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Effects of hydrological variability on the sustainable use of water in a regional economy. An application to Tuscany

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ABSTRACT

Existing input-output (IO) models have mainly focused on water demand. Some studies have incorporated water supply (availability), but do not take into account its natural variability, an essential element when performing a water stress analysis. The present study integrates the hydrological variability of water availability into a hydroeconomic IO model, considering its exogenous effects on water supply and its exogenous effects on water demand. Two endogenous effects are considered: i) changes in blue water requirements in the agricultural industry due to variations in precipitation and evapotranspiration, and ii) changes in grey water requirements in all discharging industries due to variations in runoff and groundwater recharge. By means of a T-years hydrological series and Monte Carlo simulations, the model allows estimating T values of the Extended Water Exploitation Index (EWEI), obtaining its empirical probability distribution and confronting it with scarcity thresholds. Additionally, the model includes a methodology to incorporate intra-annual variation, obtaining the critical month EWEI and defining a more transparent and endogenous scarcity threshold. Empirically tested for the Italian region of Tuscany considering a multivariate hydrological model for the generation of a 100-year hydrological series, our results allow a more in-depth analysis of water scarcity in the region.

1. Introduction

The pressure of the economic system on water resources is a key issue in the challenges of sustainable water use (European Environment Agency, 2020). Economic activities exert pressures on water resources directly through the abstraction of water from natural sources and indirectly through the virtual water embodied in goods and services purchased (Allan, 1993). The analysis of these pressures must take into account not only water demand, but also natural water availability (which determines water supply), which can exhibit significant inter-annual and intra-annual variability and will be accentuated by climate change in various geographical areas (IPCC et al., 2021). Hydrological variability (or more generally hydrological uncertainty) is an essential element when performing a water stress analysis (Hemri et al., 2005; Todini, 2011). If we consider two regions with the same water demand and supply, but one with greater hydrological variability, the latter will be more exposed to the environmental, social and economic impacts of dry years.

Input-output (IO) models have been widely used to study water pressures exerted by economic activities, determining direct and indirect water demand by industries (Lenzen et al., 2013; Velazquez, 2006; Guan and Hubacek 2008), and for the estimation of virtual water flows and water footprint at regional (Wang et al., 2013; Deng et al., 2016; Rocchi and Sturla, 2022), national (Zhuoying et al., 2011; White et al., 2015; Cazcarro et al., 2013; Distefano et al., 2022) and global scales (Feng et al., 2014; Duarte et al., 2016; Arto et al., 2016; Wood, 2017; Soligno et al., 2019). These studies have not considered water availability.

The concept of scarcity-weighted water footprint (Pfister et al., 2009; Ridoutt and Pfister, 2010; Ridoutt et al., 2018) has motivated the incorporation of water availability for the purposes of calculating the water stress index (weighting factor). This approach has been applied in several IO models at different spatial scales (Lenzen et al., 2013; Sturla et al., 2023; Zhang et al., 2018; White et al., 2015). Recently developed IO models have also been used to estimate the water balance by deriving water demand with the economic model and determining water supply from water availability data (Cámara and Llop, 2020; Garcia-Hernandez and Brouwer, 2021; Rocchi et al., 2024). A common factor in all these studies is the fact that they consider average water availability.

Although some studies evaluate the pressure on water resources

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considering the water supply for a dry, average and wet year (Rocchi et al., 2024) or considering an average climate change scenario (Garcia-Hernandez and Brouwer, 2021), so far, there are no studies that integrate an extended IO model with hydrological variability, representing it exogenous (direct) effects on water availability and it endogenous (indirect) effects on water demand. In the present study we aim to close this gap by incorporating hydrological variability into the analysis of the pressures exerted by the economic system on the water system using IO models.

Given that the hydrological system is more variable than the economic one and that IO models are generally built for a specific economic year, it is interesting to analyse the impacts of this productive system for the different possible hydrological years, in order to determine the scenarios of economic pressure on water resources. Such an analysis is much more comprehensive than analyses based on average values, and can provide very relevant information for the diagnosis of scarcity and for the design of policies to mitigate impacts.

Regarding the incorporation of hydrological variability in hidro-economic models, one of the approaches used and recommended in the literature corresponds to the Monte Carlo methodology, i.e., making hydro-economic estimates for a set of hydrological years/scenarios (Zhang et al., 2018; Ercolani and Castelli, 2018). This set of hydrological years can be generated based on multivariate stochastic models in the case where no record is available for the long-dated hydrological components (Yevjevieh, 1987). Monte Carlo analysis can also be considered as a sensitivity analysis of the results of a deterministic hydro-economic model to the uncertainty associated with hydrology, when this corresponds to an input variable (Pianosi et al., 2016). Following these recommendations, for the purposes of the extended water IO model developed in this study, we consider the existence of a hydrological series for T years including precipitation, evapotranspiration, runoff and groundwater recharge (in the empirical application of the model we use a multivariate model for the generation of the hydrological series).

The model developed in this study is based on the environmentally extended input-output models developed by Guan and Hubacek (2008) and Rocchi et al. (2024), considering the extended water demand (blue and grey water) and the feasible supply (environmental, technical and institutional constraints), which allow to obtain the Extended Water Exploitation Index (EWEI) Rocchi et al. (2024). Several authors have discussed whether it is correct to consider grey water as part of the demand (Guan and Hubacek, 2008; Pfister et al., 2009; Ridoutt and Pfister, 2010). Although grey water could be seen as a more abstract concept, in this work we consider that this water must come from the same water sources as the blue water. In other words, we assume that grey water corresponds to a demand for blue water, and that it must be considered for the purposes of maintaining the qualitative balance of water in natural sources. We follow the approach of Ridoutt and Pfister (2010).

Two endogenous effects of hydrological variability on water demand are considered: i) changes in water withdrawals and discharges coefficients in the agricultural industry due to variations in precipitation and evapotranspiration (replace green water with blue water), and ii) changes in water requirements for dilution coefficients (grey water) in all discharging industries due to variations in runoff and groundwater recharge. By means of a T-years hydrological series and Monte Carlo simulations, the model allows estimating T values of the EWEI obtaining its empirical probability distribution and confronting it with the scarcity thresholds existing in the literature.

Agriculture uses green water (precipitation and soil moisture) and blue water (groundwater and surface water). For dry hydrological years agriculture has to extract more blue water to replace the missing green water. Moreover, when evapotranspiration is higher (lower), more (less) blue water will be required for irrigation. The calculation of water required for dilution depends on the concentration of COD in the receiving bodies, as runoff and groundwater recharge vary, thus changing the volume required to restore the water quality. The mixing model integrated in the proposed hydro-economic model, considers the water discharges estimated with the IO model, generating a change in the extended demand of all discharging sectors. In the case of agriculture, a second order endogenous effect is generated, i.e., precipitation and evapotranspiration generate a change in the discharges, which is used to re-calculate the grey water with the mixing model.

A further development of the proposed model considers intra-annual hydrological variability to estimate the EWEI of the critical month, i.e. the month in which the ratio between the extended demand and the feasible supply is highest. For this purpose, intra-annual variability of agricultural water demand and intra-annual variability of surface water supply are considered. The EWEI for the critical month of each hydrological year allows the estimation of an endogenous threshold, which is defined on the basis of the condition that in none of these critical months does the outflow water demand exceed the feasible supply. This threshold is much more transparent than the thresholds defined in the literature, which implicitly consider variability, but are designed for average conditions (Raskin et al., 1997; Alcamo et al., 2000; Pfister et al., 2009). In addition, calculating the EWEI for critical months also allows the validity of the literature thresholds in a geographical region to be verified.

An important contribution of the proposed model is that it allows for the first time the joint characterisation of interannual and intra-annual variability through a hydro-economic IO model, which allows a more comprehensive characterisation of water scarcity generated by economic pressure on water resources.

The model is empirically tested for the Tuscany region in Italy for which a hydro-economic IO study was carried out considering average values (Rocchi et al., 2024). This region presents an important inter-annual and intra-annual hydrological variability (Crisci et al., 2002; Fatichi and Caporali, 2009; D'Oria et al., 2017, 2018), which makes it interesting to evaluate the results including hydrological variability with deterministic results. A multivariate statistical model was used to generate a 100-year series of hydrological components, allowing estimates of feasible supply and demand for each year based on the natural availability and the variability-corrected withdrawal and discharge coefficients for the agricultural sector and all discharge sectors.[1]

Section 2 presents the hydroeconomic input-output model with hydrological variability to estimate the EWEI for the T years, considering the adjustment of the water withdrawal and discharge coefficients in the agricultural sector and the calculation of grey water in the discharging industries using a mixing model. This section includes the methodology to estimate the EWEI for the critical month and the endogenous scarcity threshold. In section 3, the data used for the case study is presented and a multivariate statistical hydrological model is built to generate a 100-years synthetic series of hydrological components. Section 4 presents the main results of the study, i.e. the probability distribution of the extended demand by industry, the changes in the composition of the agriculture demand due to hydrological variability, the empirical probability distribution of the annual and critical month EWEI indicator, and a comparison with the scarcity thresholds. Finally, section 5 presents discussions and conclusions, highlighting the contribution of this work to a more comprehensive understanding of water stress and providing an analysis of the results of the case study.

[1] The objective of including 100 years of hydrology is to expose the productive system of Tuscany (2017) to hydrological scenarios that could have occurred. These 100 years do not correspond to the future, they are synthetic series generated based on a statistical model supported by annual records (period 1971–2010) of precipitation, evapotranspiration, runoff and recharge. In probabilistic terms, any of these hydrological scenarios could have occurred in 2017.

