

## Sensitivity analysis of climatic factors in water yield modeling in the Talar watershed: an ecosystem service perspective

Mohesn Zabihi<sup>1\*</sup>, Hamidreza Moradi<sup>2</sup>, Abdulvahed Khaledi Darvishan<sup>3</sup>, Mehdi Gholamalifard<sup>4</sup>

<sup>1</sup> PhD of Watershed Management Sciences and Engineering, Department of Watershed Management Engineering, Faculty of Natural Resources, Tarbiat Modares University, Noor, Iran

<sup>2</sup> Professor, Department of Watershed Management Engineering, Faculty of Natural Resources, Tarbiat Modares University, Noor, Iran

<sup>3</sup> Associate Professor, Department of Watershed Management Engineering, Faculty of Natural Resources, Tarbiat Modares University, Noor, Iran

<sup>4</sup> Associate Professor, Department of the Environment, Faculty of Natural Resources, Tarbiat Modares University, Noor, Iran

### Abstract

Understanding how climatic variables influence water yield is crucial for effective watershed management, particularly in regions that provide vital hydrological ecosystem services. This study investigates the sensitivity of key climatic factors—precipitation, reference evapotranspiration, and seasonality parameters—in modeling water yield ecosystem services using the InVEST model within the ecologically significant Talar watershed in northern Iran. Furthermore, the research aims to prioritize sub-watersheds based on their specific water yield to support ecosystem-based decision-making. Using a time series approach, water yield was modeled for the years 1989, 2000, and 2014, incorporating biophysical and climatic variables along with land use maps derived from Landsat TM and OLI imagery through SVM classification. A sensitivity analysis was conducted using the One-at-a-Time (OAT) method, with the year 2014 as the baseline and changes in each climatic factor assessed relative to 1989. Sub-watershed prioritization was carried out using specific water yield, defined as water yield per unit area. The results showed a declining trend in mean annual precipitation (from 552.6 mm in 1989 to 472.8 mm in 2014) and an increasing trend in temperature (from 8.92°C to 10.6°C), alongside a notable spatial shift in rainfall and evapotranspiration patterns. Sensitivity analysis revealed that water yield was most responsive to changes in precipitation, with a relative sensitivity index (Sr) approximately 0.42, indicating high model responsiveness. Reference evapotranspiration and seasonality parameters also exhibited a moderate influence. Prioritization results identified northern forested and agricultural sub-watersheds as having the highest specific water yields, highlighting their hydrological significance. These findings underscore the dominant role of precipitation variability in shaping regional hydrological services and emphasize the importance of spatially explicit watershed prioritization for sustainable water resource planning. The approach provides a practical framework for integrating ecosystem services into watershed management under climatic uncertainty and land use change, particularly in semi-humid regions like the Talar watershed.

**Keywords:** Climate variability, Environmental planning, OAT algorithm, Watershed services

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\*Corresponding Author, E-mail: mohsen\_zabihi69@yahoo.com

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## 1. Introduction

Ecosystem services in watersheds play a vital role in regulating hydrological processes such as water yield, flood control, groundwater recharge, and sediment retention (Petsch et al., 2023). These services are essential for ensuring water security, maintaining ecological balance, and supporting agriculture and human livelihoods, particularly in areas vulnerable to climate change and land use alterations (Mishra et al., 2021). A key ecosystem service integral to the hydrological cycle is water yield, a process through which ecosystems absorb, store, and release water, playing a central role in maintaining baseflow in rivers, recharging groundwater, and preserving regional hydrological balance (Brauman, 2015). This service is particularly important in mountainous and forested areas, which serve as the primary sources of water for downstream watersheds (Li et al., 2021a). Assessing water yield requires a detailed understanding of influencing factors such as precipitation, temperature, etc. Since these variables are subject to change due to climate variability and human interventions, analyzing their sensitivity within water yield modeling is essential for improving prediction accuracy and enhancing water resource management (Zhang et al., 2021; Norouzzadeh et al., 2023).

