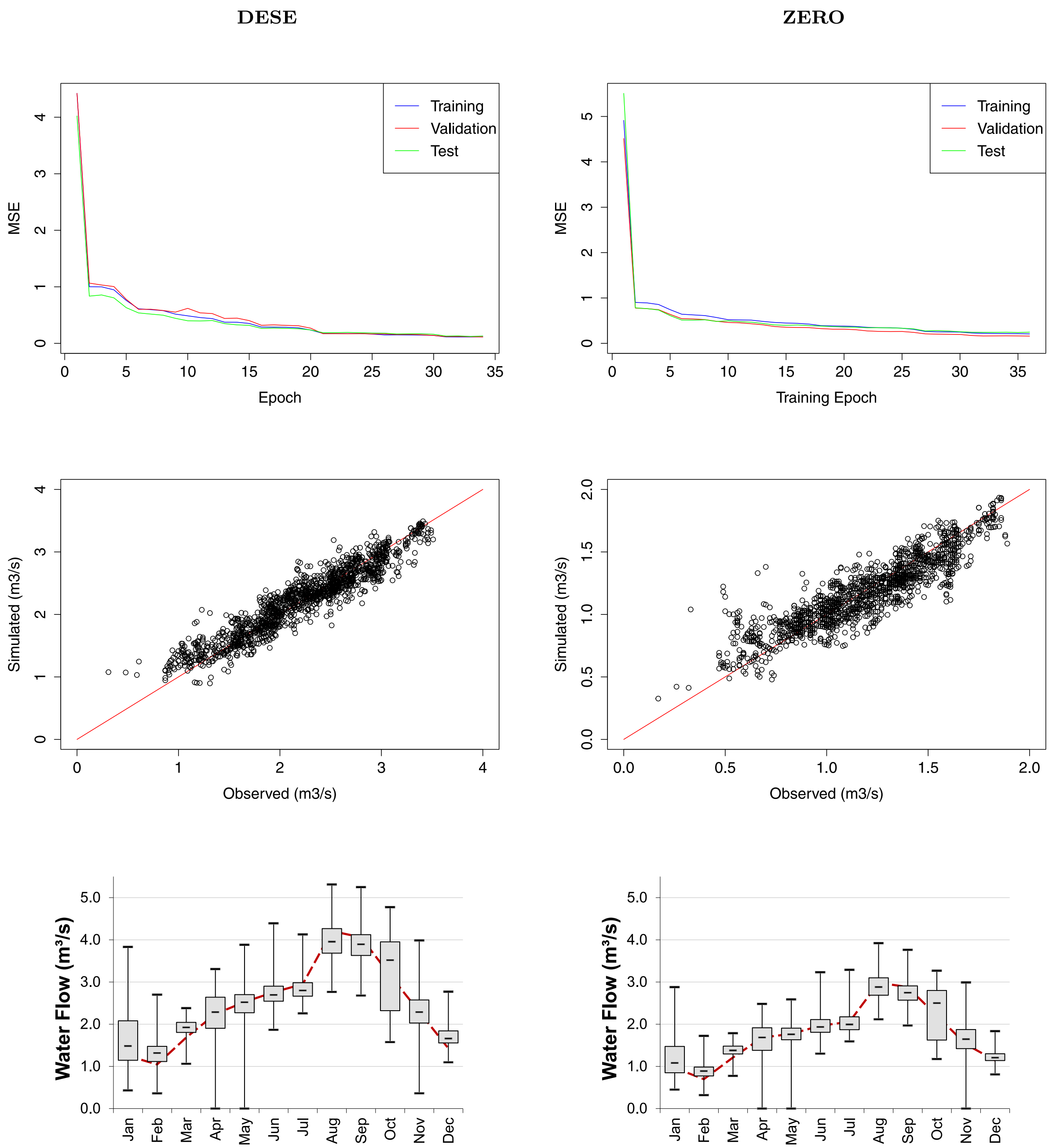

Fig. 3. ANN model results summary, for IWTs water flow estimates at monthly scale. From left to right: 1st Column: Dese; 2nd Column: Zero. From top to bottom: 1st Row: MSE evolution during training process; 2nd Row: Scatter Plot (Observed vs. Simulated values for the training dataset - a perfect fit is represented by the red diagonal line); 3rd Row: Monthly boxplots of the simulated results for the example year of 1997, for all ANN members (the red dashed-line represents the median target value).

procedure. In fact, considering only the parameters pertinent to the hydraulic balance of the studied watersheds, only one parameter show variations above an absolute threshold value of 50% with respect to the results of the pre-calibrated SWAT model when considering all three watersheds, namely GW_DELAY.