2. Methodology

2.1. Overview of the model

Fig. 1 presents a schematic representation of the model. The box "Hydrological Model" represents the generation of the T-years hydrological components series, which can be obtained from other sources of information, through the construction of a statistical hydrological model or a physically based hydrological model. In the case of this study, they correspond to 100 synthetic hydrological series, generated from the information and the multivariate model described in section 3.2 of this study. Based on this series, the feasible supply is determined (exogenously) and the withdrawal and discharge coefficients (agricultural sector) and the grey water needs of the discharging industries (using the mixing model) are adjusted (endogenously). Using this information plus the regional IO table, the extended water demand is estimated using the IO model. With the extended demand and the feasible supply a value of the EWEI is obtained for each simulated year. Furthermore, with the extended demand and the intra-annual distribution factors, the EWEI for the critical month of each year is estimated. Finally, based on the literature thresholds for the annual EWEI and the endogenous threshold proposed in this work, an analysis of water scarcity in the geographical area of study is carried out.

2.2. Extended demand and EWEI

2.2.1. Extended demand

Let A_d the *(n x n)* matrix of technical coefficients that represents the structure of intermediate consumptions per unit of output of production activities, calculated from the domestic flows input-output table ($n = 56$ industries in this study (IRPET, 2021)). The total production of the n industries can be calculated from the following equation (Miller and Blair, 2009):

$$x = (I - A_d)^{-1} y \tag{1}$$

where x is the (n x *1*) vector of gross output of the industries, y is the (n x *1*) vector of the final demand and I is the (n x n) unit matrix.

The extended water demand (n x *1*) vector e_k from the water body k (disaggregated by industry) is defined considering the environmentally extended approach for input-output models (Miller and Blair, 2009):

$$e_k = (\widehat{f_k} - \widehat{r_k} + \widehat{w_k})(I - A_d)^{-1} y \tag{2}$$

where f_k, r_k and w_k represent the (n x *1*) water use coefficient vectors (in $m^3/€$) of withdrawal, discharge and dilution requirements, from water body k (groundwater, surface water and hydrological cycle[2]). The hat symbol indicates the diagonalization of the vector.

The total extended demand for water (ED) corresponds to the sum of the components of the vector e_k for groundwater and surface water.

$$ED = \sum_{k=1}^{2} \varepsilon \bullet e_k \tag{3}$$

Where ε corresponds to an (*1 x n*) vector of ones.

2.2.2. EWEI

The extended water exploitation index (EWEI) is defined as the ratio between the extended water demand and the feasible water supply. Feasible supply takes into account environmental, technical and institutional constrains to water use (Rocchi et al., 2024).

$$EWEI = \frac{ED}{I^{feas} + R^{feas}} \tag{4}$$

where the sum considers groundwater and surface water, $k = \{1,2\}$. I^{feas} and R^{feas} represent the long term groundwater and surface water feasible supply, respectively. However, these variables are defined year by year based on annual runoff and recharge, and environmental, technical and institutional parameters.

$$I_t^{feas} = \left\{ \begin{array}{c} \bar{I}(1-B) \quad if\ I_t < \bar{I}(1-B) \\ \bar{I}(1+B) \quad if\ I_t > \bar{I}(1+B) \\ I_t \quad if\ I_t \in [\bar{I}(1-B), \bar{I}(1+B)] \end{array} \right\} \tag{5}$$

$$R_t^{feas} = \left\{ \begin{array}{c} R_t - E\bar{R} \quad if\ E\bar{R} < R_t < M\bar{R} + E\bar{R} \\ M\bar{R} \quad if\ R_t > M\bar{R} + E\bar{R} \\ 0 \quad if\ R_t < E\bar{R} \end{array} \right\} \tag{6}$$

where.

I_t	: Groundwater recharge volume in year t
$\bar{I}$	: Groundwater recharge mean volume
B	: Parameter defining the range of groundwater feasible availability
R_t	: Runoff volume in year t
$\bar{R}$	: Runoff mean volume
E	: Ecological flow as proportion of mean runoff
M	: Maximum volume of concessions as a share of mean runoff

It is important to note that, for the calculation of the feasible supply of surface water, storage capacity is not considered, due to the lack of larger or smaller reservoirs that regulate water on an interannual basis (Rocchi et al., 2024). However, and despite the few smaller reservoirs and the lack of data for smaller reservoirs, this could be relevant in the intra-annual analysis carried out in section 2.5.

2.2.3. Extended demand and EWEI with hydrological variability

When hydrologic variability is considered, the water use coefficients change according to the components of the hydrologic cycle. Let us define the extended demand associated with water body k, industry i in the year t as:

$$e_{k,i,t} = \left(f_{k,i,t} - r_{k,i,t} + w_{k,i,t}\right) \bullet x_i \tag{7}$$

For simplicity, we use x_i , which in the Leontief model represents the i component of the $\left[(I - A_d)^{-1} y\right]$ vector.

Withdrawal coefficients will change for agricultural production activities due to variations in precipitation and evapotranspiration. Discharge coefficients will depend directly on runoff and groundwater recharge and indirectly on precipitation and evapotranspiration. Sections 2.2 and 2.3 detail the methodology for estimating the time-varying terms of the water use coefficients.

A general scheme for the extended water demand dependence in hydrology is defined. Equations (7)–(9) present the water use coefficients, each of which can be written as a function of its deterministic value plus the time-varying term ($\mathscr{F}_{k,i,t}, \mathscr{R}_{k,i,t}, \mathscr{H}_{k,i,t}$) which depends on hydrological variability.

$$f_{k,i,t} = f_{k,i} + \mathscr{F}_{k,i,t}(P_t, E_t) \tag{8}$$

$$r_{k,i,t} = r_{k,i} + \mathscr{R}_{k,i,t}(P_t, E_t) \tag{9}$$

$$w_{k,i,t} = w_{k,i} + \mathscr{H}_{k,i,t}\left[I_t, R_t, \mathscr{R}_{k,i,t}(P_t, E_t)\right] \tag{10}$$

Where P_t, E_t, R_t and I_t correspond to the precipitation, evapotranspiration, runoff and groundwater recharge, respectively, for the year t. It is assumed that this information is available for a set of T years in the study

[2] For the purposes of this study, we call the hydrological cycle the natural source from which the green water collected by agriculture comes, that is, the water collected directly from precipitation and soil moisture. In addition, for the purposes of water balance, we consider discharges from other economic sectors into the hydrological cycle (mainly evaporation).

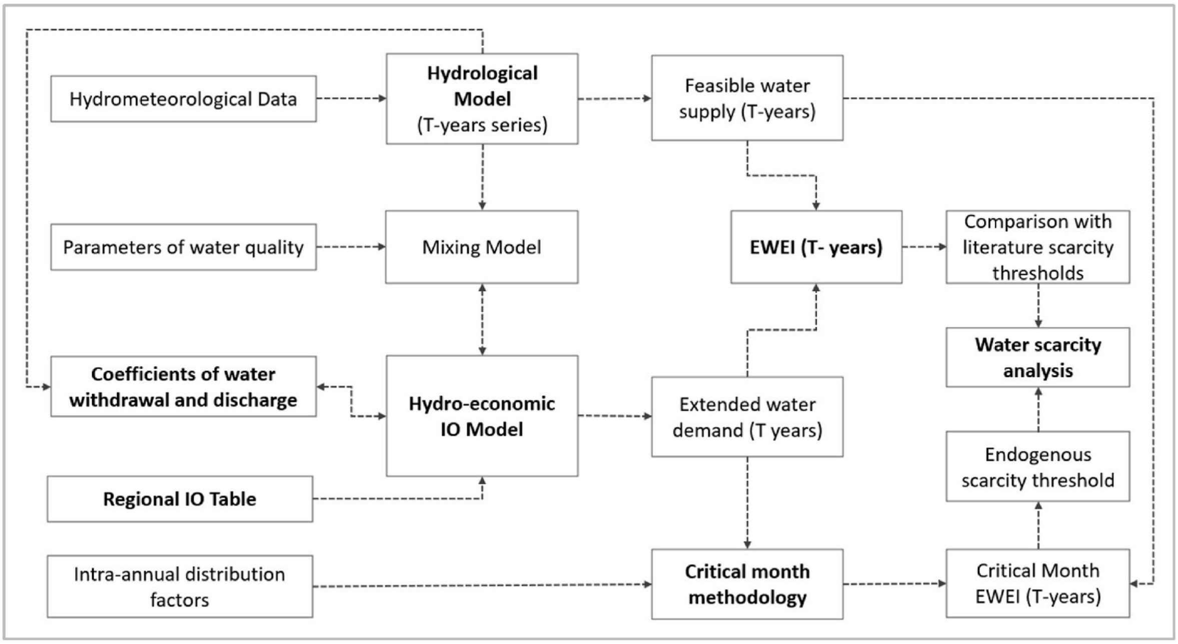

Fig. 1. Scheme of the IO model with hydrological variability.
Source: Own elaboration

region.

Using equations (7)–(10) it is possible to write the water extended demand associated with water body k, industry i and year t:

$$e_{k,i,t} = e_{k,i} + \left[\mathscr{F}_{k,i,t}(P_t, E_t) + \mathscr{R}_{k,i,t}(P_t, E_t) + \mathscr{H}_{k,i,t}\left[I_t, R_t, \mathscr{R}_{k,i}(P_t, E_t)\right]\right] \bullet x_i \tag{11}$$

Note that $\mathscr{F}_{k,i,t}(P_t, E_t) = 0$ and $\mathscr{R}_{k,i,t}(P_t, E_t) = 0$ for non-agricultural sectors, and $\mathscr{H}_{k,i,t}\left[I_t, R_t, \mathscr{R}_{k,i,t}(P_t, E_t)\right] = 0$ for non-discharging sectors.