The ecosystem service of water yield is one of the critical regulating services provided by ecosystems, referring to a region's capacity to generate surface water from precipitation (Sharp et al., 2018). This service plays a key role in supplying water resources for human consumption, agriculture, and industry, as well as in maintaining ecosystem health. Water yield serves as an important indicator in watershed management and is particularly vital in arid and semi-arid regions, where any changes in precipitation patterns or land use can significantly impact this service (Daneshi et al., 2021).

Water yield modeling plays a key role in water resource planning by assessing management scenarios, monitoring climate change, and analyzing land use impacts. It identifies areas with high water production or risk of scarcity (Bai et al., 2018; Li et al., 2021b). In tools like InVEST (Integrated Valuation of Ecosystem Services and

Tradeoffs), water yield outputs support decisions on dam site selection, land restoration, and water allocation (Meraj et al., 2022). Water yield is influenced by precipitation, vegetation, land use, soil properties, topography, and climate. Key variables, such as evapotranspiration, soil infiltration, and vegetation root depth, affect how precipitation becomes runoff or recharges groundwater (Sharp et al., 2018). Changes in these factors, whether driven by human activity or climate change, can significantly shift the spatial distribution of water yield within a watershed (Aghabeigi et al., 2019; Asgari et al., 2025).

The InVEST model, developed by the Natural Capital Project, is widely used to assess water yield by estimating average annual water production across land units using simple yet effective input data (Yin et al., 2022; Sharp et al., 2018). Its Water Yield module applies empirical relationships to produce spatially explicit maps that support sustainable water management and spatial analysis (Hamel et al., 2021). InVEST enables evaluation of land use and climate change impacts at the watershed scale and comparison of management scenarios, making it a practical tool for regional planning (Meraj et al., 2022). Its clear visual outputs also promote stakeholder engagement and participatory decision-making. Integrating water yield estimates into environmental policy and sustainable development strategies can enhance water conservation efforts and improve community resilience to water-related challenges.

Sensitivity analysis is essential in ecosystem service modeling, especially for key climatic variables like precipitation and evapotranspiration, which heavily influence model outputs such as water yield (Pianosi et al., 2016). In the InVEST model, precipitation acts as the main input, while evapotranspiration represents the primary water loss, making both critical to yield estimates (Pessacg et al., 2015). Errors in these inputs can cause major deviations and impact decision-making. Sensitivity analysis identifies which variables most affect output variability, guiding efforts to improve data quality (Iooss and Lemaître, 2015). It also helps predict the effects of climate change, supports model calibration, and quantifies uncertainty in

scenario-based studies (Ellemaume et al., 2025). Ultimately, it strengthens model reliability and supports informed, sustainable water resource planning. Sensitivity analysis of input parameters in ecosystem service modeling, especially for water and watershed management, is essential for identifying key variables that impact services like water yield, soil erosion, and sediment delivery. It helps managers focus data collection on influential inputs such as precipitation, evapotranspiration, and soil properties, improving model accuracy and reducing uncertainty. By revealing how changes in factors like rainfall or vegetation affect outputs, sensitivity analysis supports better planning, such as targeting vegetation conservation or climate adaptation. It also helps identify critical watershed zones for intervention. In climate change studies, this analysis enables scenario evaluation and ecosystem service sustainability assessments, making it a powerful tool for adaptive management. Overall, it strengthens evidence-based decision-making and enhances the effectiveness of water resource planning across scales.