The increase in the absolute value of the parameter GW_DELAY indicates that the period of time that water takes to leave the soil profile and recharge the shallow aquifer is greater in the coupled SWAT-ANN model, signalling that the pre-calibrated SWAT model was possibly over-predicting the magnitude of the return flow in order to cope with the absence of the already mentioned IWTs hydraulic influences. The variation in the GWQMN parameter corroborates this idea. The coupled SWAT-ANN model calibration points to the direction that a deeper threshold of water in the shallow aquifer necessary for the return flow to occur with regards to the results of the pre-calibrated SWAT model. Another parameter that shows interesting results it the SURLAG. The actual increase in the SURLAG parameter indicates that the pre-calibrated SWAT model was over-predicting the amount of surface runoff discharging into the streams for every day of simulation.

In any case, the GW_DELAY, GWQMN and SURLAG values obtained after the SWAT model pre-calibration procedure indicate a configuration which tried to emulate the observed hydrological behaviour of a system without, however, considering any of the IWTs hydraulic influences to the studied watershed. Consequently, the automatic calibration of the SWAT model adjusted the intrinsic watershed parametrisation in order to account for such missing information. Ultimately, this has lead to an overestimation of both groundwater and surface runoff contributions to the main channel flow when the relevant external water sources to the studied watersheds are not considered.

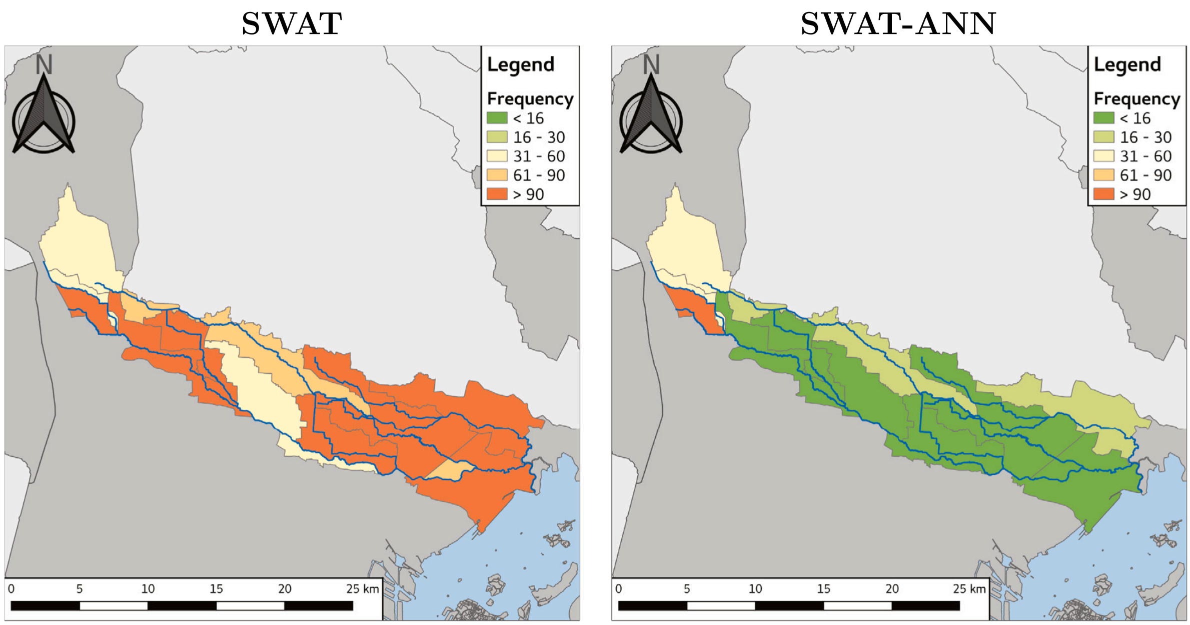

Fig. 4. Performance comparison between the pre-calibrated SWAT and the coupled SWAT-ANN model results when simulating extreme streamflow values per sub-basin. The classification represents the frequency in which the simulated values are either lower than the 1st or higher than the 99th percentiles of the observed streamflow database.

Table 6
SWAT-CUP/SUFI2 final results for the calibrated coupled SWAT-ANN model.