By summing the extended groundwater and surface water demand for all industries, it is possible to express the ED for the year t, considering hydrological variability and the average extended water demand with hydrological variability ($\overline{ED}_t$).

$$ED_t = \sum_{i=1}^{N} \sum_{k=1}^{2} e_{k,i,t} \tag{12}$$

$$\overline{ED}_t = \sum_{t=1}^{T} ED_t \tag{13}$$

By summing the extended groundwater and surface water demand for all industries, it is possible to express the EWEI indicator for the year t:

$$EWEI_t = \frac{ED_t}{I_t^{feas} + R_t^{feas}} \tag{14}$$

2.3. Variability of agricultural water demand

An important part of the water used by agriculture corresponds to green water, that is, water obtained directly from soil moisture, which is strongly dependent on rainfall (Te Chow, 2010). In this study we consider that this type of water comes from hydrological cycle (previously defined), and each sub-sector of agriculture has its own withdrawal coefficient for this type of water. In this study we assume rainfall variability as a proxy for the variability of water captured directly from the hydrological cycle, because an aggregate regional (or other scale of analysis) soil moisture value is not representative of the actual green water availability for agriculture, i.e. it is not reasonable to confront the green water needs of agriculture with the total regional soil moisture content, as not all areas are used for agriculture (Braca et al., 2021, 2022). Furthermore, long-term soil moisture series are not commonly available. To include soil moisture requires physically based hydrological models, which is not within the scope of the present study.

Since the withdrawal coefficients are representative of an average hydrology, we consider that when precipitation is less than average (less availability of green water), agriculture must withdraw more groundwater and surface water for irrigation to make up for this deficit and maintain the level of agricultural production for the reference economic year. The total green water deficit is considered, i.e., the deficit associated with irrigated and non-irrigated agriculture. Specifically, we consider that the withdrawals from the hydrological cycle is reduced in a proportion given by the ratio between the respective year's precipitation and the average annual precipitation.

Regarding blue water, the groundwater and surface water withdrawals of irrigated agriculture depends on climatic conditions such as temperature and radiation, and these requirements are well represented by evapotranspiration, which is correlated with water requirements by crops (Te Chow, 2010). The deterministic water withdrawal coefficients are representative of an average hydrological year, however, these coefficients should be higher or lower depending on the specific conditions of each hydrological year (the time-varying component). Given that a regional evapotranspiration series is available, we consider that the irrigation water withdrawals change due to annual evapotranspiration variations.

We assume that when evapotranspiration in a year is higher (lower) than the average annual evapotranspiration, irrigation water withdrawals will increase (decrease). The proportion in which these requirements increase or decrease will be given by the ratio between the respective year's evapotranspiration and the mean annual evapotranspiration.

Since the agricultural sub-sectors carry out both crops and livestock activities, the crop component only is considered for the hydrological variability effects. The withdrawal and discharge deterministic coefficients of the agricultural sub-sectors can be broken down into the part requiring irrigation (irrigated and potentially irrigated crops) and the part associated with livestock:

$$f_{k,i} = f_{k,i}^{irr} + f_{k,i}^{liv} \tag{15}$$

$$r_{k,i} = r_{k,i}^{irr} + r_{k,i}^{liv} \tag{16}$$

Where subscript i refers only to crop production activities.

The Appendix details the methodology used to modify the water withdrawal and discharge coefficients, depending on the need to substitute green water with blue water and the variability of blue water requirements in irrigated agriculture.

2.4. Variability of water demand for dilution

The deterministic coefficient $w_{k,i}$ of equation (10) can be calculated using a mixing model based on a mass balance of COD concentration (Xie, 1996; Guan and Hubacek, 2008; Rocchi et al., 2024). The $w_{k,i,t}$ term of equation (9), in this study, is calculated with the same model, but considering time dependence and two endogenous effects:

- Discharges volumes from the agricultural sector depend on precipitation (P_t) and evapotranspiration (E_t), as discussed in the preceding section.
- The COD concentration in receiving water bodies depends on groundwater recharge (I_t) and runoff (R_t).

The coefficients of water requirements for dilution by water body k and industry i for the year t, is expressed as:

$$w_{k,i,t} = \frac{u_{k,i,t}}{x_i} \tag{17}$$

where, $u_{k,i,t}$ (m^3/year) is the water for dilution, which is calculated with the following mixing model:

$$u_{k,i,t} = \left[\frac{k_{2k} \bullet c_{p_{k,i}} - c_{sk,t}}{k_{1k} \bullet c_{sk,t} - c_{0k,t}}\right] \bullet r_{k,i,t} \bullet x_i \tag{18}$$

where.

k_{1k}	total reaction rate of pollutants after entering the water body k
k_{2k}	pollution purification rate before entering the water body k
$r_{k,i,t} \bullet x_i$	discharges into the water body k associated with industry i for year t
$c_{p_{k,i}}$	COD concentration in the discharges to the water body k associated with industry i
$c_{sk,t}$	Standard COD concentration in water body k for year t
$c_{0k,t}$	COD concentration in water body k for year t

Note that $r_{k,i,t} = r_{k,i} + \mathscr{R}_{k,i,t}(P_t, E_t)$ (equation (8)) is completely defined by the hydrological variability in the agricultural sectors. This is the first endogenous component.

Note also that $u_{k,i,t}$ is linearly dependent in the output x_i, and from equations (14) and (15) we can write $w_{k,i,t}$ as:

$$w_{k,i,t} = \left[\frac{k_{2k} \bullet c_{p_{k,i}} - c_{sk,t}}{k_{1k} \bullet c_{sk,t} - c_{0k,t}}\right] \bullet r_{k,i,t} \tag{19}$$

The second endogenous component corresponds to $c_{0k,t}$, the COD concentration in the water bodies. We propose an expression for this term that takes into account decreases in COD concentration due to wetter hydrology and increases in COD concentration due to drier hydrology; this is based on the fact that the discharge of organic matter depends on the economic system (fixed in this work).

The third endogenous component is $c_{sk,t}$. When COD concentration in water bodies $(c_{0k,t})$ is higher than the standard concentration in average conditions (c_{sk}), the standard concentration for the year t $(c_{sk,t})$ is considered to be that of the water body, since in the model the water for dilution come from the hydrological system. Then:

$$c_{sk,t} = \begin{cases} c_{sk} & if\ c_{0k,t} \leq c_{sk} \\ c_{0k,t} & if\ c_{0k,t} > c_{sk} \end{cases} \tag{20}$$

To characterize $c_{0k,t}$, we define the variable $\pi_{k,t}$, based on the hydrological model, as the ratio between the supply volume in year t and the mean supply volume, given by the hydrological model, for groundwater and surface water:

$$\pi_{gw,t} \equiv \frac{I_t}{\overline{I}} \tag{21}$$

$$\pi_{sw,t} \equiv \frac{R_t}{\overline{R}} \tag{22}$$

Let define the following parameters.

c_{0k}^{min}.	Minimum concentration in water body k
c_{0k}^{max}.	Maximum concentration in water body k
c_{0k}^{mean}	Mean concentration in water body k
π_k^{min}.	Ratio of minimum volume to average volume in water body k
π_k^{max}.	Ratio of maximum volume to average volume in water body k
π_k^{mean}	Equal to 1 by definition

A linear model is assumed to represent the relationship between COD concentration in water bodies before discharge and the hydrology. The following linear relation is considered for $c_{0k,t} \in \left(c_{0k}^{min}, c_{0k}^{max}\right)$:

$$c_{0k,t} = a \bullet \pi_{k,t} + b \tag{23}$$

where,

$$a = \frac{c_{0k}^{max} - c_{0k}^{min}}{\pi_k^{min} - \pi_k^{max}}$$

$$b = c_{0k}^{mean}. - a$$

For concentrations below the minimum and above the maximum, the ratio of the maximum COD concentration to runoff or groundwater recharge is considered constant. Thus, the function representing the COD concentration of water body k in the year t is:

$$c_{0k,t} = \begin{cases} c_{0k}^{min} & if \quad \pi_{k,t} \leq \pi_k^{min}. \\ a \bullet \pi_{k,t} + b & if \quad \pi_k^{min} < \pi_{k,t} < \pi_k^{max} \\ c_{0k}^{max} & if \quad \pi_{k,t} \geq \pi_k^{max} \end{cases} \tag{24}$$

With equations (20) and (24), the term $w_{k,i,t}$ expressed in equation (19) is characterized. Thus, the additional water for dilution with hydrological variability can be calculated as the difference between the time-varying and the deterministic coefficient:

$$\mathscr{H}_{k,i,t}\left[I_t, R_t, \mathscr{R}_{k,i}(P_t, E_t)\right] = \left[\frac{k_{2k} \bullet c_{p_{k,i}} - c_{sk,t}}{k_{1k} \bullet c_{sk,t} - c_{0k,t}}\right] \bullet r_{k,i,t} - w_{k,i} \tag{25}$$

With this last equation, the input-output model with hydrologic variability is fully determined, including endogenous changes in water use coefficients, due to the natural hydrologic variability.

2.5. Critical month

Up to this point, the EWEI has been proposed on the basis of the extended water demand and annual feasible supply of water. The incorporation of interannual variability allows a better approximation to reality; however, it is possible that pressures on water resources occur at smaller time scales. In this section we propose a methodology to approximate the EWEI at monthly scales.

In this study, the intra-annual regulation capacity for surface waters and groundwater is not considered. In the case of surface waters, the seasonal structure is considered, and in the case of groundwater, it is assumed that it is distributed homogeneously, considering only part of the intra-annual regulation capacity. That is, although recharge phenomena do not occur homogeneously throughout the year, it is possible to extract a fixed amount monthly given the regulation capacity of the aquifers.