Many studies have been conducted on water yield modeling and sensitivity analysis of climatic parameters using the InVEST model. Sánchez-Canales et al. (2012) assessed the sensitivity of the InVEST water provisioning model in Spain's Llobregat basin, finding precipitation and evapotranspiration critical, while seasonal rainfall distribution had little effect. Yang et al. (2019) analyzed the InVEST model in a South China monsoon catchment, showing precipitation's dominant influence on water yield, with proper calibration improving results. Bai et al. (2019) studied climate and land use impacts on water-related ecosystem services in Kentucky, USA, revealing that climate change more strongly affected water retention, while land use influenced soil and nutrient retention. Zhang et al. (2021) examined urbanization effects on ecosystem services in China's Pearl River Delta, noting decreased supply and increased demand with population density and artificial land cover as major drivers. Yohannes et al. (2021) reported rising water yield and sediment export in Ethiopia's Beressa watershed due to farmland expansion, emphasizing soil and water

conservation. Yu et al. (2022) found variable water yield trends in Northwestern Yunnan, China, highlighting precipitation, evapotranspiration, vegetation, and terrain as key factors. Wu et al. (2022) detected a slight upward water yield trend in China's Weihe River Basin, mainly driven by precipitation. Ma et al. (2024) concluded that climate change had stronger effects than land use on water yield and soil conservation in Southwest China, stressing climate-adaptive land use planning. Lu et al. (2024) revealed deficits in ecosystem services in China's Yangtze River city cluster, calling for stricter carbon policies and coordinated land use. Finally, Wang et al. (2025) optimized InVEST parameters in China's Qilian Mountains, confirming precipitation and evapotranspiration as the most sensitive climatic factors, highlighting the need for accurate data and validation.

Previous studies highlight precipitation and evapotranspiration as key factors affecting the InVEST water yield model accuracy. This research fills a gap by analyzing these climatic sensitivities in the Talar watershed. Using localized data and calibration, it adapts the model to the Hyrcanian ecosystem and offers a practical tool for water resource management in northern Iran. This study aims to analyze the sensitivity of key climatic factors in water yield modeling within the Talar watershed from an ecosystem service perspective. Additionally, the research seeks to prioritize sub-watersheds according to their water production potential. Identifying the most sensitive climatic factors is essential for better management of ecosystem services, as these factors account for a significant portion of the variability in water yield across the watershed. These objectives will support more effective, ecosystem-based water resource management in this ecologically important region.

## 2. Materials and Methods

### 2.1. Study Area:

The study was conducted in the Talar watershed, Mazandaran Province of Iran, covering 1,764 km<sup>2</sup> on the northern slope of the Alborz Mountains. Elevations range from 216 to 3,983 meters, with an average of 1,980 meters and an

average basin slope of 42%. The watershed's main stream runs approximately 100 km in a north-south direction (Ruigar et al., 2024). The climate is Mediterranean-like and semi-humid, influenced by proximity to the Caspian Sea, the Alborz Mountains, and Mediterranean air masses. Average annual precipitation is 547 mm, evaporation is 446.6 mm, and temperatures range

from 6.6°C (minimum) to 18.3°C (maximum), with a mean of 12.4°C (Gholami et al., 2018). The location of the research area in the world, Iran, and Mazandaran Province is presented in Figure 1.

