Integrating an MRIO hydro-economic model with a physically-based hydrological model to characterize water scarcity in local economies of central Italy

Gino Sturla[1]
Tommaso Pacetti[2]
Benedetto Rocchi[3]

June, 2025

Abstract

Traditional input-output models linking economic activity to water resources often rely on economic units of analysis, overlooking the geographical and hydrological relevance of river basins—the fundamental units for water-related assessments. This study evaluates the balance between water demand and supply across five local labor systems (LLS) in the upper Arno River basin, Tuscany, Italy. Water supply is modeled using the Soil and Water Assessment Tool (SWAT), while water demand—blue (from surface and groundwater), green (from soil moisture), and gray (for pollutant dilution)—is estimated through a multiregional input-output hydro-economic model (MRIO) integrated with a water quality mixing model. Spatial harmonization is achieved by aligning sub-basins with their corresponding LLS, enabling comprehensive analysis. The integrated modeling framework uncovers two key endogenous effects: (i) adjustments in agricultural water withdrawal intensity based on green water availability and (ii) changes in industrial gray water requirements due to variations in runoff and groundwater recharge. Furthermore, the model characterizes green water supply, offering a more precise depiction of agricultural water demand dynamics compared to models lacking physical hydrological integration. Results are synthesized into multiple scarcity indicators to assess water scarcity at the LLS level, incorporating diverse demand approaches (withdrawals, net demand, extended demand) and supply perspectives (natural ecological supply, feasible supply). This approach highlights the importance of integrating physical and economic models to address water scarcity and sustainability challenges effectively.

Key Words: Input-output analysis, Hydrological models, Water scarcity, Local systems, Arno river, Tuscany.

[1] FAE, Universidad Diego Portales, Chile. ginostefano.sturla@mail.udp.cl
[2] DICEA, Università degli Studi di Firenze, Italy. tommaso.pacetti@unifi.it
[3] DISEI, Università degli Studi di Firenze, Italy, benedetto.rocchi@unifi.it

Contents

1 Introduction

Water scarcity has been characterized at different territorial scales. From an economic perspective, national, regional, or local scales are typically used. In contrast, hydrology relies on more appropriate units of analysis such as basins or sub-basins. Although river basins are best suited to characterize hydrological processes, the disaggregation of productive activities generally does not align with these hydrological units (Ridoutt et al., 2018; Wichelns, 2017).

This mismatch between scales and units of analysis is particularly relevant in the assessment of interconnected economic systems. Unlike hydro-economic studies focused on individual basins, such assessments incorporate data from the productive system across an entire region, country, or even globally, disaggregated into local economies or regions (Duarte et al., 2016; Arto et al., 2016; Lenzen et al., 2013; Feng et al., 2011; Sturla et al., 2023). Determining economic variables for each basin within a region, and subsequently quantifying interregional flows of goods and services, would be highly complex. Moreover, countries do not disaggregate their national accounts based on hydrological boundaries.

Therefore, the most feasible and effective approach is to adjust the hydrological scale to match the economic scale. This allows for the representation of variables such as surface and groundwater supply in a manner that is consistent with economic data.

The present study focuses on the Tuscany region of Italy, which constitutes an interesting case study. At the regional level, Tuscany does not exhibit significant water scarcity, either in average conditions (Rocchi et al., 2024) or when exposed to hydrological variability (Sturla and Rocchi, 2023). However, due to spatial heterogeneity in both climate and productive structure, local water scarcity problems are significant.

The issue of territorial scale in Tuscany's water scarcity was addressed by Rocchi and Sturla (2022). That study employed a spatial stochastic hydrological model that estimated hydrological components for each Local Labour System (LLS) in Tuscany and generated synthetic series over N years. Results indicated that 14 out of 49 LLSs experienced significant water scarcity, based on the Extended Water Exploitation Index (EWEI) and endogenous scarcity thresholds (STg), for both blue water (surface and groundwater) and grey water (water required to dilute pollutants from effluents). However, the study faced certain limitations, including the inability to estimate surface water supply in natural conditions due to lack of data, the intrinsic characteristics of the model which do not represent physical hydrological processes, and the fact that the hydrological unit of analysis did not correspond to a basin or sub-basin. Furthermore, the model did not characterize green water (soil moisture) availability, thus precluding an assessment of green water scarcity.

To address these limitations, the present study adopts a more realistic approach, using a physically based hydrological model (SWAT) integrated with a multiregional input–output (MRIO) model. The study focuses on five LLSs located in the upper Arno River basin. Hydrological analysis is conducted at the sub-basin level and aggregated to the LLS scale, thereby aligning the hydrological and economic scales.

The concrete benefits of this approach include:

- Greater accuracy in estimating hydrological components: precipitation, evapotranspiration, surface runoff, groundwater recharge, and soil moisture.
- The estimation of surface runoff under natural conditions allows for the assessment of natural water availability to improve the accuracy of scarcity indicators and enhance the grey water estimation through the mixing model.
- Soil moisture enables the estimation of green water supply for agriculture and better simulation of increased surface and groundwater withdrawals during deficit years.

The proposed model is integrated; hydrological and economic calculations are not performed independently. Hydrological components influence the determination of water use intensity coefficients in agriculture (which substitutes green water with blue water), and both economic and hydrological calculations are used to determine grey water through a mixing model. The analysis incorporates climatic variability (2014–2020) and evaluates its impact on the 2017 productive system.

The study's main methodological innovations in the literature are: (i) aligning the hydrological system to the economic system; and (ii) developing a green water scarcity indicator.

The calculations enable the estimation and comparison of five scarcity indicators across the five LLSs analyzed, allowing for an integrated characterization of water scarcity. The indicators used are:

- Water exploitation index (WEI): The ratio between blue water withdrawals natural to mean natural ecological supply. Developed by European Environmental Agency (2020).
- Water exploitation index plus (WEI^+): The ratio between blue water net demand to mean natural ecological supply. Developed by Faergemann (2012) and European Environmental Agency (2020).
- Natural extended water exploitation index ($EWEI^*$): The ratio between blue and gray water extended demand to natural ecological supply. Developed in this study.
- Extended water exploitation index (EWEI): The ratio between blue and gray water extended demand to feasible supply. Developed by Rocchi et al. (2024)

- Green water scarcity index(GWSI): The ratio between green water withdrawals to soil moisture availability (for agriculture in the irrigation period). Developed in this study.

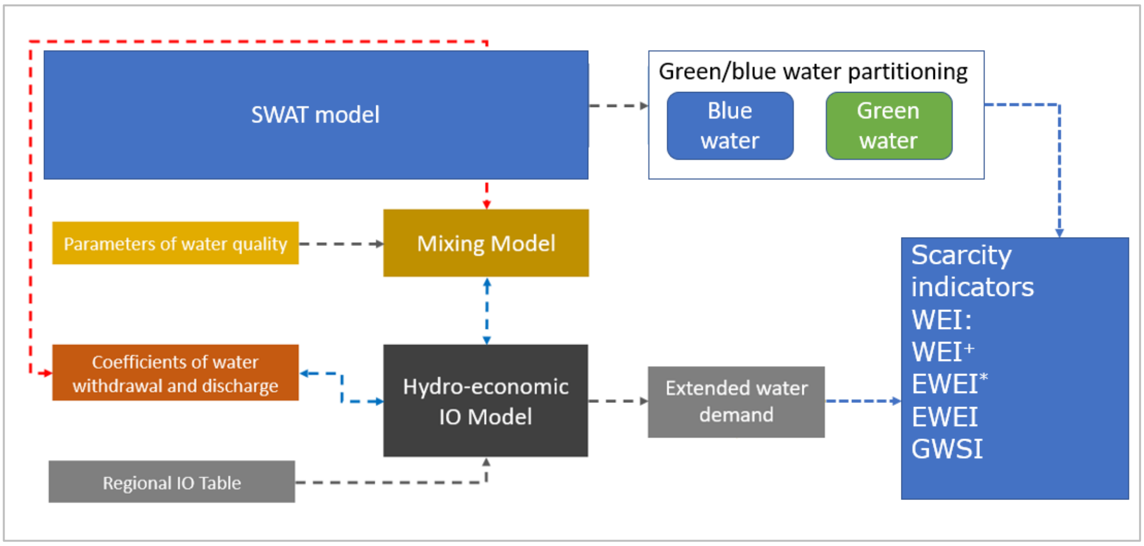
2 Methods and Data

2.1 Methodology overview

Figure 1 presents the schematic of the methodology used in this study. The SWAT hydrological model is used to generate the natural supply of blue water (surface and groundwater) and green water (soil moisture) in each LLS. In parallel, the MRIO model allows for the estimation of extended water demand in each LLS, based on water use intensity coefficients and the MRIO table for Tuscany. The hydrological and economic components are linked through: (i) the mixing model used to determine grey water intensity coefficients, which requires information on water supply and demand, as well as water quality parameters; and (ii) the agricultural water use coefficients, which depend on hydrological variability, as this determines the substitution of green water with blue water.

Based on the extended demand and the natural supply, the various scarcity indicators used to characterize water scarcity in the analyzed local economies can be constructed.