2.5.1. Feasible supply of the critical month

In the case of groundwater, since this water body has a storage capacity, we do not consider an intra-annual distribution factor. Then the feasible groundwater supply in month j and year t is:

$$IM_{j,t}^{feas} = \frac{1}{12} I_t^{feas} \tag{26}$$

We conversely model the feasible surface water supply in month j and year t as follows:

$$RM_{j,t}^{feas} = \frac{1}{12} R_t^{feas} \bullet g_{R,j} \tag{27}$$

where $g_{R,j}$ is the surface water supply factor associated with month j.

The feasible supply of groundwater and surface water in month j and year t, is written as:

$$FSM_{j,t} = \frac{1}{12}\left[R_t^{feas} \bullet g_{R,j} + I_t^{feas}\right] \tag{28}$$

3.2. Hydrological series

3.2.1. Data

Rocchi et al. (2024) generated a series for the water balance in Tuscany (Braca et al., 2021, 2022) with the components: precipitation (P), evapotranspiration (E), groundwater recharge (I), and runoff (R). This series contains 40 years, and its statistics are presented in Table 1.

These series have been analysed to evaluate their normality and linear independence; this in order to build a model that allows to generate synthetic hydrological series in Tuscany.[3]

The test used for normality is the Jarque-Bera test (Hamilton, 1994), in which the null hypothesis that the distribution is normal for each of the 4 series is rejected. Regarding linear independence, the Ljung-Box autocorrelation test is used (Hamilton, 1994), where the null hypothesis of linear independence of the series is not rejected in any of them. The main results are shown in Tables 2 and 3.

According to these results, the hydrological series can be considered independent and identically distributed, which is usual in annual series, while the temporal structure of autocorrelation in climates such as Tuscany is appreciated on a monthly or daily scale (Te Chow, 2010).

3.2.2. Multivariate model

The hydrological series for Tuscany comes from a normal distribution and do not present a linear autocorrelation structure. It is then possible to represent them by means of a multivariate normal model, through which values can be generated for n years, that is, synthetic series longer than the 40-year recording period.

Table 1
Statistics of the hydrological series of Tuscany (1971–2010).

Statistics	P	E	I	R
Mean (Mm^3)	20,269	11,892	4155	3802
S. Deviation (Mm^3)	3084	1129	1258	1157
C. Variation	15%	9%	30%	30%
Skewness	0.2	−0.2	0.4	1.3

Source: Own elaboration base on Rocchi et al. (2024).

[3] The value of runoff in 2010 is an anomalous figure within the series, excessively high. As this figure does not correspond to the precipitation of the same year, it has not been considered in the normality and independence analysis.

Table 2
Normality Test to hydrological series.

Parameter	P	E	I	R
JB Statistic	0.63	0.33	0.94	8.33
p-value	0.66	0.83	0.53	0.79
H0 (Normality)	Not rejected	Not rejected	Not rejected	Not rejected

Source: Own elaboration

Table 3
Autocorrelation Test to hydrological series.

Parameter	P	E	I	R
LB Statistic	0.02	0.06	1.30	0.78
p-value	0.88	0.81	0.25	0.37
H0 (Independence)	Not rejected	Not rejected	Not rejected	Not rejected

Source: Own elaboration

The vector $\vec{X}$ represents all the components of the hydrological balance, $\vec{\mu}$ the mean and Σ the matrix of variances and covariances. The multivariate model collects the relationship between the different components.

$$\vec{X} = \left(\vec{P}, \vec{E}, \vec{I}, \vec{R}\right)$$

$$\vec{X} \sim \mathscr{N}_4(\vec{\mu}, \Sigma)$$

Based on hydrological statistics we have the vector of sample averages $\vec{\mu}$. The variance and covariance matrix Σ is presented in Table 4.

$$\vec{\mu} = (20,269\ ;\ 11,892\ ;\ 4,155\ ;\ 3,802)$$

In this way, a model is available that allows the generation of synthetic hydrological series for Tuscany. The simulation for 100 years that is used in the input-output model of this study is presented in Fig. 2. Table 5 presents the statistics of the 100-year series, where it can be seen that the model replicates the structure of the historical series quite well, especially the coefficient of variation where differences of more than 10% are not detected.

2.5.2. Extended demand of the critical month

Regarding the water demand, we assume that it is constant throughout the year, except for agriculture (Venturi et al., 2014).

To calculate the agriculture extended demand we consider equation (11), which includes the hydrological variability. The extended demand of the agricultural sectors in month j and year t, for groundwater ($AED_{j,t}^{gw}$) and surface water ($AED_{j,t}^{sw}$) are defined as:

$$ADM_{j,t}^{gw} = \frac{1}{12} \bullet \sum_s e_{s,gw,t} \bullet g_{A,j} \tag{29}$$

$$ADM_{j,t}^{sw} = \frac{1}{12} \bullet \sum_s e_{s,sw,t} \bullet g_{A,j} \tag{30}$$

Where the subscript s represents the agricultural sub-sectors and $g_{A,j}$ is the monthly agricultural extended demand factor associated with month j. The same factor is assumed for all agricultural sub-sectors.

Table 4
Variance and covariance matrix in (Mm^3).

Var-Cov	P	E	I	R
P	9,513,099	1,709,308	3,603,712	3,058,521
E	1,709,308	1,274,309	230,111	127,168
I	3,603,712	230,111	1,581,925	1,313,728
R	3,058,521	127,168	1,313,728	1,337,715

Source: Own elaboration

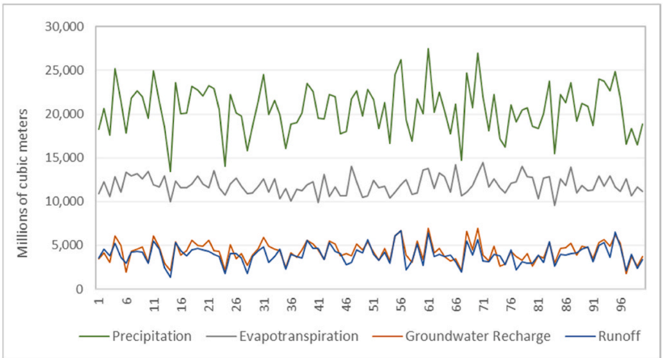

Fig. 2. 100-year synthetic hydrological series.
Source: Own elaboration

Table 5
Statistics of the 100-year synthetic hydrological series.

Statistics	P	E	I	R
Mean (Mm^3)	20,269	11,892	4155	3802
S. Deviation (Mm^3)	2766	1068	1140	1075
C. Variation	13%	9%	27%	27%
Skewness	−0.1	0.2	0.1	0.1

Source: Own elaboration

Total groundwater extended demand for month j in year t $\left(EDM_{j,t}^{gw}\right)$ and total surface water extended demand for the month j and the year t $\left(EDM_{j,t}^{sw}\right)$ can be written using equations (11), (29) and (30):

$$EDM_{j,t}^{gw} = \frac{1}{12}\sum_{q} e_{q,gw,t} + \frac{1}{12} \bullet \sum_{s} e_{s,gw,t} \bullet g_{A,j} \tag{31}$$

$$EDM_{j,t}^{sw} = \frac{1}{12}\sum_{q} e_{q,sw,t} + \frac{1}{12} \bullet \sum_{s} e_{s,sw,t} \bullet g_{A,j} \tag{32}$$

Where the subscript q represents the non-agricultural sectors.

2.5.3. Critical month EWEI and endogenous scarcity threshold

The critical month corresponds to the month in which the EWEI reaches its maximum (CM). Reformulating equations (14)–(16), and using equations (26), (27), (31) and (32), the EWEI of the critical month is calculated as follows:

$$EWEI_{t,CM} = \max_{j} \frac{EDM_{j,t}^{gw} + EDM_{j,t}^{sw}}{IM_{j,t}^{feas} + RM_{j,t}^{feas}} \tag{33}$$

An endogenous water scarcity threshold is defined under the criterion that the EWEI in the critical month is less than 1 for each of the T years:

$$EWEI_{t,CM} < 1, \forall\, t \in T \tag{34}$$

Thus, the proposed sustainability criterion ensures that in no month the extended demand exceeds the feasible supply. Or, more precisely, the scarcity threshold ensures water supply in volume and quality for the whole period, taking into account the economic and hydrological characteristics of the geographical area of study (considering monthly resolution). Since the feasible supply does not consider the ecological flow in surface bodies, a value equal to unity for the EWEI does not imply the absence of water. This threshold jointly considers surface and groundwater as the fixed thresholds in the literature, however, it is possible to apply it separately.

2.5.4. Montecarlo procedure

The input-output model applied to Tuscany by Rocchi et al. (2024) considers the average values of hydrology, which translates into deterministic results (single value) for the extended demand and the EWEI.

The following procedure is applied n times to obtain the stochastic results. In each step the section where the methodology can be found is indicated.

1. With the multivariate hydrological model, an annual value is generated for each component of the hydrological balance: precipitation, evapotranspiration, surface runoff and groundwater recharge (section 3.2)
2. Withdrawals and water discharges are calculated with the IO model and the deterministic coefficients of water use (section 2.1.1).
3. Corrections are made to the withdrawal and discharge coefficients using the proposed model for agriculture (section 2.2), based on precipitation and evapotranspiration.
4. The withdrawals and water discharges for the agricultural sector are recalculated (section 2.2).
5. Based on the results of the IO model discharges (corrected in the previous point), surface runoff and groundwater recharge, the water dilution coefficients are estimated using the mixing model (section 2.3).
6. The IO model is used to estimate the volumes of water required for dilution (section 2.1.3).
7. The input-output model procedure is carried out to obtain the water extended demand by industry and water body (section 2.1.3).
8. The feasible supply is calculated based on surface runoff and groundwater recharge (section 2.1.2).
9. The EWEI is calculated for the year considering the water extended demand and the feasible supply (section 2.1.3).
10. The EWEI for the critical month is calculated (section 2.4)

The most relevant results are presented and detailed in the next section with $n = 100$ years.