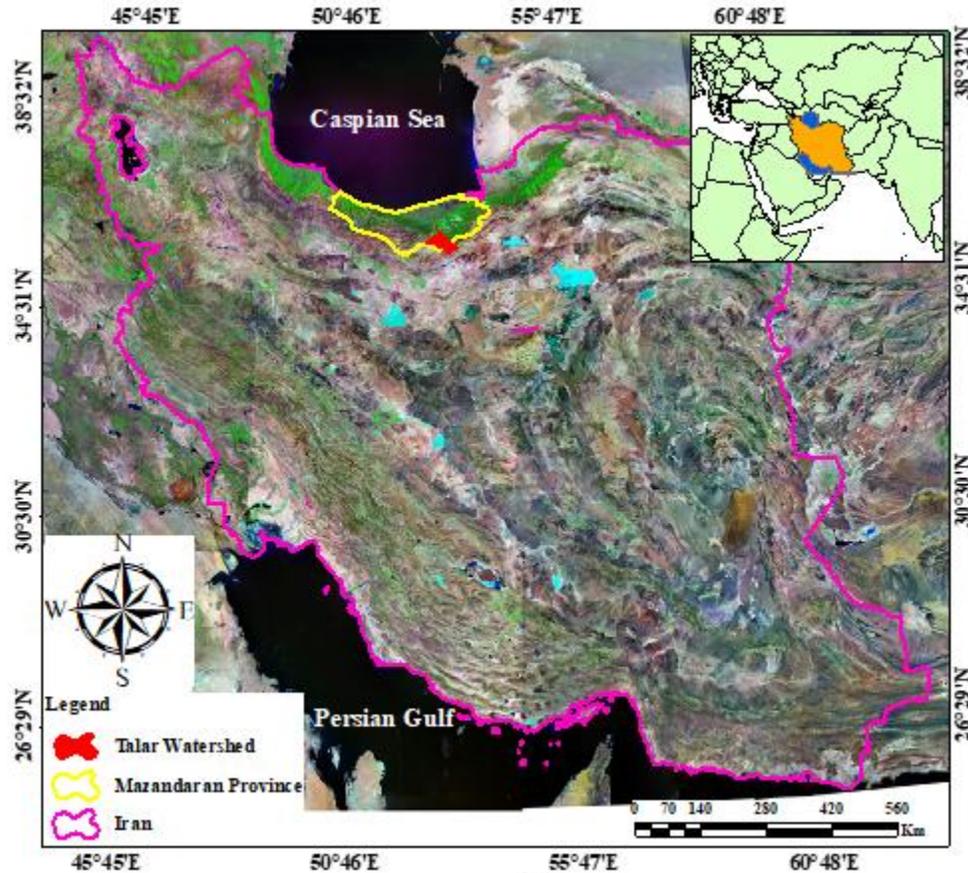
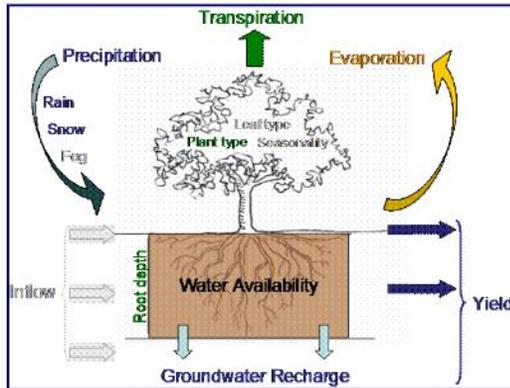


Figure 1. The location of the study area in the World, Iran, and Mazandaran Province

## 2.2. Methodology:

The water yield module in the InVEST model estimates the relative contribution of water from different parts of the watershed or corresponding sub-watersheds using a water balance approach, with an emphasis on how land use patterns affect annual water yield (Redhead et al., 2016; Sharp et al., 2018; Basha et al., 2024; Ocloo, 2025). The schematic framework employed in the InVEST model for estimating water yield, which is provided by Sharp et al (2018), is shown in Figure 2.



**Figure 2.** The schematic framework employed in the InVEST model for estimating water yield (Sharp et al., 2018)

This module is based on the curve introduced by Budyko and the mean annual precipitation. The water yield in each watershed cell is calculated according to Equation 1.

$$Y_{xj} = \left(1 - \frac{AET_{xj}}{P_x}\right) * P_x \quad (1)$$

In this equation,  $Y_{xj}$  represents the annual water yield,  $AET_{xj}$  is the actual evapotranspiration, and  $P_x$  is the annual precipitation, all corresponding to each cell with land use type  $j$  (Yang et al., 2019). The ability of InVEST to simplify hydrological processes and apply at various spatial scales makes it highly suitable for water resource management planning and assessing the impacts of climate change and land use alterations. Furthermore, InVEST plays a key role in ecosystem services analysis and supports sustainable environmental decision-making. This study involved simulating water yield with the InVEST ecosystem service model for the years 1989, 2000, and 2014. Additionally, sub-watersheds were prioritized based on water yield per unit area, and a sensitivity analysis was conducted to evaluate the impact of climatic variables included in the model. The research was carried out through the following sequential steps.