Figure 1. Schematic representation of the methodology

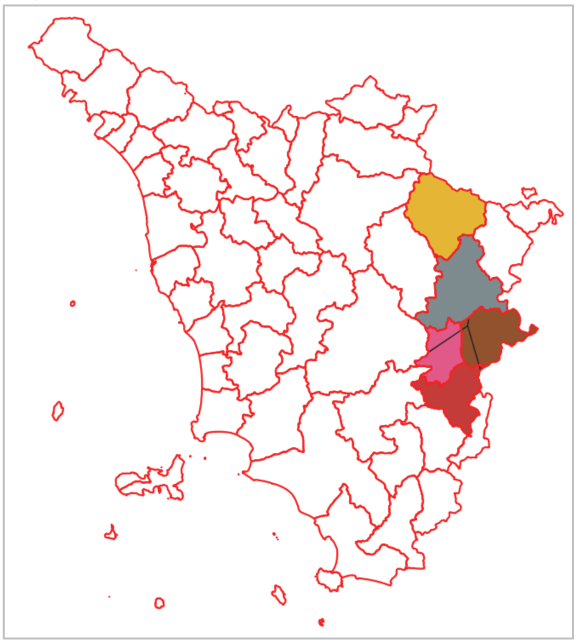


Source: Own elaboration

2.2 Study area

The study area is located in the upper Arno River basin and includes the LLS of Arezzo, Bibbiena, Cortona, Montepulciano, and Sinalunga. Figure 2 illustrates the geographical location of these LLS.

Figure 2. Study area (5 LLS)



Source: Own elaboration

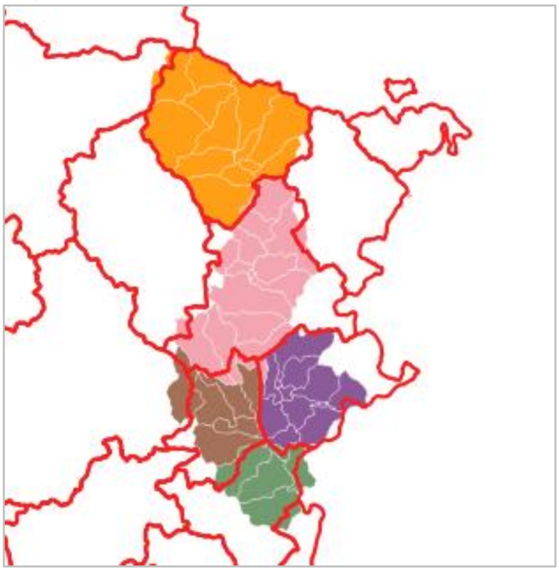
2.3 Hydrology (SWAT Model)

To characterize water supply in the local economies considered in this study, the SWAT (Soil and Water Assessment Tool) hydrological model was employed. This model enables the spatially explicit estimation of key components of the hydrological cycle at the sub-basin scale. Specifically, it was used to estimate the natural supply of surface water, groundwater recharge, and soil moisture—the latter serving as a proxy for green water availability for agricultural use. The simulation was conducted on a monthly scale and subsequently aggregated to an annual scale for integration with the economic model. SWAT requires a comprehensive set of input data, including time series of precipitation, minimum and maximum temperature, solar radiation, relative humidity, and wind speed. In addition, detailed information on topography (digital elevation model), land use, vegetation cover types, and soil properties was incorporated for each sub-basin within the LLS. Model calibration was carried out using observed streamflow data from hydrometric stations located at strategic points in the upper Arno River basin. This calibration process allowed for the adjustment of key model parameters to realistically represent runoff and recharge processes under local conditions.

In addition to the blue water supply generated within the sub-basins, the model also accounts for transfers from the Montedoglio reservoir, located outside the study area.

Figure 3 presents the sub-basins associated with each of the five LLS.

Figure 3. Sub-basins (5 LLS)



Source: Own elaboration

2.4 MRIO hydro-economic model

The environmentally extended multiregional input-output model (Miller and Blair, 2009) allows to calculate the total environmental resource *(E)* used by an economic system with *n* subregions and *m* industries:

$$E = C^T \cdot x \qquad (1)$$

Where x is the *(mn x 1)* vector of outputs by economic sector and subregion and C is the *(mn x 1)* vector of environmental resource use intensities. T denotes the transpose.

The vector x can be expressed in function of the technical coefficients *(mn x mn)* matrix A and the *(mn x 1)* vector y of total final demand

$$x = (I - A)^{-1} \cdot y \qquad (2)$$

Defining $L = (I - A)^{-1}$ as the multiregional Leontief inverse *(mn x mn)* matrix,

$$E = C^T \cdot L \cdot y \qquad (1)$$

For the purposes of this study, the environmental resource is water. The extended water demand is defined as withdrawals (blue and green water) minus discharges plus the water requirements for dilution (grey water).

The extended demand of water *(n x 1)* vector for each subregion (e_k^s) could be expressed as:

$$e_k^s = (\widehat{f_k^s} - \widehat{r_k^s} + \widehat{w_k^s}) \cdot L^s \cdot y \tag{4}$$

Where the L^s *(m x mn)* matrix corresponds to the Leontief inverse matrix blocks associated with production in the subregion *s* , *y (mn x 1)* vector is the final demand and f_k^s, r_k^s and correspond to the *(m x 1)* vectors (in m^3/€) of intensity coefficients for withdrawals, discharges and water for dilution, respectively, by water body k (groundwater, surface water and soil moisture) in subregion s. The hat symbol indicates the diagonalization of the vector.

When hydrologic variability is considered, the water use coefficients change according to the components of the hydrologic cycle. Let us first define the water extended demand for the subregion *s* associated with water body *k*, industry *i* and year *t* (for notation simplicity we use x^s instead of $L^s y$)*:*

$$e_{k,i,t}^s = (f_{k,i,t}^s - r_{k,i,t}^s + w_{k,i,t}^s) \cdot x_i^s \tag{5}$$

Withdrawal coefficients will change for agricultural sectors, due to variations in soil moisture availability, which will imply higher withdrawals from surface and groundwater bodies when demand for green water exceeds supply for agriculture. Discharge coefficients also change because withdrawing water from surface water and groundwater involves considering irrigation losses. The dilution water requirement coefficients will change for all sectors discharging polluted water, depending on runoff, groundwater recharge, which define the concentration of pollutant in the receiving bodies. The latter coefficients depend indirectly on soil moisture due to their estimation as a function of discharge volume.

The above will be explained and formalized in later sections, however, a general scheme for extended demand dependence in hydrology is defined here.

Equations (6), (7) and (8) present the water use coefficients, each of which can be written as a function of its deterministic value (Rocchi and Sturla, 2021) plus time-varying term, which depends on hydrological components:

$$f_{k,i,t}^s = f_{k,i}^s + F_{k,i,t}^s(S_t^s) \tag{6}$$

$$r_{k,i,t}^s = r_{k,i}^s + R_{k,i,t}^s\,(S_t^s) \tag{7}$$

$$w_{k,i,t}^s = w_{k,i}^s + H_{k,i,t}^s[I_t^s, R_t^s, R_{k,i,t}^s(S_t^s)] \tag{8}$$

Where I_t^s, R_t^s and S_t^s are the groundwater recharge, the runoff and the soil moisture, respectively, in subregion *s* for year *t*, obtained with the hydrological model.

Using equations (6) to (8) it is possible to write a general form to the extend demand associated with the water body *k*, the industry *i* and the year *t*.

$$e^s_{k,i,t} = e^s_{k,i} + \left[F^s_{k,i,t}(S^s_t) + R^s_{k,i,t}\,(S^s_t) + H_{k,i,t}\left[I^s_t, R^s_t, R_{k,i,t}(S^s_t)\right]\right] \cdot x^s_i \tag{9}$$

Note that $F^s_{k,i,t}(S^s_t) = 0$ and $R^s_{k,i,t}\,(S^s_t) = 0$ for non-agricultural sectors, and $H_{k,i,t}[I^s_t, R^s_t, R_{k,i,t}(S^s_t)] = 0$ for non-discharging sectors.

Based on the above, it is possible to define the water demand considering only withdrawals ($q^s_{k,i,t}$) and the net demand, corresponding to withdrawals minus discharges ($z^s_{k,i,t}$). These definitions will be of importance for the calculation of scarcity indicators.

$$q^s_{k,i,t} = \left[f^s_{k,i} + F^s_{k,i,t}(S^s_t)\right] \cdot x^s_i \tag{10}$$

$$z^s_{k,i,t} = \left[f^s_{k,i} + r^s_{k,i} + F^s_{k,i,t}(S^s_t) + R^s_{k,i,t}\,(S^s_t)\right] \cdot x^s_i \tag{11}$$

2.5 Agriculture

The withdrawal and discharge deterministic coefficients of the agricultural sectors can be broken down into the part requiring irrigation and the part associated with livestock (Sturla and Rocchi, 2022; Sturla and Rocchi, 2024):

$$f^s_{k,i} = f^{s,irr}_{k,i} + f^{s,liv}_{k,i} \tag{14}$$

$$r^s_{k,i} = r^{s,irr}_{k,i} + r^{s,liv}_{k,i} \tag{15}$$

In this section, subscript *i* refers only to agricultural sectors.

The following subsections details the methodology used to modify the water withdrawal and discharge coefficients for a year, depending on precipitation and evapotranspiration.

Let define $T^s_{i,t}$ as the additional groundwater and surface water withdrawals by the agricultural sector i, subregion s, year t, due to changes in soil moisture (SM^s). Then,

$$T^s_{i,t} = \begin{cases} \left(f^{s,irr}_{sm,i} \cdot x^s_i - SM^s_t\right) \cdot \gamma & if\ \ S^s_t < f^{irr}_{hc,i} \cdot x^s_i \\ 0 & if\ \ S^s_t \geq f^{irr}_{hc,i} \cdot x^s_i \end{cases} \tag{17}$$

where,

$$\gamma_i^s = \frac{1}{1-\rho_i^s} \tag{18}$$

The parameter ρ_i^s corresponds to the losses associated with the irrigation process in region *s* and agricultural sector *i*. When irrigation is used to supply agricultural requirements, an additional water withdrawal due to irrigation efficiency must be considered.