3. Case study

The application of the model to the Tuscany region in Italy is considered, with the aim of deepening the deterministic analysis of the pressures of the economic system on the water system carried out by Rocchi et al. (2024). The data and parameters of the aforementioned study are used and new parameters are considered for the estimation water requirements for dilution and the EWIE of the critical month. A multivariate statistical model is built for the generation of a synthetic 100-year series with the hydrological components necessary to apply the methodology.

3.1. Data for the model

We consider the input-output matrix of the Tuscany region, for the year 2017, with 56 industries (IRPET, 2021). The water withdrawal and restitution coefficients for the average hydrology condition (deterministic coefficients), the water quality parameters for the mixing model and the parameter to calculate the feasible supply correspond to those used by Rocchi et al. (2024).

The new parameters included in this study correspond to the intra-annual runoff and agricultural demand distribution factors (Section A of the Supplementary Materials), and to the COD concentration model parameters and runoff/recharge ratios, which are detailed below.

c_{sk}	20 mg/l
$c{o}_k^{min}$	15 mg/l
$c{o}_k^{max}$	25 mg/l

(continued on next page)

(*continued*)

co_k^{mean}	= 20 mg/l
π_k^{min}	= 0.5
π_k^{max}	= 1.5
π_k^{mean}	= 1.0

4. Results

4.1. Extended demand of water

A first result is the cumulative probability function of the extended water demand of all industries, both total and disaggregated by water body (Fig. 3). This is a fundamental outcome of the model allowing to study the probability distribution of the extended demand, given by all the sources of variability included. Table 6 shows the main statistics for each of the distributions represented in the graph. Although water from the hydrological cycle (precipitation captured directly by agriculture and soil moisture; green water) is not part of the extended demand, it has been included in the figures and tables to highlight the large amount of green water consumed by agriculture, which in dry years must be replaced by blue water (represented in the model with hydrological variability).

The comparison of the extended demand estimated with the present model and the deterministic results of Rocchi et al. (2024) is relevant due to the role played by agriculture and water for dilution (endogenous effects). As can be seen in Fig. 4, for the model with hydrological variability developed in this study there is a decrease from 42.3% to 41.0% (−36.9 Mm^3) in the use of surface water and an increase from 10.8% to 12.5% in the case of groundwater (+29.9 Mm^3). In the case of surface water, while agricultural demand increases by 30.4 Mm^3 (years in which there is insufficient precipitation), the water required for dilution decreases by 67.3 Mm^3, due to the variability of the concentration in the mixing model; the effect of the dilution requirement dominates. For surface water, agricultural demand increases by 32.5 Mm^3 and dilution water decreases by 2.6 Mm^3; the effect of agricultural demand dominates. The percentage of water demand from the hydrological cycle (green water) decreases from 46.9% to 46.6% (−56.8 Mm^3) only due to the effect of hydrological variability on the agricultural sector.

Sections B and C of Supplementary materials show the detailed results for the variability of the extended water demand in agriculture and the variability of water demand for dilution, respectively.

Regarding the extended demand by macro-sectors, Table 7 presents the summary statistics by water body. Services and water supply industry do not present any variability of the extended demand, the first one because it does not use water directly from the water bodies and the second one because it discharges good quality water and does not need water for dilution (not affected by hydrologic variability).

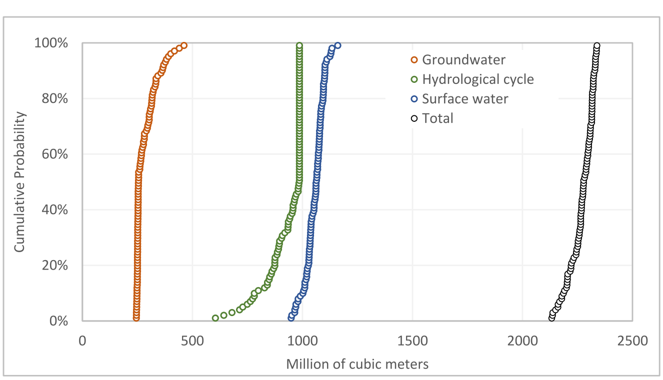

Fig. 3. Cumulative probability of extended water demand (ED_t), including hydrological cycle (total and by water body).
Source. Own elaboration

Table 6
Summary statistics of the extended water demand (ED_t) by water body, including hydrological cycle.

Water body	Mean (Mm^3)	S. Deviation (Mm^3)	C. Variation (%)
Groundwater	283.4	48.2	17.0%
Surface water	1057.3	41.8	4.0%
Hydrological cycle	930.2	86.4	9.3%
Total	2271.0	52.9	2.3%

Source. Own elaboration

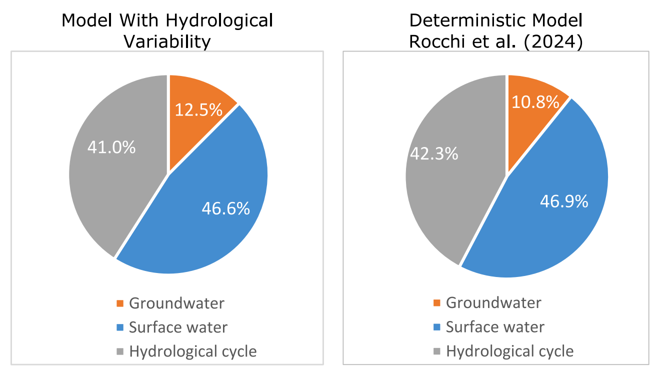

Fig. 4. Structure of the extended water demand(ED_t) by water body, including hydrological cycle.
Source. Own elaboration

In this work we have considered that the sectors classified as Services do not withdraw water directly from groundwater or surface water bodies. All the physical water consumed by these economic sectors (Services) comes from the "Water Supply Industry" economic sector, that is, it is represented in IO table. In a previous work (Rocchi et al., 2024) they estimated the water uses reclassified by demand sectors, obtaining the water consumed indirectly by the Services sector (virtual water), which corresponds to 129 Mm^3.

Section D of Supplementary materials provides the result (mean, standard deviation and coefficient of variation) for the extended water demand for the 56 industries represented in the IO table.

Fig. 5 presents the water extended demand (average of the 100 hydrological years, i.e. including variability) of the different macro-sectors, as a proportion of the total extended demand. The Manufacturing and Construction macro-sector represents 48% of the total extended demand, which is largely explained by the grey water associated with this macro-sector (Fig. 6). The Agriculture represents 13% of the total extended demand, due to the large amount of water it uses corresponding to green water (hydrological cycle, in this study). Grey water in "Agriculture" represents only 12% of its extended demand (Fig. 6). The Sewerage sector represents 22% of the total extended demand, which is explained by the large amount of grey water (Fig. 6), associated with its discharges of water with levels of contamination higher than the standard contamination. The Water Supply Industry sector represents 17% of the total extended demand, which is 100% blue water (Fig. 6).

Fig. 7 presents the extended annual demand (100 hydrological years) for each of the macrosectors. The greatest variability can be seen in the Agriculture sector, whose demand for blue water and grey water varies with the hydrology. For the Manufacturing and Construction and Sewerage sectors, the variability is lower since only their demand for grey water changes. For the Water Supply Industry sector there is no variability since it returns water of equal or better quality than water from natural sources.

Table 7
Summary statistics of extended water demand (ED_t) by macro-sector and water body, including hydrological cycle (by extracting sector).

Macro-sector	Groundwater			Surface water			Hydrological cycle		
	Mean (Mm^3)	SD (Mm^3)	Cv	Mean (Mm^3)	SD (Mm^3)	Cv	Mean (Mm^3)	SD (Mm^3)	Cv
Agriculture	82.5	48.7	59%	95.0	44.8	47%	1013.3	86.4	9%
Manufacture	83.1	0.8	1%	562.8	21.5	4%	−74.1	0.0	0%
Water Supply	117.9	0.0	0%	110.0	0.0	0%	0.0	0.0	NA
Sewerage	0.0	0.0	NA	289.5	36.2	13%	−8.9	0.0	0%
Services	0.0	0.0	NA	0.0	0.0	NA	0.0	0.0	NA

Source. Own elaboration

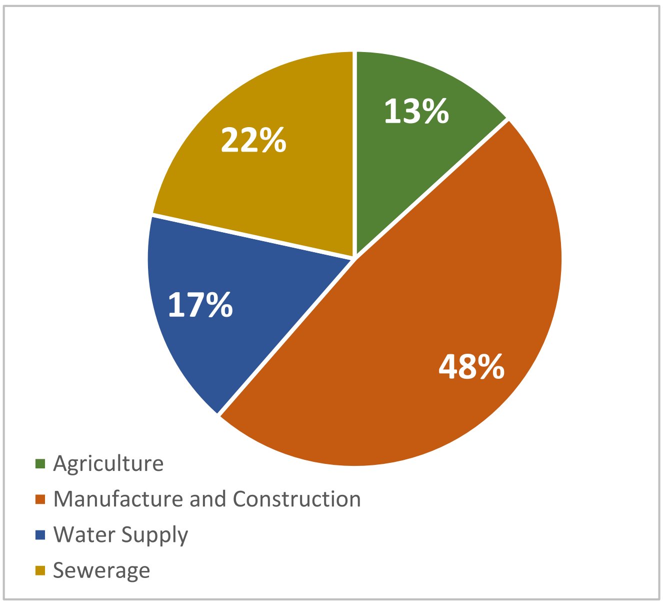

Fig. 5. Structure of the average extended water demand ($\overline{ED_t}$) by macro-sector.
Source. Own elaboration