## 2.2.1 Model inputs

### 2.2.1.1 Precipitation

Annual precipitation data from stations located within and around the study watershed were calculated for the three selected years (1989, 2000, and 2014). Precipitation maps were then generated for each year using a precipitation gradient approach (Raziei et al., 2014).

Ultimately, an exponential function was selected and applied, considering constraints such as spatial distribution patterns, minimum and maximum precipitation values (typically observed in upstream and downstream areas, respectively), and the average annual precipitation.

### 2.2.1.2 Evapotranspiration

The reference evapotranspiration ( $ET_0$ ) was estimated according to the InVEST model guideline using the modified Hargreaves equation (Subburayan et al., 2011), expressed as Equation 2.

$$ET_0 = 0.0023 R_a (T_{max} - T_{min})^{0.653} \left( \frac{T_{max} + T_{min}}{2} + 17.8 \right) \quad (2)$$

In this equation,  $ET_0$  is the reference evapotranspiration in millimeters,  $R_a$  is the extraterrestrial radiation in megajoules per square meter, and  $T_{max}$  and  $T_{min}$  are the maximum and minimum air temperatures in degrees Celsius (Droogers & Allen, 2002). The solar radiation ( $R_a$ ) was calculated based on geographic coordinates, daily maximum and minimum temperatures, and daily relative humidity extremes using data from the Gharakhil synoptic station, which is the nearest station with the required parameters (Allen et al., 1998). The mean air temperature for each station was computed and spatially interpolated to generate a temperature gradient map. The minimum and maximum air temperatures used in the model were taken from the Sangdeh station, as it is located at an elevation close to the average elevation of the Talar watershed during the study years.

### 2.2.1.3 Land use

To prepare land use maps of the research watershed for the study years, Landsat TM and OLI images were used. Atmospheric correction was applied using the FLAASH method in ENVI 5.3 to remove atmospheric effects (Rozenstein & Karnieli, 2011). At least 50 training samples per land use class were collected via field surveys and analysis of true and false-color composites. Training samples for 1989 and 2000 were selected from unchanged areas using image comparison and Google Earth (Zabihi et al., 2020). Six land use classes, rainfed agriculture,

forest, irrigated agriculture, orchard, rangeland, and residential area, were identified. Supervised classification was performed using the Support Vector Machine (SVM) algorithm with an RBF kernel; error factor and gamma parameters were set to 250 and 0.167, respectively (Jiang et al., 2015). Accuracy assessment employed the kappa coefficient and overall accuracy by comparing ground truth points with classified maps (Yousefi et al., 2015).

#### 2.2.1.4 Root-restricting layer depth

The root-restricting layer depth was considered equal to the soil depth in the sampled profiles for each land unit, due to the absence of a specific restricting layer. This decision was based on previous studies conducted in the study area (DNRWM, 2001).

#### 2.2.1.5 Plant available water content

Plant available water content is defined as the difference between the volumetric field capacity and the permanent wilting point. This value was calculated for each land unit within the study watershed based on soil texture characteristics (Alizadeh, 2015) and according to the data provided in the detailed watershed management study conducted in the region.

#### 2.2.1.6 Biophysical characteristics

The biophysical characteristics input into the model include root depth, evapotranspiration coefficient, and land cover status for each land use class, which together represent the vegetation and land surface conditions that influence water processes.

##### - Root depth

Root depth was determined based on the dominant vegetation in the study area provided in DNRWM of Mazandaran Province (2001), and considering soil depth as a limiting factor for each land use type. In some cases, the root depth of dominant plant species in different vegetation types, according to relevant scientific sources, exceeded the actual soil depth; in such instances, the soil depth was used as the root depth in the model.