The term $f_{hc,i}^{irr} \cdot x_i^s$ corresponds to the water withdrawal from soil moisture for the average year (deterministic case).

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

δ_i^s: proportion of groundwater irrigation in sector *i* of subregion *s*
η_i^s: proportion of surface water irrigation in sector *i* of subregion *s*

where,

$$\delta_i^s = \frac{f_{gw,i}^{s,irr}}{f_{gw,i}^{s,irr} + f_{sw,i}^{s,irr}} \tag{19}$$

$$\eta_i^s = \frac{f_{sw,i}^{s,irr}}{f_{gw,i}^{s,irr} + f_{sw,i}^{s,irr}} \tag{20}$$

Then, $T_{i,gw,t}^s$ and $T_{i,sw,t}^s$ correspond to the increase in the withdrawals of groundwater and surface water in sector i for year t, respectively, due to the eventual decrease in precipitation:

$$T_{i,gw,t}^s = \begin{cases} \delta_i^s \cdot \left(f_{sm,i}^{s,irr} \cdot x_i^s - SM_t^s\right) \cdot \gamma_i^s & if\ \ S_t^s < f_{hc,i}^{irr} \cdot x_i^s \\ 0 & if\ \ S_t^s \geq f_{hc,i}^{irr} \cdot x_i^s \end{cases} \tag{21}$$

$$T_{i,sw,t}^s = \begin{cases} \eta_i^s \cdot \left(f_{sm,i}^{s,irr} \cdot x_i^s - SM_t^s\right) \cdot \gamma_i^s & if\ \ S_t^s < f_{hc,i}^{irr} \cdot x_i^s \\ 0 & if\ \ S_t^s \geq f_{hc,i}^{irr} \cdot x_i^s \end{cases} \tag{22}$$

Adding the effect of precipitation (equations (21) and (22)) and evapotranspiration (equations (25) and (26)), and dividing by x_i, yields the stochastic component of the withdrawal coefficient for groundwater and surface water in agricultural sectors:

$$F_{gw,i,t}^s(S_t^s) = \begin{cases} \dfrac{\delta_i^s \cdot \left(f_{sm,i}^{s,irr} \cdot x_i^s - SM_t^s\right) \cdot \gamma_i^s}{x_i^s} & if\ \ S_t^s < f_{hc,i}^{irr} \cdot x_i^s \\ 0 & if\ \ S_t^s \geq f_{hc,i}^{irr} \cdot x_i^s \end{cases} \tag{27}$$

$$F_{sw,i,t}^{s}(S_t^s) = \begin{cases} \dfrac{\eta_i^s \cdot \left(f_{sm,i}^{s,irr} \cdot x_i^s - SM_t^s\right) \cdot \gamma_i^s}{x_i^s} & if \;\; S_t^s < f_{hc,i}^{irr} \cdot x_i^s \\ 0 & if \;\; S_t^s \geq f_{hc,i}^{irr} \cdot x_i^s \end{cases} \quad (28)$$

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

$$F_{sm,i,t}^{s}(S_t^s) = \begin{cases} \dfrac{SM_t^s - f_{sm,i}^{s,irr} \cdot x_i^s}{x_i^s} & if \;\; S_t^s < f_{hc,i}^{irr} \cdot x_i^s \\ 0 & if \;\; S_t^s \geq f_{hc,i}^{irr} \cdot x_i^s \end{cases} \quad (29)$$

In this work it is assumed that discharges from the agricultural sector are entirely to groundwater. Considering α_i^s 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:

$$R_{sm,i,t}^{s}(S_t^s) = [F_{gw,i,t}^{s}(S_t^s) + F_{sw,i,t}^{s}(S_t^s)] \cdot \alpha_i^s \quad (30)$$

$$R_{sm,i}^{s}(S_t^s) = 0 \quad (31)$$

where,

$$\alpha_i^s = \frac{r_{gw,i}^{s,irr}}{f_{gw,i}^{s,irr} + f_{sw,i}^{s,irr}} \quad (32)$$

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) of the input-output model.

Note that parameters $(\delta_i^s, \eta_i^s, \alpha_i^s)$ are all defined based on the average hydrological condition, that is, for the deterministic situation. It is assumed an irrigation losses in groundwater and surface water equal to $\rho_i^s = 30\%$, obtaining $\gamma_i^s = 1.42$, for all agricultural sectors and subregions.

2.6 Water for dilution

The deterministic coefficient $w_{k,i}^s$ of equation (33) was calculated by Rocchi et al. (2024) with a mixing model base on a mass balance of COD concentration with intermediate chemical reaction, improving the previous versions (Xie, 1996; Guan and Hubacek, 2008).

The $w^s_{k,i,t}$ of equation (33), for this study, is calculated based on 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:

$$w^s_{k,i,t} = \frac{u^s_{k,i,t}}{x^s_i} \tag{33}$$

Where, $u^s_{k,i,t}$ (m³/year) is the water for dilution, which is calculated with the following mixing model:

$$u^s_{k,i,t} = \frac{1}{k_{1_k} \cdot {c_s}^s_{k,t} - {c_0}^s_{k,t}} \left[r^s_{k,i,t} \cdot x^s_i \cdot (k_{2_k} \cdot {c_p}^s_{k,i,t} - {c_s}_{k,t}) \right] \tag{34}$$

where,

k_{1_k}	:	total reaction rate of pollutants after entering the water body *k*
k_{2_k}	:	pollution purification rate before entering the water body *k*
$r^s_{k,i,t} \cdot x^s_i$	:	discharges into the water body *k* associated with economic sector *i* and subregion *s,* for year t
${c_p}^s_{k,i,t}$	:	COD concentration in the discharges to the water body *k* associated with economic sector *i* and subregion *s*
${c_s}^s_{k,t}$	:	Standard COD concentration in water body *k* and subregion *s* for year *t*
${c_0}^s_{k,t}$	:	COD concentration in water body *k* and subregion *s* for year t

Note that $r^s_{k,i,t} = r^s_{k,i} + R^s_{k,i,t}(S^s_t)$ (equation (8)) is completely defined by the hydrological variability in the agricultural sectors. This is the first endogenous component.

The other endogenous component corresponds to ${c_0}_{k,t}$, 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 (whose indicator used is COD) depends on the economic system, which, in the case of this work, is considered constant, or more generally, its variability is much smaller than the hydrologic variability.

The variable $\pi_{k,t}^{s}$ is define by the hydrological model, for groundwater and surface water, like the ratio between the natural supply (hydrological model) in year *t* and the long-term natural supply, for the water body *k* and subregion *s*:

$$\pi_{gw,t}^{s} \equiv \frac{I_t^s}{I^s} \tag{35}$$

$$\pi_{sw,t}^{s} \equiv \frac{R_t^s}{R^s} \tag{36}$$

Let define the following parameters:

${c_0}_k^{min}$	:	Minimum concentration in water body *k*
${c_0}_k^{max}$	:	Maximum concentration in water body *k*
${c_0}_k^{mean}$	:	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 constructed to represent the relationship between the concentration in water bodies before discharge and hydrology (both surface and groundwater). The following linear relation is considered for ${c_0}_{k,t} \in ({c_0}_k^{min}, {c_0}_k^{max})$:

$${c_0}_{k,t}^{s} = a \cdot \pi_{k,t}^{s} + b \tag{37}$$

where,

$$a = \frac{{c_0}_k^{max} - {c_0}_k^{min}}{\pi_k^{min} - \pi_k^{max}}$$

$$b = {c_0}_k^{mean} - a$$

For concentrations below the minimum and above the maximum, the ratio of the maximum concentration to the runoff or recharge level indicator (hydrology) is considered constant. Thus, the linear function is defined as follows:

$${c_0}_{k,t}^{s} = \begin{cases} {c_0}_k^{min} & if\ \pi_{k,t} \leq \pi_k^{min} \\ a \cdot \pi_{k,t} + b & if\ \pi_k^{min} < \pi_{k,t}^{s} \\ {c_0}_k^{max} & if\ \pi_{k,t} \geq \pi_k^{max} \end{cases} \tag{38}$$

When the concentration in the water bodies (${c_0}_{k,t}^{s}$) is higher than the standard concentration in average conditions (${c_s}_k$), the standard concentration for the year t in subregion s ($c_{s_{k,t}}^{s}$) is considered to be that of the water body, since in the model the water for dilution come from the hydrological system. Then:

$$c_{s_{k,t}}^{s} = \begin{cases} c_{s_k}^{s} & if \;\; c_{0_{k,t}}^{s} \leq c_{s_k} \\ c_{0_{k,t}}^{s} & if \;\; c_{0_{k,t}}^{s} > c_{s_k} \end{cases} \tag{39}$$

With equation (38) this expression it is calculated $u_{k,i,t}$ in equation (34) and $w_{k,i,t}$ with equation (33). Thus, the additional water for dilution with hydrological variability can be calculated as the difference between the stochastic model coefficient ($w_{k,i,t}$) and deterministic model coefficient ($w_{k,i}$):

$$H_{k,i,t}^{s}[I_t^s, R_t^s, R_{k,i,t}^s(S_t^s)] = w_{k,i,t}^{s} - w_{k,i}^{s} \tag{40}$$

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

The parameter considered are:

c_{s_k} = 20 mg/l
$c_{0_k}^{min}$ = 15 mg/l
$c_{0_k}^{max}$ = 25 mg/l
$c_{0_k}^{mean}$ = 20 mg/l
π_k^{min} = 0.5
π_k^{max} = 1.5
π_k^{mean} = 1.0

2.7 Long-term natural supply

The long-term natural water supply is calculated based on the natural supply estimated using the SWAT model and an adjustment factor derived from historical precipitation data for the period 1971–2020 (Bartolini, 2014, 2018; SIR Toscana, 2021). This methodology allows for the correction of climatic biases present in the study period considered in this work (2005–2013).