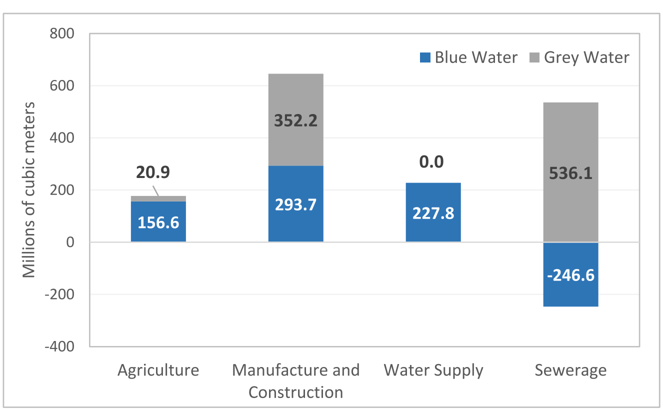

Fig. 6. Blue and grey water by macro-sector (average of 100 hydrological years). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)
Source. Own elaboration

4.2. Stochastic EWEI

The EWEI indicator for the pressure of the economic system on water resources in this study corresponds to a probability distribution function for the 100 simulated hydrological years. These results are presented considering also a frequency analysis, i.e., the number of times the

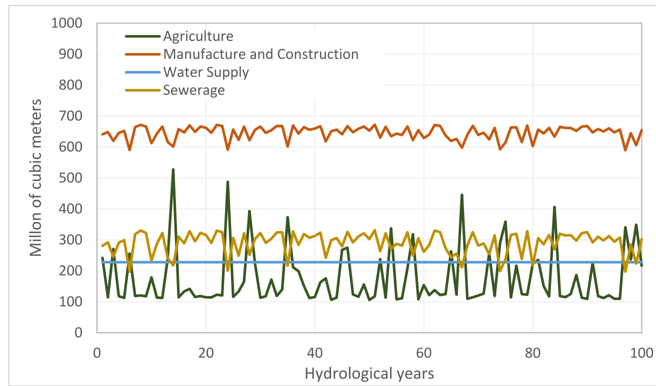

Fig. 7. Extended water demand(ED_t) by macro-sector and hydrological year.
Source. Own elaboration

indicator is above a certain threshold. The values of 0.2 and 0.4 are considered, which represent, according to the literature, thresholds for moderate and severe water scarcity, respectively (Raskin et al., 1997; Alcamo et al., 2000; Pfister et al., 2009).

Considering the EWEI for the total resource (Fig. 8), it presents an average value of 0.20 with a standard deviation of 0.04 (Table 8). In 43 over 100 years the threshold of 0.2 is exceeded while the threshold of 0.4 is never exceeded (Table 9).

When groundwater and surface water are considered separately, the results change. For groundwater (Fig. 9) the average EWEI value is 0.07 and the thresholds of 0.2 and 0.4 are not exceeded in any year. For surface water (Fig. 10) the average EWEI value is 0.42, the 0.2 threshold is always exceeded in 100 years while the 0.4 threshold is exceeded in 40 over 100 years. Moreover, it can be seen that in 2 years the threshold of 1.0 is exceeded, i.e., the extended demand exceeds the feasible supply.

Table 8 presents the mean, standard deviation and the coefficient of variation for the EWEI while Table 9 presents the frequency analysis for the EWEI.

Section E of Supplementary Materials shows the results for the Water Exploitation Index (WEI^+), (Faergemann, 2012; European

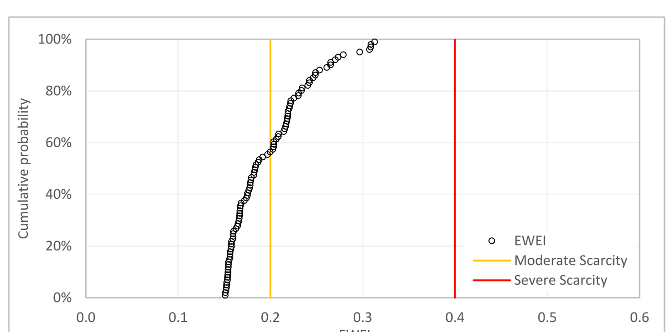

Fig. 8. Cumulative distribution of probability for EWEI.
Source. Own elaboration

Table 8
Summary statistics for the EWEI.

Statistics	EWEI	Groundwater EWEI	Surface water EWEI
Mean (Mm3)	0.20	0.07	0.42
Standard Deviation (Mm3)	0.04	0.02	0.21
Coefficient of Variation	0.22	0.27	0.50

Source. Own elaboration

Table 9
Frequency analysis for the EWEI by water body (number of years exceeding a given threshold).

Threshold	EWEI	Groundwater EWEI	Surface water EWEI
0.2	43	0	100
0.4	0	0	40
0.6	0	0	9
0.8	0	0	4
1.0	0	0	2

Source. Own elaboration

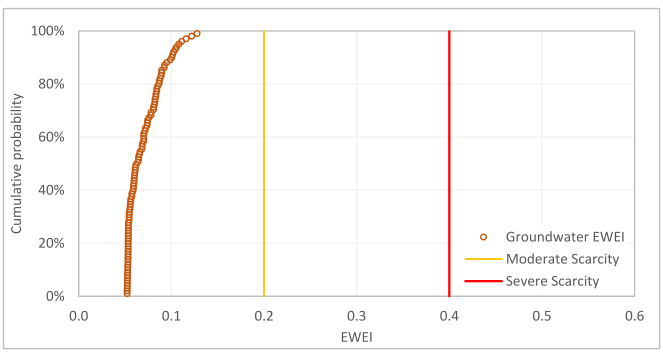

Fig. 9. Cumulative distribution of probability for EWEI, groundwater. Source. Own elaboration

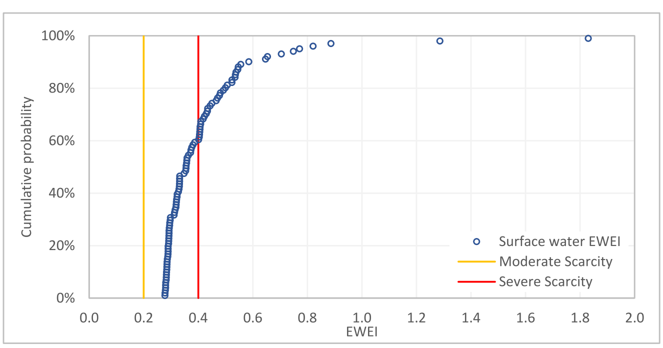

Fig. 10. Cumulative distribution of probability for EWEI, surface water. Source. Own elaboration

Environmental Agency, 2020), and a comparison with the deterministic model.

4.3. Critical month EWEI

The critical month is the one when the EWEI is maximum considering the intra-annual distribution of extended demand (agriculture) and feasible supply (surface water). Based on the information available, this month in Tuscany corresponds to July.

The literature thresholds for moderate and severe shortages are also used on a monthly scale (Garcia-Hernandez and Brouwer, 2021), so they have been included in the critical month analysis.

Fig. 11 shows the cumulative probability for the EWEI in critical month considering all water resources. The mean value is 0.45 (Table 10), the threshold of 0.2 (moderate shortage) is always exceeded, the threshold of 0.4 (severe shortage) 49 times. In no case the value of 1 is exceeded (Table 11), i.e., in Tuscany the extended demand does not exceed the feasible supply for any month in any year of the Monte Carlo simulation.

This result is quite interesting since it illustrates the endogenous threshold defined in the methodology, i.e. the no scarcity condition corresponds to the one where the EWEI never exceeds the unit value for the critical month. If this condition is met, the extended demand does not exceed the feasible supply for any month of the 100 years simulated. When groundwater and surface water are considered together, the condition (perfect substitution between surface water and groundwater) is fulfilled for the Tuscany region, however, this is not the case when the different natural water sources are analysed separately.

Figs. 12 and 13 show the critical month EWEI for groundwater and surface water. The situation is much more asymmetric than in the annual case. For groundwater the average value is 0.15 and the threshold of 0.4 is exceeded only once; conversely, for surface water the situation is quite worrying, the EWEI taking an average value of 3.11 and exceeding 1 in all the years (extended demand greater than feasible supply). That is, without considering the intra-annual regulation capacity of surface water resources, there is always a deficit in the critical month.

5. Discussion and conclusions

In this paper we build a hydro-economic input-output model that allows the incorporation of natural hydrological variability in the analysis of the pressure of the different economic sectors on water resources. The model considers inter-annual and intra-annual variability, which allows the calculation of the water stress indicator (EWEI) for T hydrological years and for each month. In addition, the calculation for the critical month allows the definition of an endogenous scarcity threshold that is more transparent than the thresholds in the literature. This more comprehensive analysis of the relationship between the economic and water system allows a more comprehensive characterisation of water scarcity in a geographical area.

The model considers the direct effects of hydrological variability on feasible supply and its indirect (endogenous) effects on water demand. These effects are estimated on the basis of a series of T-year hydrological components. Two endogenous effects are considered: i) changes in water withdrawals and discharges in the agricultural sector due to variations in precipitation and evapotranspiration; and ii) changes in water requirements for dilution in all discharging industries due to variations in runoff and groundwater recharge. In the case of agriculture, functional relationships between precipitation and evapotranspiration and crop water requirements are considered. The dilution water is calculated on

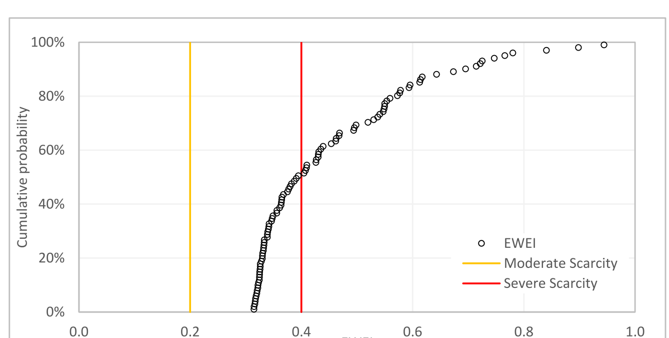

Fig. 11. Cumulative distribution of probability for EWEI, total water resource (Critical Month). Source. Own elaboration

Table 10
Summary statistics for the EWEI, Critical Month.