##### - Evapotranspiration coefficient

The evapotranspiration coefficient, used to estimate potential evapotranspiration in the

InVEST model, adjusts the reference evapotranspiration (based on alfalfa) according to the physiological characteristics of different vegetation types. This coefficient was applied for various land use types based on the recommendations of Sharp et al. (2018).

##### - Land cover condition

Land cover condition was defined based on the presence (1) or absence (0) of vegetative cover for each land use type, and corresponding values were assigned accordingly. In this context, all land use categories except residential areas were identified as having vegetation cover.

##### - Seasonality factor

The seasonality factor (Z parameter) represents the variation in precipitation distribution throughout the year. In this study, it was set to 10, reflecting the climate and rainfall pattern of the study area, where most precipitation occurs in winter (Lang et al., 2017).

##### - Water consumption

Water consumption represents the portion of watershed water yield that is removed from the water balance through incorporation into products or crops, consumption by humans or livestock, or other uses. In this context, consumptive water use for rainfed agriculture, irrigated agriculture, and orchards was calculated based on dominant crop types using the OptiWAT software (Dehghan and Galdavi, 2024). For residential land use, water use was estimated using county-level population data (Statistical Center of Iran, 2016) and per capita water consumption (Hamdi Ahmadabad et al., 2019) for the study years. For all other land use types, consumptive water use was considered zero, as their water use is accounted for through evapotranspiration calculations according to the InVEST model user guide (Sharp et al., 2018). A table of land use/land cover classes with their respective consumptive water use values is provided.

#### 2.2.1.7 Sub-watersheds delineation

The Talar watershed boundary was delineated using ArcGIS 10.8.1 software with the ArcHydro extension, based on a digital elevation model and the geographic location of the Shirgah hydrometric station (as the watershed outlet). In the next step, considering the hydrological conditions and using the 1:25,000 topographic

map of the study area along with AutoCAD 2007 software, ten independent hydrological sub-watersheds and one internal zone were identified

to model the hydrological service of water yield. These sub-watersheds are presented in Figure 3.