Long-term groundwater recharge and surface runoff volumes are estimated as:

$$\bar{I}^s = \frac{\tau^s}{T} \sum_{t=1}^{T} I_t^s \tag{41}$$

$$\bar{R}^s = \frac{\tau^s}{T} \sum_{t=1}^{T} R_t^s \tag{42}$$

Where τ^s corresponds to a bias correction factor for the analysis period calculated on the basis of the precipitation for a longer period $(T^*, 1971 - 2020)$ and the precipitation for the analysis period (T).

$$\tau^s = \frac{\frac{1}{T^*}\sum_{t=1}^{T^*} P_t^s}{\frac{1}{T}\sum_{t=1}^{T} P_t^s} \tag{43}$$

2.8 Natural ecological supply and feasible supply

Natural ecological supply (ES) refers to the long-term natural water supply net of the ecological flow requirement.

$$ES^s = \bar{I}^s + (1 - E)\bar{R}^s \tag{44}$$

The estimation of feasible water supply follows the methodology proposed by Rocchi et al. (2021), which incorporates environmental, institutional, and technical constraints into the natural supply of surface and groundwater.

$$I_t^{s,feas} = \left\{ \begin{array}{cc} \bar{I}^s(1 - B^s) & if \;\; I_t^s < \bar{I}^s(1 - B^s) \\ \bar{I}^s(1 + B^s B) & if \;\; I_t^s > \bar{I}^s(1 + B^s) \\ I_t^s & if \;\; I_t^s \in [\bar{I}^s(1 - B^s), \bar{I}^s(1 + B^s)] \end{array} \right\} \tag{45}$$

$$R_t^{s,feas} = \left\{ \begin{array}{cc} R_t^s - E\bar{R}^s & if \;\; E\bar{R}^s \leq R_t^s \leq M^s\bar{R}^s + E\bar{R}^s \\ M^s\bar{R}^s & if \;\; R_t^s > M^s\bar{R}^s + E\bar{R}^s \\ 0 & if \;\; R_t^s < E\bar{R}^s \end{array} \right\} \tag{46}$$

where,

I_t^s	:	Groundwater recharge volume in year t in subregion *s*
$\bar{I}^s$	:	Long-term groundwater recharge volume in subregion *s*
B^s	:	Parameter defining the range of groundwater feasible availability in subregion *s*
R_t^s	:	Runoff volume in year t (multivariate model)
$\bar{R}^s$	:	Long-term runoff volume in subregion *s*
E	:	Ecological flow as proportion of mean runoff
M^s	:	Maximum volume of concessions as proportion of mean runoff in subregion *s*

An environmental flow of 20% is considered for surface water (Rossi et al., 2010), a depletion threshold of 13% for groundwater (Rocchi et al., 2024). In this case, the Maximum Volume of Concessions as a Proportion of Mean Runoff is set to 1, since no external water concessions are considered; the analysis is restricted to water naturally generated within the basin, along with transfers from the Montedoglio reservoir— in contrast to Sturla and Rocchi (2022), who consider surface water supply based on concession volumes.

2.9 Green water supply

La oferta de agua verde se obtiene en base a la humedad del suelo (SM) y la evapotranspiración (ET) (Pacetti et al., 2021). Sin embargo, como en este estudio interesa la oferta de agua verde para para el sector agrícola durante el periodo de riego, por lo tanto se aplican dos factores: el porcentaje de area agrícola en cada LLS (β_A^s) y los meses del año en que hay riego (5). De esta forma el indicador de disponibilidad de agua

$$GWA^s = (ET^s + SM^s) \cdot \beta_A^s \cdot \frac{5}{12} \tag{47}$$

2.10 Scarcity indicators

The following water scarcity indicators will be used to characterize the LLS.

a) WEI

The WEI corresponds to the ratio between blue water withdrawals of groundwater and surface water, and the long term natural availability net of the ecological flow (natural ecological supply, ES) (European Environmental Agency, 2005).

$$WEI_t = \frac{\sum_{i=1}^{N} \sum_{k=1}^{2} f_{k,i,t}^s \cdot x_i^s}{ES^s} \tag{48}$$

b) WEI⁺

The WEI$^+$, is an upgraded version of the WEI, which incorporates returns from water uses, therefore taking into account the net water demand (Faergemann, 2012; European Environmental Agency, 2020)

$$WEI_t^+ = \frac{\sum_{i=1}^{N} \sum_{k=1}^{2} (f_{k,i,t}^s - r_{k,i,t}^s) \cdot x_i^s}{ES^s} \tag{49}$$

c) EWEI

The EWEI indicator is estimated as the extended water demand divided by the feasible supply (Sturla and Rocchi, 2022).

$$EWEI_t = \frac{\sum_{i=1}^{N} \sum_{k=1}^{2} (f_{k,i,t}^s - r_{k,i,t}^s + w_{k,i,t}^s) \cdot x_i^s}{I_t^{s,feas} + R_t^{s,feas}} \tag{50}$$

d) EWEI*

The EWEI* indicator corresponds to the EWEI calculated using the natural ecological supply in the year of analysis, rather than in the long term. It is defined as the groundwater recharge and surface runoff, minus the ecological flow. This indicator is proposed in the present study.

$$EWEI_t^{*s} = \frac{\sum_{i=1}^{N}\sum_{k=1}^{2}(f_{k,i,t}^{s} - r_{k,i,t}^{s} + w_{k,i,t}^{s}) \cdot x_i^s}{I_t^s + R_t^s - E\bar{R}^s} \tag{51}$$

e) GWSI

The green water scarcity index (GWSI) is derived based on agricultural soil moisture demand and green water supply. v

$$GWSI_t^s = \frac{\sum_{i=1}^{N} f_{sm,i,t}^{s} \cdot x_i^s}{GWA_t^s} \tag{52}$$

This study considers the standard scarcity threshold values, 20% for scarcity and 40% for severe scarcity (OECD, 2015; Pfister et al., 2009).

2.11 Data

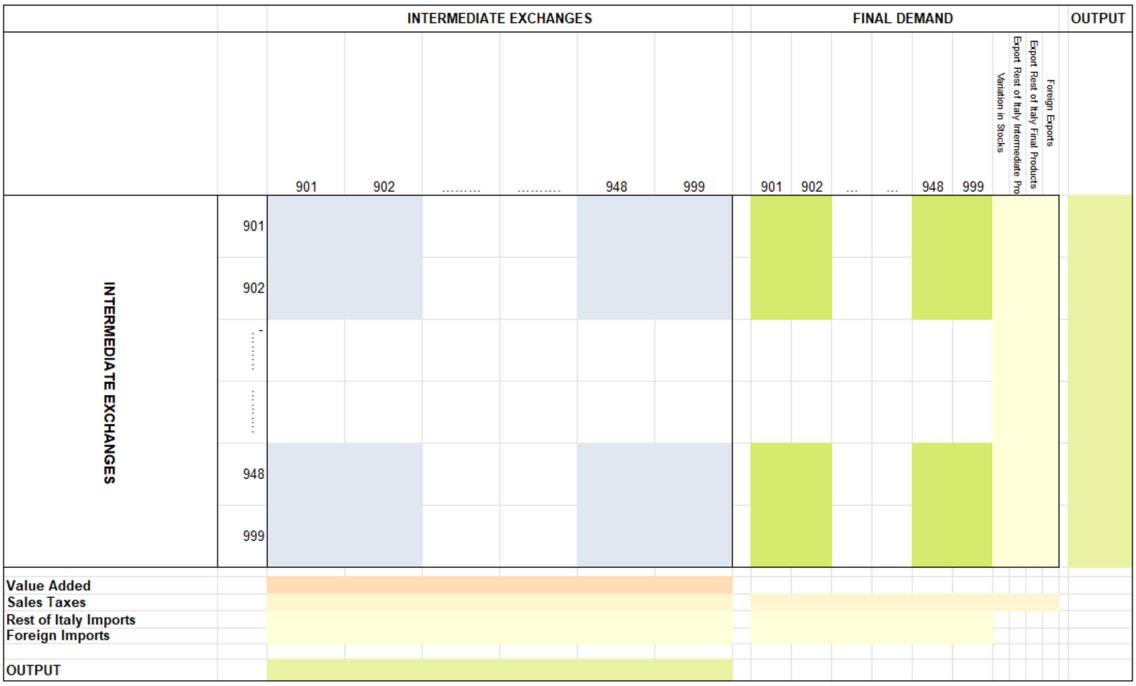
The input data for the SWAT model—including precipitation, temperature, solar radiation, relative humidity, and other climatic variables—were obtained from Braca et al. (2021, 2022), Sir Toscana (2021), and ISTAT (2021).

The intensity coefficients for blue and green water use were sourced from the study by Sturla and Rocchi (2022). For water quality parameters related to effluent discharges (COD), the legally permitted maximum values were used, based on ISTAT (2019).

The thresholds for moderate and severe water scarcity indicators were obtained from the European Environmental Agency (2020), with values of 0.2 and 0.4, respectively.