Parameter	Description	Calibrated value (min–max)
CN2	Initial SCS CN II value	73.5 (64.5–82.4)
ESCO	Soil evaporation compensation factor	0.95
EPCO	Plant uptake compensation factor	0.90
SURLAG	Surface runoff lag coefficient	7.10
OV_N	Manning's 'n' - overland flow	0.18 (0.01–0.41)
CH_N1	Manning's 'n' - tributary channels	0.12
CH_N2	Manning's 'n' - main channel	0.18
GW_DELAY	Groundwater delay time	35.80
ALPHA_BF	Baseflow alpha factor	0.7758
GWQMN	Shallow aquifer water depth for return flow to occur	893.43
REVAPMN	Shallow aquifer water depth for "revap" to occur	365.75
GW_REVAP	Groundwater "revap" coefficient	0.0855
RCHRG_DP	Deep aquifer percolation fraction	0.0404
ALPHA_BF_D	Deep aquifer alpha factor	0.0610
SOL_AWC()	Available water capacity of the soil layer	0.12 (0.03–0.16)
SOL_K()	Saturated hydraulic conductivity	14.80 (0.10–89.52)

Regarding the modelling capabilities of the coupled SWAT-ANN model, it can be verified a significant improvement of the model's performance, as shown in Table 7 and Fig. 4, particularly at the monthly scale. An interesting result attributed to the difference in the composition of the calibration and validation datasets can be verified when analysing the results shown in Table 7. While the coupled SWAT-ANN model exhibits a tendency to overestimation the streamflow for the calibration dataset, it shows the opposite behaviour when applied to the validation dataset. This discrepancy can be attributed to particularities of both calibration and validation datasets, such as the presence of wetter years in the calibration dataset. Anyhow, the results of the coupled SWAT-ANN model for case study area can be considered to be satisfactory and significantly improved from the results of pre-calibrated SWAT model.

The results shown in Table 7 and Fig. 4 confirms the importance of IWTs flows for the water balance of the DZRB. By applying the methodology described in Section 2, it is possible to quantify these influences, even under a situation of data scarcity. For the case study area, the mean percentage of the total streamflow of the DZRB that can be attributed to sources external to the watershed varies from 19% during wet weather conditions to 59% during dry weather conditions during the simulation run from 1996 to 2014.

Table 7
Coupled SWAT-ANN model results.

Dataset	Scenario	R2	NSE	PBIAS
Calibration	Daily basis	0.817	0.797	14.171
	Monthly basis	0.905	0.837	14.096
Validation	Daily basis	0.635	0.593	17.432
	Monthly basis	0.765	0.662	17.049

4. Conclusions

The DZRB is characterised for being a very complex catchment. Several modifications in its superficial watercourses throughout the centuries have resulted in a very unique environment requiring specialised hydraulic management practices. From a number of external hydraulic contributions capable of affecting the water dynamics of the VLW, two stand-out, namely: i. Groundwater entering the VLW from the big unconfined aquifer to the north/north-west of the VLW, and; ii. Artificially controlled superficial waters deviated from/to bordering watersheds that do not discharge into the Lagoon of Venice.

This study proposed a framework to estimate the total external hydraulic contributions to the DZRB, a sub-basin of the VLW. The proposed methodological framework is built upon the use of a coupled mechanistic-empirical modelling technique based on the hypothesis that the mechanistic model (i.e. SWAT) is capable of simulating the hydrological processes and water movement occurring inside boundaries of the studied watersheds, while the empirical model is capable of simulating the total external hydraulic contributions. The mechanistic model used in this research is the SWAT model while the empirical counterpart is an Artificial Neural Networks (ANN) model.

The results obtained from the implementation of the proposed methodological framework suggest that the coupled SWAT-ANN model is not only capable of satisfactory reproducing the water balance of the studied watershed, but also to increase the hydrological modelling capability of the SWAT model when performing under an intricate and complex environment such as the DZRB.

The results obtained from the application of the proposed methodology also confirm the findings of previous studies in the same area, indicating that under ordinary flow conditions and in dry periods, the water balance of the DZRB is in general highly affected by water flowing into the watershed from bordering watersheds, particularly during the spring and summer seasons.

Finally, as some recommendations for further developments in this field of research, it is proposed the consideration of other hydro-meteorological variables, such as snow coverage area, snow depth and potential snow melt flux in the pre-alpine region affecting the recharge processes of the aquifer system, and the water table depth of the aquifer system in the vicinities of the VLW, if at a compatible time-scale. Moreover, the use of more robust modelling tools, such as the SWAT-MODFLOW model could also lead to better simulation results, particularly in what pertains to the groundwater flow dynamics.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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