Statistics	EWEI	Groundwater EWEI	Surface water EWEI
Mean (Mm3)	0.45	0.15	3.11
Standard Deviation (Mm3)	0.15	0.08	2.03
Coefficient of Variation	0.32	0.49	0.65

Source. Own elaboration

Table 11
Frequency analysis for the EWEI, Critical Month
(number of years exceeding a given threshold).

Threshold	EWEI	Groundwater EWEI	Surface water EWEI
0.2	100	24	100
0.4	49	1	100
0.6	15	0	100
0.8	3	0	100
1.0	0	0	100

Source. Own elaboration

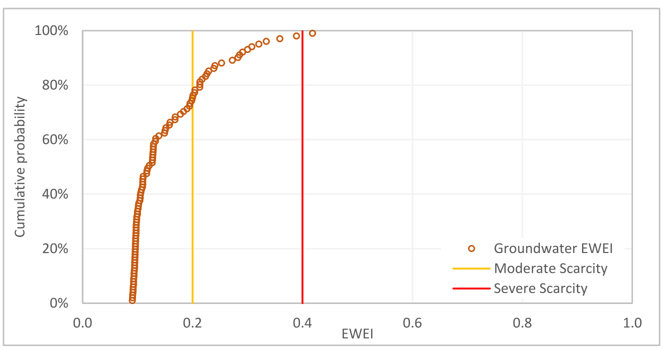

Fig. 12. Cumulative distribution of probability for IPRI, groundwater (Critical Month).
Source. Own elaboration

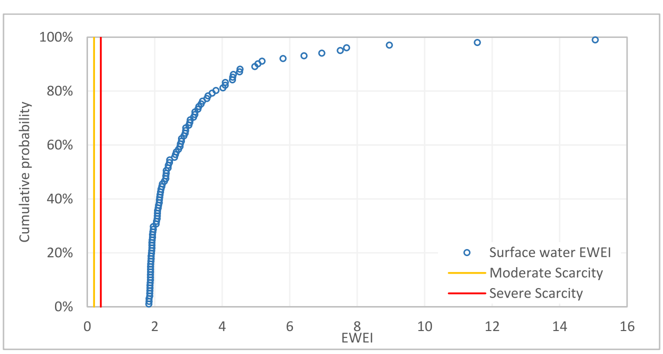

Fig. 13. Cumulative distribution of probability for IPRI, surface water (Critical Month).
Source. Own elaboration

the basis of a mixing model.

The model has been applied in the Tuscany region of Italy, with the aim of deepening the deterministic analysis carried out by Rocchi et al. (2024). For this purpose, a multivariate hydrological model is built, generating synthetic series of precipitation, evapotranspiration, surface runoff and groundwater recharge.3.

Based on a Monte Carlo simulation for 100 hydrological years, an empirical probability distribution of the extended demand and feasible supply was obtained. The EWEI was estimated with hydrological variability, obtaining a mean value of 0.20, slightly higher than the 0.19 of the deterministic model of Rocchi et al. (2024). These values are very similar due to the existence of two opposing effects: i) the increase in water demand in the agricultural sector due to the substitution of green for blue water in dry years, and ii) the decrease in water for dilution due to the higher standard concentration in dry years.

A frequency analysis was carried out for the EWEI. In 49 over 100 years the value of 0.2 defined in the literature as the threshold for moderate scarcity is exceeded, while the value of 0.4, defined in the literature as the threshold for severe scarcity, is never exceeded. However, when groundwater and surface water are considered separately, while for groundwater the thresholds of 0.2 and 0.4 are not exceeded in any year, for surface water the 0.2 threshold is always exceeded while the 0.4 threshold is exceeded in 40 years. In 2 over 100 years the threshold exceeds the value of 1, i.e., the extended demand exceeds the feasible supply.

These are relevant results because although Tuscany for 49% of the hydrological scenarios would be in a moderate scarcity condition according to the standard thresholds, this is supported by two relevant assumptions: i) the perfect substitution between surface and groundwater, and ii) the annual resolution of the analysis. The first assumption can be removed by separating the indicator by water body, as has been done in this study, or by performing a hydro-economic analysis at a smaller spatial resolution. The second assumption has been considered in this study by proposing a methodology to determine the EWEI on a monthly scale, in particular for the critical month, based on the intra-annual disaggregation of the extended demand and the feasible supply.

For the critical month (July) an average EWEI of 0.45 is obtained, always exceeding the threshold of moderate scarcity and that of severe scarcity in 49 over 100 years; the value of 1 for the EWEI is conversely never exceeded. The situation is much worse when considering surface water only, with the value of 1 exceeded in all years.

A central element of the analysis carried out in this study is the fact that the EWEI indicator itself already includes inter- and intra-annual hydrological variability and the environmental, technical and institutional constraints associated with water availability. It therefore constitutes a tool for a specific analysis of the Tuscany case study, dispensing with the use of standard thresholds defined in the literature. The model allows to know how many years the extended demand exceeds the feasible supply (EWEI>1) in the critical month, i.e. whether or not the defined endogenous threshold is met.

Based on the results it is possible to affirm that Tuscany, at regional scale and considering a perfect substitution between surface and groundwater, does not present water scarcity (in quantity and quality) because the extended demand is always lower than the feasible supply considering the worst case (critical month in the driest year).

The input-output model with hydrological variability constitutes an important contribution to the literature and to the design of public policies, since it allows a better understanding of the relationship between the economic and water systems, including the essentially stochastic nature of hydrological processes, which is reflected in the results. The model offers powerful tools for answering questions in the current context of climate change and increasing pressure on water resources. Three specific applications can be mentioned. First, to assess what would happen under climate change scenarios, which can be represented by modifying the parameters of the normal multivariate model or by incorporating hydrological climate change series for Tuscany. Second, to evaluate the economic benefits, in a context of hydrological uncertainty, of investing in water infrastructure for an efficient water use, for example, by varying parameters such as the irrigation efficiency in agriculture. Third, it is possible to evaluate the effect on the EWEI (cumulative probability) of changes in surface water concessions, of the incorporation of stronger environmental restrictions, and of changes in the COD concentration limits in the discharges.

A relevant element in the design of public policies to address climate change corresponds to the ability to adapt to changes in the intra-annual profile of precipitation and natural water supply (seasonal variation), and to extreme events, which will worsen in the coming decades (IPCC et al., 2021). In this sense, the analysis of the critical month (or critical months) carried out in this work serves as a basis for evaluating and designing management policies that increase water security in the face of expected climate changes, considering the interannual and intra-annual structure of the productive system. Given the highly variable nature of climate projections (precipitation and temperature), which depend on the shared socioeconomic trajectories (SSP) and different general circulation models (GCM) (IPCC et al., 2021), it is important to have indicators that take into account hydrological uncertainty. In addition, the expected climate changes increase the heterogeneity between different areas of the planet, making the construction of local indicators increasingly important. Thus, the EWEI for the critical month (stochastic) and the endogenous threshold (local characteristics) proposed in this study, constitute indicators that can give greater resilience to water policies to adapt to climate change, whether in the Tuscany region or in another area where the methodology proposed here could be applied. Finally, although the monthly scale would not necessarily be the most fine-grained to evaluate droughts or floods (they can last a few days), this scale represents a significant advance with respect to annual models that estimate the hydro-economic balance, and corresponds to an adequate scale to determine the water demands of the productive sector (greater granularity is almost impossible). Moreover, policies such as the design of reservoirs to manage water within the year or to control floods, have commonly been evaluated on a monthly or seasonal scale.

In relation to the extended water demand by macrosectors, the results obtained have implications for water management and policies to address the relationship between the productive system and hydrological variability. On the one hand, it is necessary to have water policies to supply agricultural demand in drier years (regulation systems, water efficiency, etc.). But on the other hand, the qualitative aspect must be taken into account; that is, to maintain the quality of water in natural sources during dry years, it is necessary to improve the quality of water in the discharges of the Agriculture, Manufacturing and Construction, and Sewerage sectors (especially in these last two macrosectors). Consideration of hydrological variability (possibility of dry years) is necessary to define water quality policies, such as the amount of pollutants allowed in the discharges (regulatory aspects) or the increase in ecological flows that would ensure a greater dilution capacity in surface water bodies.

Among future developments, and consistently with the findings of the previous paragraph, it is important to take into consideration the temporal and spatial limitations of the model. In the analysis an approximation of the hydrological variability of the extended demand and feasible supply at a monthly level has been carried out, however, it would be possible to achieve greater precision based on a more detailed modeling of the hydrology at a monthly scale, considering a statistical or a physical-based hydrological model, thus achieving greater reliability in the results. It is also possible, with more information on the regional economic structure, to disaggregate the extended demand for other sectors of the Tuscan economy that may present significant variations in water use within the year.