The MRIO table used in this study (Figure 4) was developed by the Tuscan Regional Institute for Economic Planning (IRPET, 2021). The original table included agriculture as a single industry. The final multi-regional matrix is referred to year 2017 and contains 53 economic sectors, 49 LLSs, 5 components of the internal final demand and 4 components of external final demand (Rest of Italy and Rest of the World).

Figure 4. Structure of the IRIO table of Tuscany



Source: own elaboration based on IRPET (2021)

All other data sources have been described in the previous sections.

3 RESULTS

3.1 Hydrological results

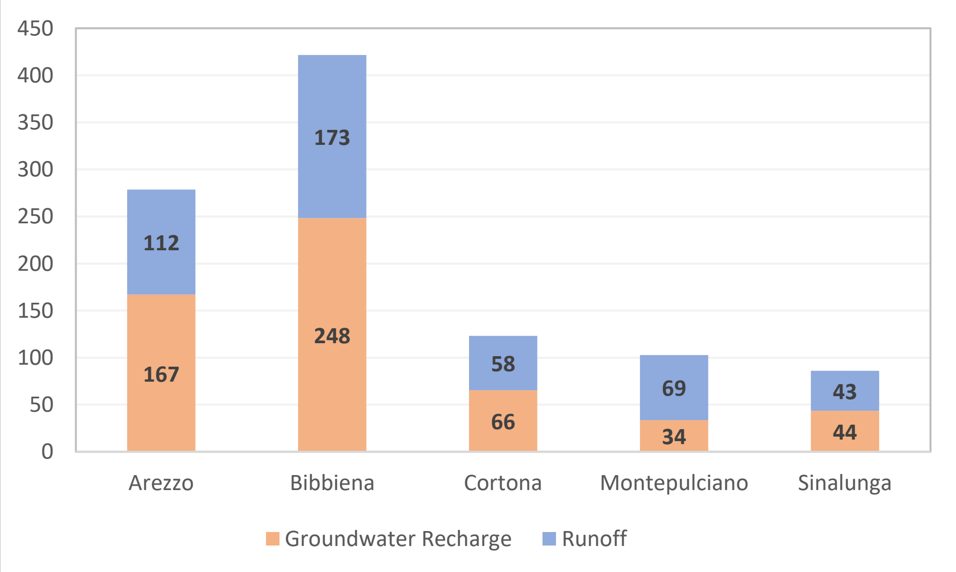
Table 1 presents the results of the hydrological model by LLS and year, which are used in this study to estimate both water supply and demand in their various forms. Figure 5 shows the average natural supply of groundwater (recharge) and surface water (runoff).

Table 1. Hydrological results by LLS and year

LLS	Year	Precipitation [Mm3]	Evapotranspiration [Mm3]	Groundwater Recharge [Mm3]	Surface Runoff [Mm3]	Soil Moisture [Mm3]	Green Water Supply [Mm3]
Arezzo	2014	686.9	396.0	178.9	93.5	80.0	73.4
	2015	552.1	410.1	99.2	74.3	68.1	73.7
	2016	856.6	422.8	217.7	153.2	78.7	77.3
	2017	487.5	343.6	91.0	54.1	63.4	62.7
	2018	735.1	365.9	212.3	116.2	71.7	67.4
	2019	805.3	373.6	214.0	183.2	82.9	70.4
	2020	655.1	366.3	155.7	106.0	76.1	68.2
Bibbiena	2014	902.8	333.0	321.5	199.4	81.4	29.4
	2015	568.2	356.1	136.3	82.5	67.4	30.0
	2016	881.7	357.7	285.9	188.5	78.9	30.9
	2017	575.8	342.6	127.2	76.1	62.1	28.7
	2018	897.5	326.0	319.3	207.3	79.8	28.7
	2019	983.9	328.7	310.1	298.2	81.4	29.0
	2020	820.8	335.5	238.5	159.4	78.7	29.3
Cortona	2014	414.5	259.6	82.8	54.8	58.5	68.9
	2015	283.8	249.6	30.9	45.9	45.2	63.9
	2016	489.2	281.8	83.4	74.0	58.3	73.7
	2017	338.9	247.1	53.1	45.6	45.9	63.5
	2018	434.7	241.8	80.4	84.0	51.9	63.6
	2019	371.2	235.9	59.1	60.8	57.3	63.5
	2020	308.1	205.8	68.9	37.8	48.1	55.0
Montepulciano	2014	368.9	240.9	46.2	62.7	71.1	84.5
	2015	259.9	246.1	17.9	46.8	54.8	81.5
	2016	439.6	267.3	37.0	88.3	68.0	90.8
	2017	159.6	178.9	6.4	7.9	46.0	60.9
	2018	434.0	231.1	46.6	111.7	59.7	78.8
	2019	424.3	224.0	54.3	127.5	71.0	79.9
	2020	291.0	221.7	27.6	38.7	67.9	78.4
Sinalunga	2014	270.6	175.3	50.2	33.4	44.9	56.9
	2015	205.5	179.9	25.7	30.6	35.8	55.7
	2016	338.8	190.8	55.4	59.4	43.6	60.6
	2017	133.4	134.5	11.9	7.3	31.4	42.8
	2018	305.5	163.6	55.6	58.8	37.7	52.0
	2019	324.7	159.3	72.3	82.7	44.7	52.7
	2020	226.0	160.1	33.5	25.7	42.3	52.3

Source: Own elaboration

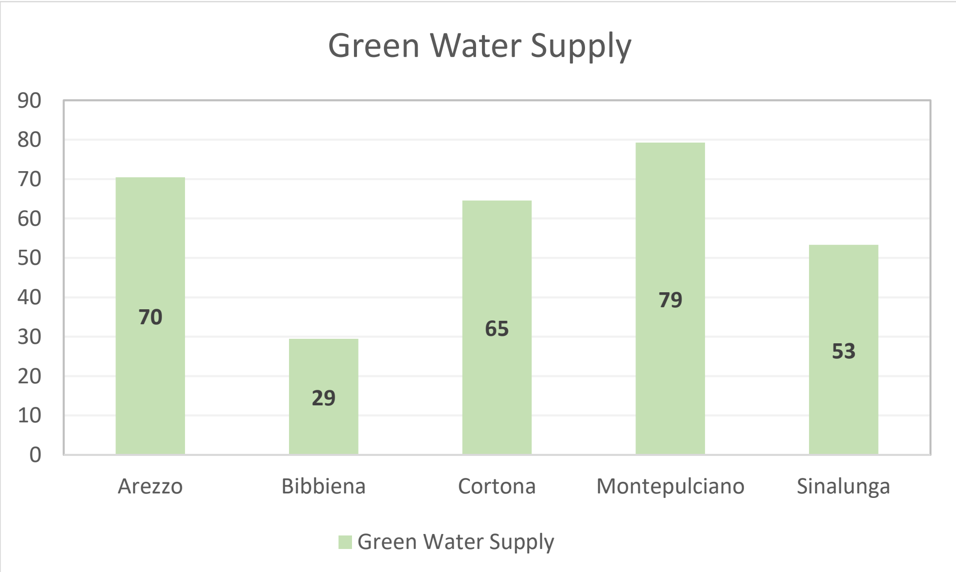
Figure 5. Natural supply by LLS (blue water)



Source: Own elaboration

Figure 6 shows the green water supply by LLS, estimated as the soil moisture in agricultural areas during the irrigation months.

Figure 6. Green water supply by LLS



Source: Own elaboration

3.2 Water demand

Water demand by LLS has been estimated based on the interaction between the MRIO model and the hydrological model. Four types of demand have been characterized: water withdrawals (WD), net demand or blue water (ND), extended demand, which includes blue and grey water (ED), and green water demand (GD). All types of demand exhibit annual variability due to the green-to-blue water substitution mechanism in agriculture. However, this variability is only observed in Cortona, Sinalunga, where green water deficits trigger substitution; in Arezzo and Bibbiena, no green water shortage occurs. ED consistently shows variability as well, due to the mixing model—dependent on water supply—used to estimate grey water for discharging industries. Table 2 presents these results by LLS and by year.

Table 2. Water demand by LLS and year

LLS	Demand Category	2014	2015	2016	2017	2018	2019	2020
Arezzo	WD	12.2	12.2	12.2	12.2	12.2	12.2	12.2
	ND	23.8	23.8	23.8	23.8	23.8	23.8	23.8
	ED	57.9	57.9	57.9	57.9	57.9	57.9	57.9
	GD	30.3	29.7	26.9	29.1	30.3	25.8	30.8
Bibbiena	WD	2.4	2.4	2.4	2.4	2.4	2.4	2.4
	ND	6.4	6.4	6.4	6.4	6.4	6.4	6.4
	ED	26.1	26.1	26.1	26.1	26.1	26.1	26.1
	GD	9.0	9.0	9.2	9.0	8.9	8.0	9.5
Cortona	WD	9.3	14.7	9.4	14.4	12.0	9.8	13.5
	ND	30.2	49.2	30.6	48.3	39.7	32.0	45.1
	ED	65.4	65.4	65.4	65.4	65.4	65.4	65.4
	GD	30.9	47.4	29.9	47.1	37.3	33.0	44.1
Montepulciano	WD	1.4	1.4	1.4	3.3	1.4	1.4	1.4
	ND	6.3	6.3	6.3	16.2	6.3	6.3	6.3
	ED	79.0	79.0	79.0	79.0	79.0	79.0	79.0
	GD	7.5	7.5	7.2	16.3	6.7	6.7	7.5
Sinalunga	WD	4.0	6.6	4.4	7.8	6.0	4.1	4.8
	ND	10.6	23.6	12.4	30.0	20.9	10.9	14.4
	ED	51.9	51.9	51.9	51.9	51.9	51.9	51.9
	GD	12.7	23.5	13.1	28.5	20.0	11.4	15.7

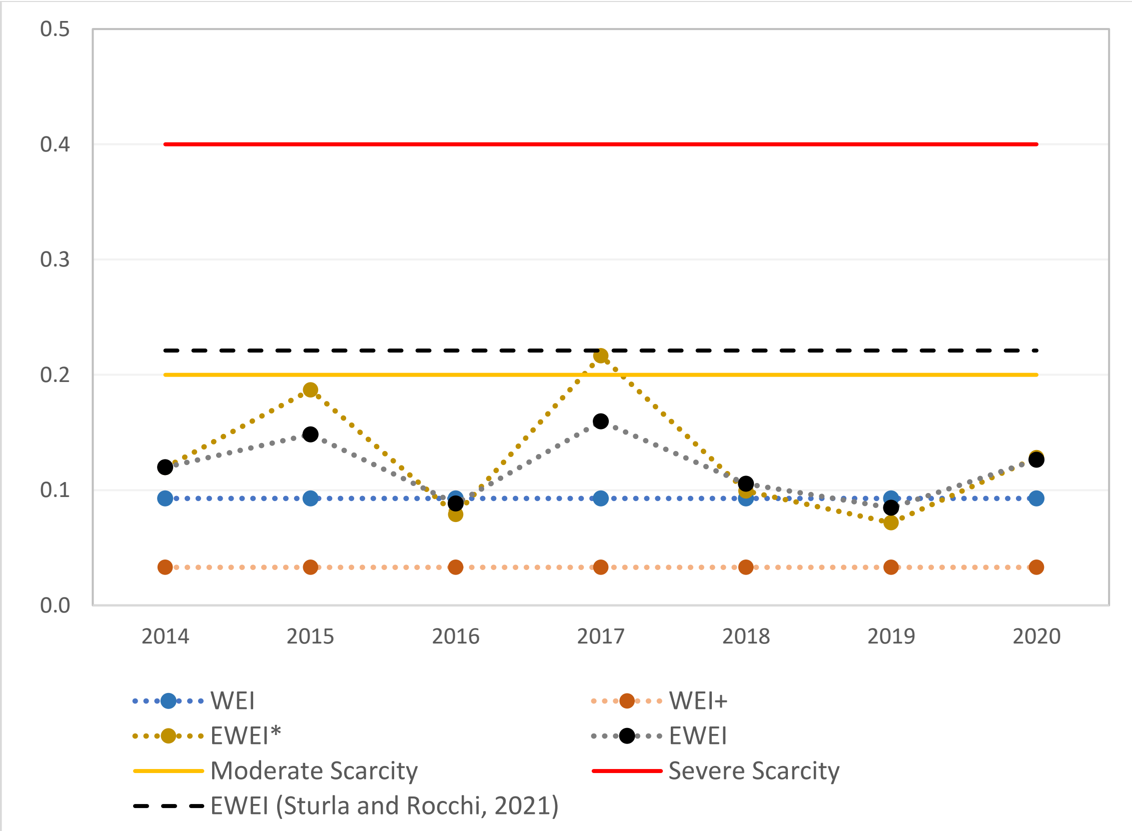
Source: Own elaboration

3.3 Scarcity indicators

Figures 7 to 11 show the temporal evolution of the four indicators related to blue and grey water (WEI, WEI+, EWEI, EWEI*). These figures include the thresholds for moderate (0.2) and severe (0.4) water scarcity. In addition, the EWEI obtained in the study by Sturla and Rocchi (2022) is included for comparison.

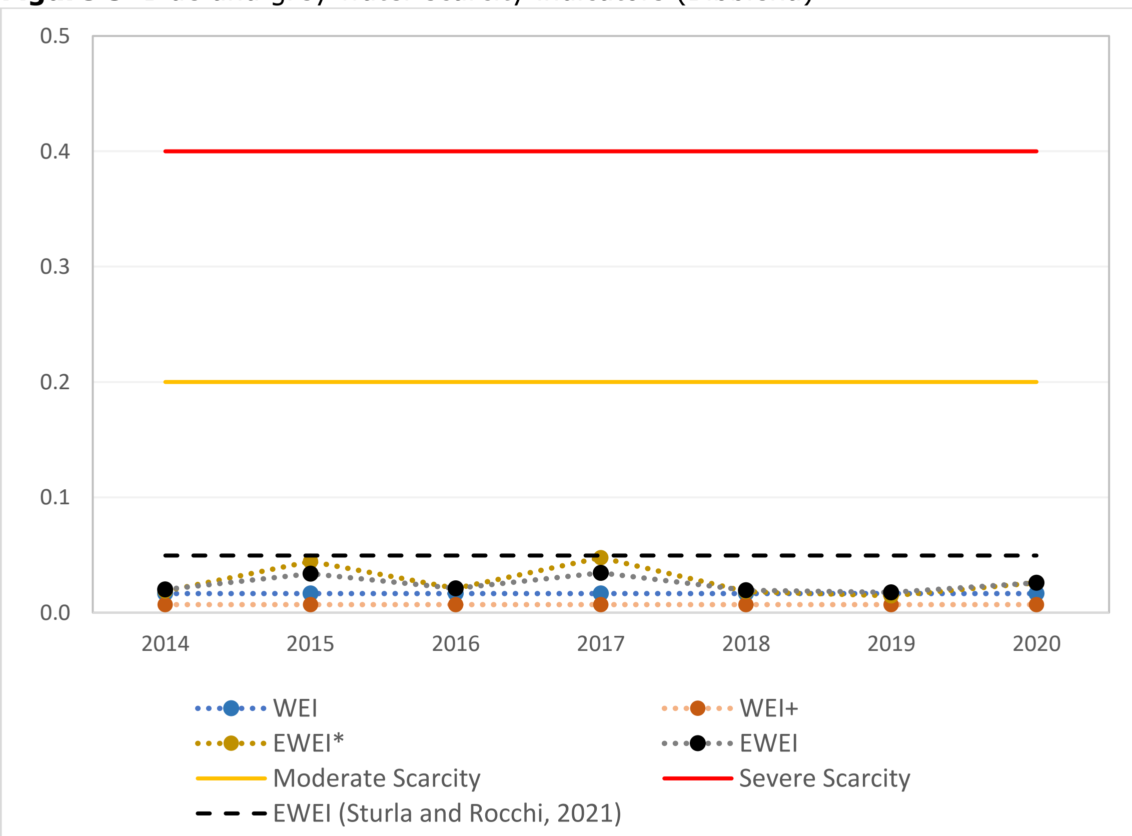
Figure 12 presents the green water scarcity indicator (GWSI) proposed in this study for all LLS. This indicator reflects situations in which a green water deficit occurs and must be compensated by blue water. It can be observed that the three previously mentioned LLS experience green water scarcity in certain years.

Figure 7. Scarcity indicators (Arezzo)



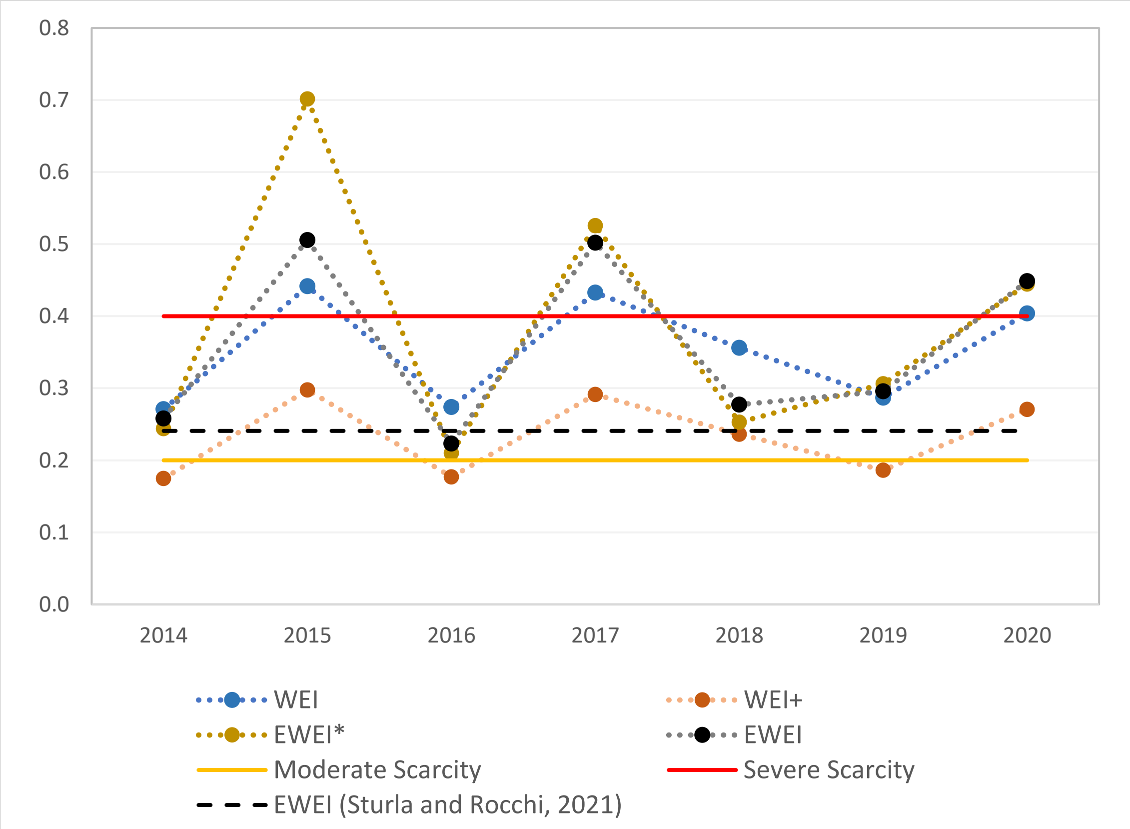
Source: Own elaboration

Figure 8. Blue and grey water scarcity indicators (Bibbiena)