Another relevant aspect for future work is to include the intra-annual regulation capacity for both surface and groundwater. In the case of surface water, drinking water and irrigation reservoirs that make it possible to manage water within the year must be considered, making assumptions based on the number and size of the reservoirs. Regarding groundwater, although it was assumed that a constant monthly extraction is possible throughout the year, users can manage water optimally, extracting more quantity in critical months. Considering these aspects, the endogenous threshold estimated in this work should rise (more management capacity). In this sense, our results are conservative. Furthermore, in this work we do not use a methodology to build a disaggregated intra-annual IO table, we only consider an approximation of the variability in demand in the agricultural sector, since we are not interested in virtual water flows, only direct withdrawals and restitutions from and to natural water bodies. However, this could imply a lower precision in the extended demand for the critical month and, therefore, a lower precision in the EWEI for this month. An intra-annual disaggregation of the Tuscany IO table following methodologies proposed in the literature (Avelino, 2017; Tobarra et al., 2018) could be an alternative. Avelino (2017) bases the disaggregation on a variant of the EURO method (T-EURO) and applies it to the case of Brazil 2004), finding that the most significant variations occur in agriculture. Tobarra et al. (2018) focuses on the seasonality of the agricultural sector (fruits and vegetables) in Spain, assessing the trade-off between imports and local consumption on ecological footprints (CO2 and water). This latter approach (Tobarra et al., 2018) could prove very useful for the analysis of the water footprint that the Tuscany region exerts on the rest of Italy and the rest of the world (Sturla et al., 2024), identifying the pressures in the critical months. And, also, for analysing virtual water flows between the Tuscan economic sectors. These disaggregation of the IO tables are considered relevant for the analysis of climatic events, which could be very useful in areas for which significant intra-annual changes in monthly runoff are projected (acceleration of snowmelt, for example). In the case of the analysis in this study, while these methodologies could improve the accuracy of the estimation of the extended demand for the critical month, it is likely that this could also be achieved with a better intra-annual disaggregation of the production of the economic sectors (EWEI does not depend on virtual flows). As future work, firstly, a more detailed approximation of the monthly variability in agriculture and the other economic sectors could be carried out; and subsequently, the construction of a disaggregated intra-annual IO table could be evaluated, recalculating the EWEI for the critical month (and comparing it with previous results), but, above all, to carry out an analysis of the virtual water flows between the region and the rest of the world, and between the different economic sectors of the region.

For what concerns the spatial dimension of the analysis, the model considers the whole Tuscany as the unit of analysis. However, both in hydrological and economic terms the spatial units for more relevant analyses should be smaller, for example basins or sub-basins in the case of hydrology and local labor systems in the case of the economy. Such a spatial precision corresponds to an important challenge regarding the gathering and disaggregation of data, as well as greater computational efforts. A better approximation of the trade-off between green and blue water in agriculture could be achieved by considering a hydro-economic model with higher spatial resolution and accurately determining the amount of soil moisture available, i.e., the supply of green water. With respect to water requirements for dilution, it would be possible to improve the model by considering more and possibly better water quality indicators (not only chemical oxygen demand), as long as reliable data from specific measurements and modeling, where available.

CRediT authorship contribution statement

Gino Sturla: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Bendetto Rocchi:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

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.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.indic.2024.100488.

Appendix

Variability of withdrawal and discharge coefficients of agriculture

Substitution of green water with blue water

Let define $\mathscr{E}_t$ as the ratio of the precipitation in year t (P_t) to the average precipitation ($\overline{P}$):

$$\mathscr{E}_t \equiv \frac{P_t}{\overline{P}} \tag{A1}$$

Let define $T^P_{i,t}$ as the additional groundwater and surface water withdrawals by the agricultural sector i, in year t, due to changes in precipitation. Then,

$$T^P_{i,t} = \begin{cases} (1 - \mathscr{E}_t) \bullet f^{irr}_{hc,i} \bullet x_i \bullet \gamma \quad if \quad \mathscr{E}_t < 1 \\ 0 \quad if \quad \mathscr{E}_t \geq 1 \end{cases} \tag{A2}$$

where,

$$\gamma = \frac{1}{1 - \rho} \tag{A3}$$

The parameter ρ corresponds to the losses associated with the irrigation process. When irrigation is used to supply crops requirements, an additional water withdrawal due to irrigation inefficiency must be considered.

The term $f^{irr}_{hc,i} \bullet x_i$ corresponds to the water withdrawals from hydrological cycle for the average year (deterministic case).

To disaggregate the need for additional irrigation between groundwater and surface water, we consider the following parameters:

δ_i: proportion of groundwater irrigation of sector i

η_i: proportion of surface water irrigation of sector $i$where,

$$\delta_i = \frac{f^{irr}_{gw,i}}{f^{irr}_{gw,i} + f^{irr}_{sw,i}} \tag{A4}$$

$$\eta_i = \frac{f^{irr}_{sw,i}}{f^{irr}_{gw,i} + f^{irr}_{sw,i}} \tag{A5}$$

Then, $T^P_{i,gw,t}$ and $T^P_{i,sw,t}$ correspond to the increase in the withdrawals of groundwater and surface water in sector i for year t, respectively, to make up for the deficit of green water:

$$T^P_{i,gw,t} = \begin{cases} \delta_i \bullet (1 - \mathscr{E}_t) \bullet f^{irr}_{hc,i} \bullet x_i \bullet \gamma \quad if \quad \mathscr{E}_t < 1 \\ 0 \quad if \quad \mathscr{E}_t \geq 1 \end{cases} \tag{A6}$$

$$T^P_{i,sw,t} = \begin{cases} \eta_i \bullet (1 - \mathscr{E}_t) \bullet f^{irr}_{hc,i} \bullet x_i \bullet \gamma \quad if \quad \mathscr{E}_t < 1 \\ 0 \quad if \quad \mathscr{E}_t \geq 1 \end{cases} \tag{A7}$$

Change in blue water irrigation requirements

Let define θ_t as the ratio of the evapotranspiration in year t (E_t) to the average evapotranspiration ($\overline{E}$):

$$\theta_t \equiv \frac{E_t}{\overline{E}} \tag{A8}$$

The change in the use of groundwater and surface water by agriculture due to interannual changes in evapotranspiration is defined as:

$$T^{E}_{i,t} = (\theta_t - 1) \bullet \left(f^{irr}_{gw,i} \bullet x_i + f^{irr}_{sw,i} \bullet x_i \right) \tag{A9}$$

The terms $f^{irr}_{gw,i} \bullet x_i$ and $f^{irr}_{sw,i} \bullet x_i$ corresponds to the water withdrawals from groundwater and surface water for the deterministic case.

The additional withdrawals of groundwater and surface water is written as:

$$T^{E}_{i,gw,t} = \delta_i \bullet (\theta_t - 1) \bullet f^{irr}_{gw,i} \bullet x_i \tag{A10}$$

$$T^{E}_{i,sw,t} = \eta_i \bullet (\theta_t - 1) \bullet f^{irr}_{sw,i} \bullet x_i \tag{A11}$$

$T^{E}_{i,gw,t}$ and $T^{E}_{i,sw,t}$ correspond to the increase (decrease) in the withdrawals of groundwater and surface water in sector i for year t, due to the eventual increase (decrease) in blue water irrigation requirements.

Coefficients with hydrological variability

Adding the effect of precipitation (equations (A6) and (A7)) and evapotranspiration (equations (A10) and (A11)), and dividing by x_i, yields the stochastic component of the withdrawal coefficient for groundwater and surface water in agricultural sectors:

$$\mathscr{F}_{gw,i,t}(P_t, E_t) = \begin{cases} \delta_i \left[\left(\dfrac{\overline{P} - P_t}{\overline{P}} \right) \bullet f^{irr}_{hc,i} \bullet \gamma + \left(\dfrac{E_t - \overline{E}}{\overline{E}} \right) \bullet f^{irr}_{gw,i} \right] & if \ \ \mathscr{E}_t < 1 \\ \delta_i \left[\left(\dfrac{E_t - \overline{E}}{\overline{E}} \right) \bullet f^{irr}_{gw,i} \right] & if \ \ \mathscr{E}_t \geq 1 \end{cases} \tag{A12}$$

$$\mathscr{F}_{sw,i,t}(P_t, E_t) = \begin{cases} \eta_i \left[\left(\dfrac{\overline{P} - P_t}{\overline{P}} \right) \bullet f^{irr}_{hc,i} \bullet \gamma + \left(\dfrac{E_t - \overline{E}}{\overline{E}} \right) \bullet f^{irr}_{sw,i} \right] & if \ \ \mathscr{E}_t < 1 \\ \eta_i \left[\left(\dfrac{E_t - \overline{E}}{\overline{E}} \right) \bullet f^{irr}_{sw,i} \right] & if \ \ \mathscr{E}_t \geq 1 \end{cases} \tag{A13}$$

For the withdrawal coefficient associated with the hydrologic cycle, its stochastic component (negative) is:

$$\mathscr{F}_{hc,i,t}(P_t) = \begin{cases} \left(\dfrac{P_t - \overline{P}}{\overline{P}} \right) \bullet f^{irr}_{hc,i} & if \ \ \mathscr{E}_t < 1 \\ 0 & if \ \ \mathscr{E}_t \geq 1 \end{cases} \tag{A14}$$

We assume that discharges from the agricultural sector are entirely towards groundwater. Considering α_i as the proportion of the discharged water with respect to the groundwater and surface water withdrawals for the agricultural sector i, it is obtained that the additional discharges due to hydrologic variability are:

$$\mathscr{R}_{gw,i,t}(P_t, E_t) = \left[\mathscr{F}_{gw,i,t}(P_t, E_t) + \mathscr{F}_{sw,i,t}(P_t, E_t) \right] \bullet \alpha_i \tag{A15}$$

$$\mathscr{R}_{sw,i,t}(P_t, E_t) = 0 \tag{A16}$$

where,

$$\alpha_i = \frac{r^{irr}_{gw,i}}{f^{irr}_{gw,i} + f^{irr}_{sw,i}} \tag{A17}$$

Since hydrologic variability influences only the withdrawal and discharge coefficients of the agricultural sectors, the above equations are sufficient to characterize equations (7) and (8) in section 3.1.3.

Note that parameters $(\delta_i, \eta_i, \alpha_i)$ are defined based on the average hydrological condition. It is assumed irrigation losses in groundwater and surface water equal to $\rho = 30\%$, obtaining $\gamma = 1.42$ for all crops.

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