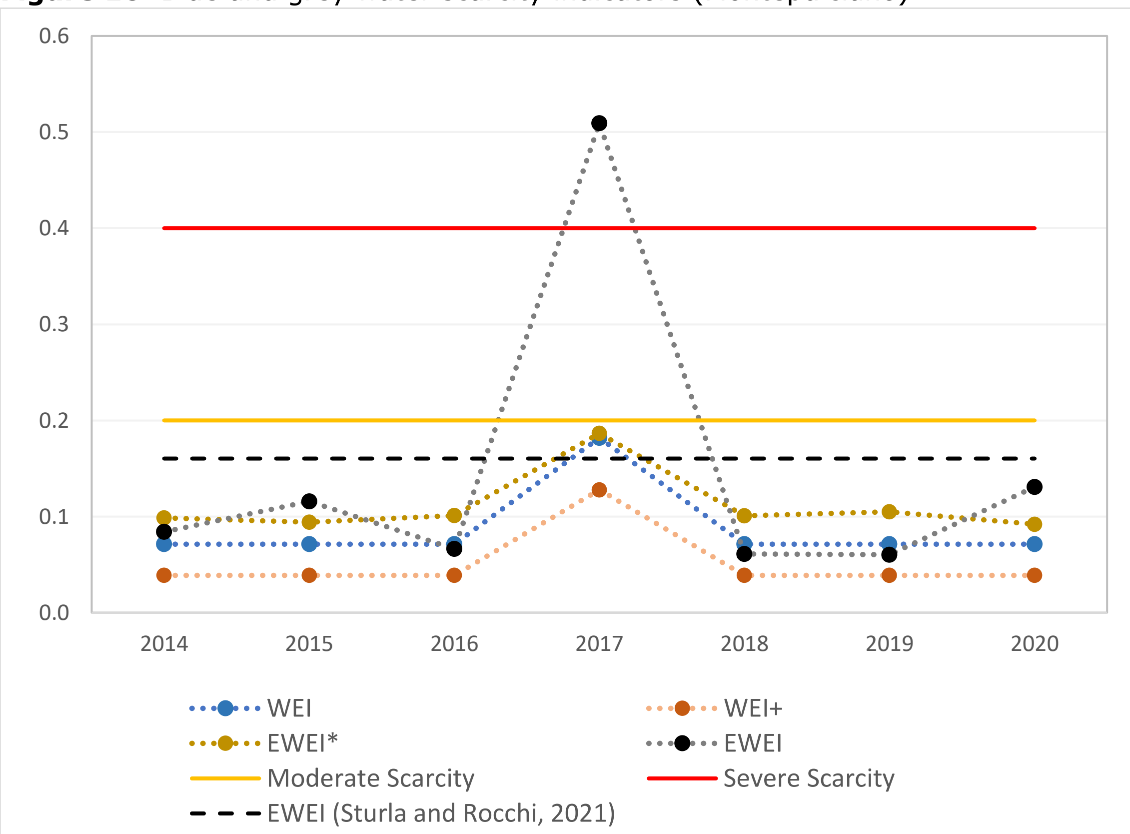
Source: Own elaboration

Figure 9. Blue and grey water scarcity indicators (Cortona)



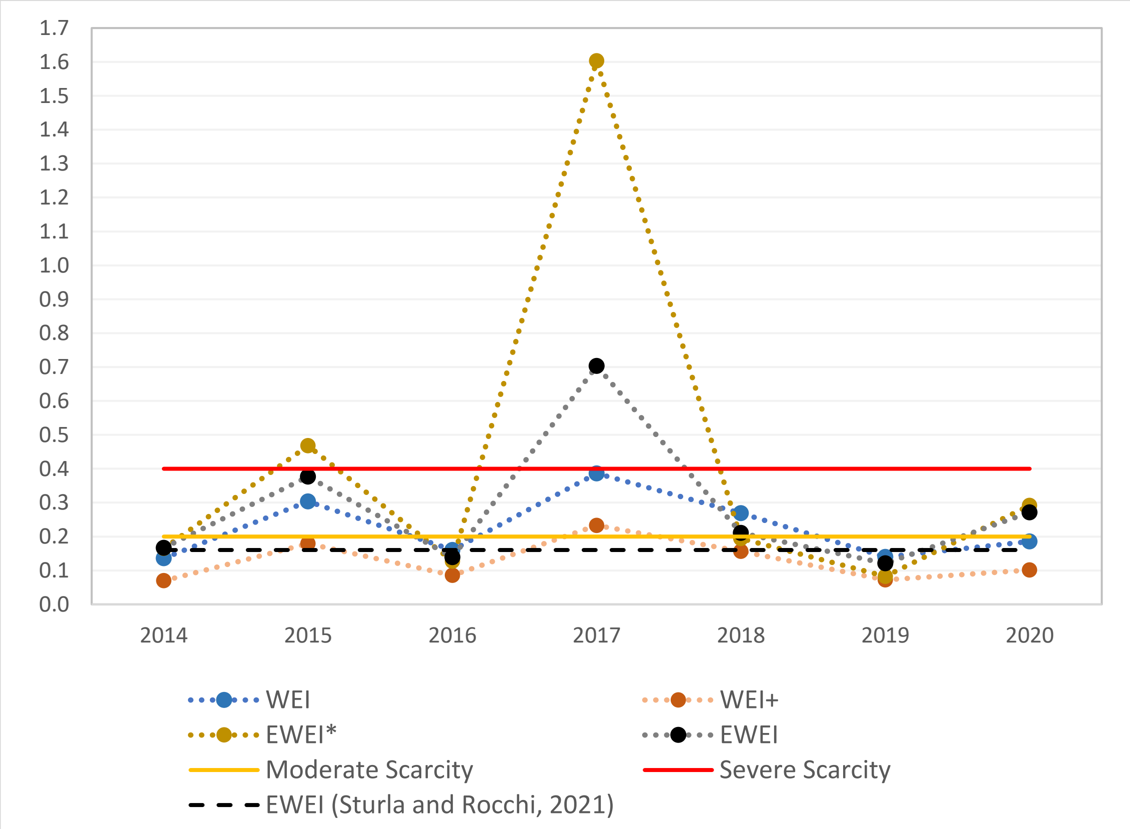
Source: Own elaboration

Figure 10. Blue and grey water scarcity indicators (Montepulciano)



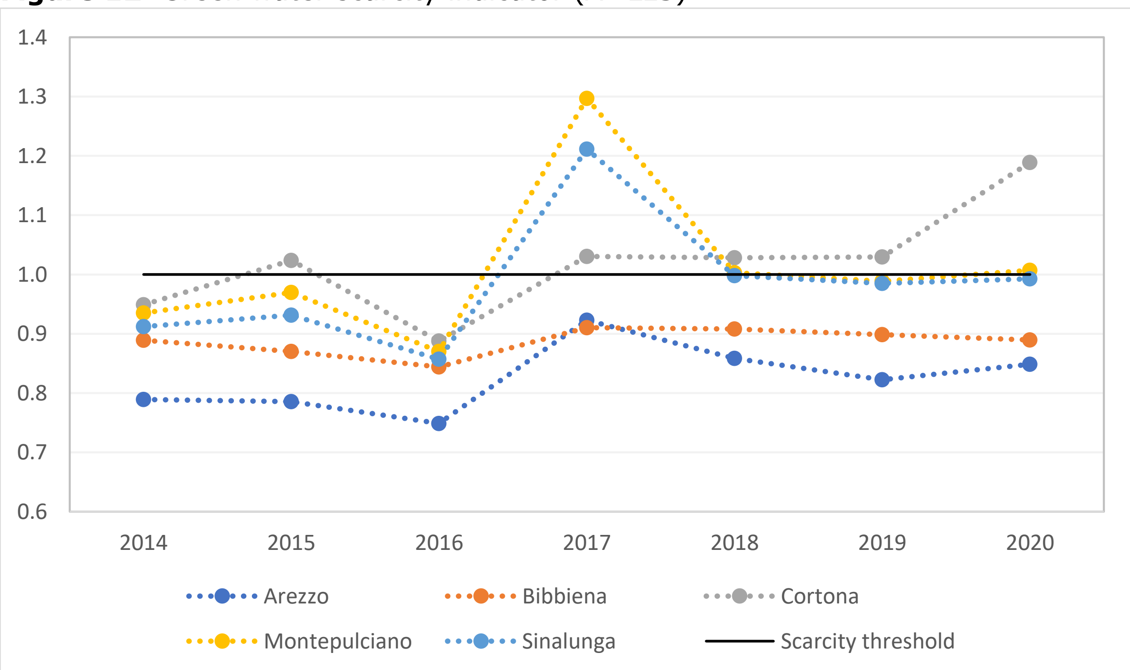
Source: Own elaboration

Figure 11. Blue and grey water scarcity indicators (Sinalunga)



Source: Own elaboration

Figure 12. Green water scarcity indicator (All LLS)



Source: Own elaboration

4 DISCUSSION

The results indicate that:

- Arezzo: Only in one year does the EWEI* exceed the moderate scarcity threshold, and there is no green water deficit throughout the period. All indicators remain below the EWEI estimated by Sturla and Rocchi (2022), which had suggested moderate scarcity. This LLS does not experience water scarcity.
- Bibbiena: None of the indicators exceed the moderate scarcity threshold, and there is no green water deficit. These results are consistent with the findings of Sturla and Rocchi (2022).
- Cortona: The WEI (3 years), EWEI* (2 years), and EWEI (3 years) indicators exceed the severe scarcity threshold. This LLS experiences green water deficits in 5 out of the 7 simulated years. Sturla and Rocchi (2022) had estimated only moderate scarcity.
- Montepulciano: Only the EWEI exceeds scarcity thresholds, indicating severe scarcity in one year, which coincides with a strong green water deficit.
- Sinalunga: The EWEI* (2 years) and EWEI (1 year) indicators exceed the severe scarcity threshold. The other indicators exceed the moderate scarcity threshold in at least one year. Green water deficit occurs in only one year.

The results reveal significant water scarcity issues in Cortona, Montepulciano, and Sinalunga, with Cortona and Sinalunga being the most critical cases. Severe scarcity is primarily captured by the EWEI* and EWEI indicators, as they include grey water. In the years of greatest scarcity, lower blue water availability and green water deficits result in increased grey water requirements (due to reduced surface flows for pollutant dilution) and greater use of blue water to sustain agricultural activity.

The analysis reflects a comprehensive characterization of water scarcity, incorporating hydrological and economic realism. The interaction between the hydrological and hydroeconomic modules enables dynamic representation of critical aspects such as grey water and the additional blue water used in agriculture. This constitutes a key contribution to both the academic literature and water management policies in the upper Arno River basin. From a policy design perspective, the study underscores the importance of explicitly considering water–economy interactions, which are often overlooked. Both hydrology and the economy are inherently dynamic, and this framework captures that complexity.

Limitations and future work: This study relies on exogenous scarcity thresholds, which could be endogenously defined in future research by incorporating intra-annual variability in agricultural and domestic water demand. Moreover, the spatial scope is limited to a subset of the Tuscany region, which restricts regional-scale analysis of scarcity and the design of coherent public policies. Future work should expand hydrological modeling to include the remaining basins in the region. This extension would also enable the use of the MRIO model to evaluate virtual water flows across the local economies of Tuscany—offering valuable insights into the economic use and governance of water. Such an approach would also allow for the estimation of the water footprint of each LLS, adjusted by scarcity and incorporating social criteria, such as the local capacity for socio-institutional water governance (Sturla et al., 2023; Wilkens, 2017; Wang et al., 2021; Pfister et al., 2009).

5 CONCLUSIONS

This study focuses on the harmonization of hydrological and economic scales, a relevant issue in the literature on environmentally extended input–output (EEIO) models. This is achieved by aggregating sub-basins by LLS, allowing the estimation of natural water supply in local economies using a SWAT model, including green water supply—typically omitted in previous input–output models. The interaction between the SWAT model and the hydro-economic MRIO model enables the estimation of blue, grey, and green water demand.

The integrated model is applied to five local economies located in the upper Arno River basin in Tuscany, Italy. Based on this model, five indicators are estimated to characterize water scarcity in each LLS (WEI, WEI+, EWEI*, EWEI, and GWSI), two of which (EWEI* and GWSI) are proposed in this study.

Unlike previous MRIO models, this study enables the characterization of both blue and green water supply at the hydrological scale (i.e., sub-basin). The inclusion of green water supply allows for a realistic simulation of the green-to-blue water substitution mechanism in agriculture—affecting all blue water scarcity indicators—by explicitly estimating soil moisture scarcity. This represents a notable improvement over the study by Sturla and Rocchi (2022), which used precipitation as a proxy for soil moisture.

The results show that three LLS experience green water scarcity in some years, which is reflected in an increase in blue water scarcity indicators. Regarding scarcity levels, two LLS (Arezzo and Bibbiena) exhibit virtually no scarcity. The other three LLS (Cortona, Montepulciano, and Sinalunga) present years of severe scarcity, especially when considering the EWEI* and EWEI indicators. This is because these indicators incorporate grey water and water supply; in the case of EWEI, feasible supply is considered, which is on average 10% lower than the natural ecological supply. Notably, EWEI*—although based on a higher supply—can sometimes exceed EWEI because it does not account for the groundwater storage capacity.

In conclusion, this study makes a significant contribution: by integrating a hydro-economic model with a physically based model, it enables, for the first time, a precise simulation of the green-to-blue water substitution mechanism and the reduced dilution capacity of water bodies during dry years. Moreover, by comparing various indicators from the literature with two newly proposed ones, it allows for a more comprehensive characterization of water scarcity.

6 REFERENCES

1. Bartolini, G., Grifoni, D., Mano, R., Torrigiani, T. and Gozzini, B. (2018). "Changes in temporal distribution of Precipitation in a Mediterranean area (Tuscany, Italy) 1955–2013". *International Journal of Climatology.* V. 38, pp. 1366-1374.
2. Bartolini, G., Messeri, A., Grifoni, D., Mannini, D. and Orlandi, S. (2014). "Recent trends in seasonal and annual precipitation indices in Tuscany (Italy)". *Theoretical and Applied Climatology.* 118:147-157. DOI 10.1007/s00704-013-1053-3
3. Braca, G., Bussettini, M., Lastoria, B., Mariani, S., and Piva, F. (2021)." Il Bilancio Idrologico Gis BAsed a scala Nazionale su Griglia regolare – BIGBANG: metodologia e stime". Rapporto sulla disponibilità naturale della risorsa idrica. *Istituto Superiore per la Protezione e la Ricerca Ambientale*. Rapporti 339/21, Roma.
4. Braca, G., Bussettini, M., Lastoria, B., Mariani, S., and Piva, F. (2022). "Il modello di bilancio idrologico nazionale BIGBANG: sviluppo e applicazioni operative. La disponibilità della risorsa idrica naturale in Italia dal 1951 al 2020". The BIGBANG National Water Balance Model: Development and Operational Applications. *The Availability of Renewable Freshwater Resources in Italy from 1951 to 2020*. L'Acqua, 2/2022.
5. Bras, L. and Rodríguez-Iturbe, I. (1993). "Random Functions
6. Faergemann, H. (2012). "Update on Water Scarcity and Droughts indicator development. In EC Expert Group on Water Scarcity & Droughts". *European Environment Agency*. Brussels, Belgium; pp. 1–23.
7. Guan, D., and Hubacek, K. (2008). "A new and integrated hydro-economic accounting and analytical framework for water resources: a case study of North China". *Journal of Environmental Management*, 88: 1300-1313.
8. IRPET (2021). "Interregional Input-Output Table for the Tuscany Region, Italy". *Istituto Regionale di Programmazione Económica Regione Toscana.*
9. ISTAT (2019). "Water Use and Quality in Italy". *Istituto Nazionale di Statistica.* Italia. https://www.istat.it/it/archivio/234904
10. ISTAT (2021). "Banchi di dati e sistemi informazioni". https://www.istat.it/it/dati-analisi-e-prodotti/banche-dati
11. OECD. (2015). "Water: Freshwater abstractions (Edition 2015)". OECD Environment Statistics (database). https://doi.org/10.1787/f9f5fcd1-en
12. Pacetti, T., Castelli, G., Schröder, B., Bresci, E. and Caporali, E. (2021). "Water Ecosystem Services Footprint in Agricultural Production in Central Italy". Science of the Total Environment. 797, 149095.
13. Pfister, S., Koehler, A. and Hellweg, S. *(2009).* "Assessing the Environmental Impacts of Freshwater Consumption in LCA*". Environ. Sci. Technol. 43, 11, 4098–4104.* https://doi.org/10.1021/es802423e
14. Ridoutt, B.G., Hadjikakou, M., Nolan, M. and Bryan, B.A. (2018). "From Water-Use to Water-Scarcity Footprinting in Environmentally Extended Input−Output Analysis". *Environ. Sci. Technol*. 52, 6761−6770.
15. Rocchi, B., Sturla, G. and Viccaro, M. (2024). "A hydro-economic input-output model to assess economic pressures on water resources". *Bio-based and Applied Economics.* Vol. 13, No 2, pp. 203-2017.
16. Rossi, G. and Caporali, E. (2010). "Regional Analysis of low flow in Tuscany (Italy)". *Global Change: Facing Risk and Threats to Water Resources*. IAHS Publ. 340.
17. SIR Toscana (2021). "Strati GIS". https://www.sir.toscana.it/strati-gis

18. Sturla, G. and Rocchi, B. (2022). "An interregional input-output model with spatiotemporal hydrological variability. The case of Tuscany". Working Papers Economics N° 22/2022. DISEI. UNIFI.
19. Sturla, G. and Rocchi, B. (2024). "Effects of hydrological variability on the sustainable use of water in a regional economy. An application to Tuscany". *Environmental and Sustainability Indicators, 24 100448.*
20. Sturla, G., Ciulla, L. and Rocchi, B. (2023). "Natural and social scarcity in water footprint: an input-output analysis for Italy". *Ecological Indicators*. Vol 147, pp. 1-20.
21. Wichelns, D. (2017). "Volumetric water footprints, applied in a global context, do not provide insight regarding water scarcity or water quality degradation". *Ecological Indicators. 74, 420-426.*
22. Xie, Y. (1996). "Environment and Water Quality Model". *China Science and Technology Press*, Beijing, China.