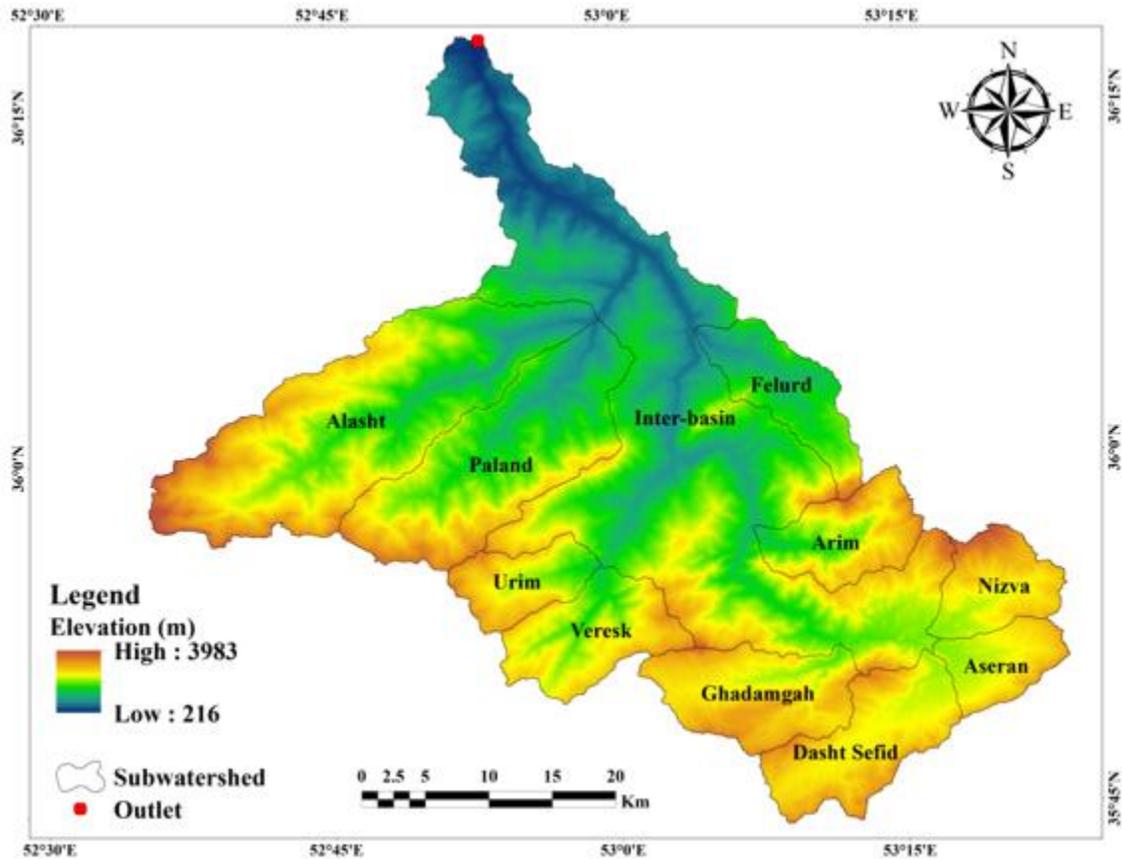


Figure 3. Delineated sub-watersheds in the Talar Watershed

### 2.3 Sensitivity analysis of model input parameters

To identify and distinguish the contribution and sensitivity of input factors influencing water yield in the InVEST ecosystem service model, the year 2014 was selected as the baseline. Subsequently, by altering only one factor at a time during each model run, replacing it with the corresponding input from 1989, the impact of that specific factor on changes in the watershed's hydrological services over the 25-year study period was assessed. Sensitivity analysis of the input parameters in the used model was conducted using the One-At-a-Time (OAT) approach (Sánchez-Canales et al., 2012; Yang et al., 2019), and the relative sensitivity index was calculated based on Equation 3 following the methodology of Kumar et al. (2004) and Mostafazadeh et al. (2018).

$$S_r = \frac{O_2 - O_1}{P_2 - P_1} \left( \frac{P}{O} \right) \quad (3)$$

In this equation,  $S_r$  represents the relative sensitivity index (the rate of change in the output per unit change in the input factor),  $O$  is the average of the model output values ( $O_1$  and  $O_2$ ), and  $P$  is the average of the model input values ( $P_1$  and  $P_2$ ). It is worth noting that, based on the nature of the model inputs used in this study, only the variables that changed over the statistical period (1989–2014) were considered for sensitivity analysis and contribution assessment. These variables in the water yield model include precipitation, reference evapotranspiration, and the seasonality parameter. Land use was also considered in the contribution analysis; however, due to its qualitative nature and spatial heterogeneity, it was not feasible to evaluate the model's sensitivity to changes in land use.

## 2.4 Prioritizing Sub-watersheds by specific water yield

Prioritizing sub-watersheds in terms of water yield is crucial for effective water resource management. It enables the identification of key areas contributing significantly to runoff and water yield. This prioritization supports more targeted decision-making for land use planning, conservation, and vegetation restoration. In this study, specific water yield was used for sub-watershed prioritization in the Talar watershed, as it allows for effective comparison between sub-watersheds. Specific water yield refers to the amount of water yield per unit area.

## 3. Results and Discussion

### 3.1 Model Inputs

In line with the modeling of ecosystem services and the sensitivity analysis of input factors in the water yield model, Table 1, Figure 4, and Figure 5 present key climatic characteristics of the Talar watershed. Specifically, Table 1 illustrates the relationship between elevation, precipitation, and temperature during the study period. Figure 4 displays the spatial distribution of annual precipitation, while Figure 5 highlights the spatial variation of mean annual temperature. These data provide essential inputs for understanding hydrological dynamics and evaluating the response of the water yield model to climatic variations.

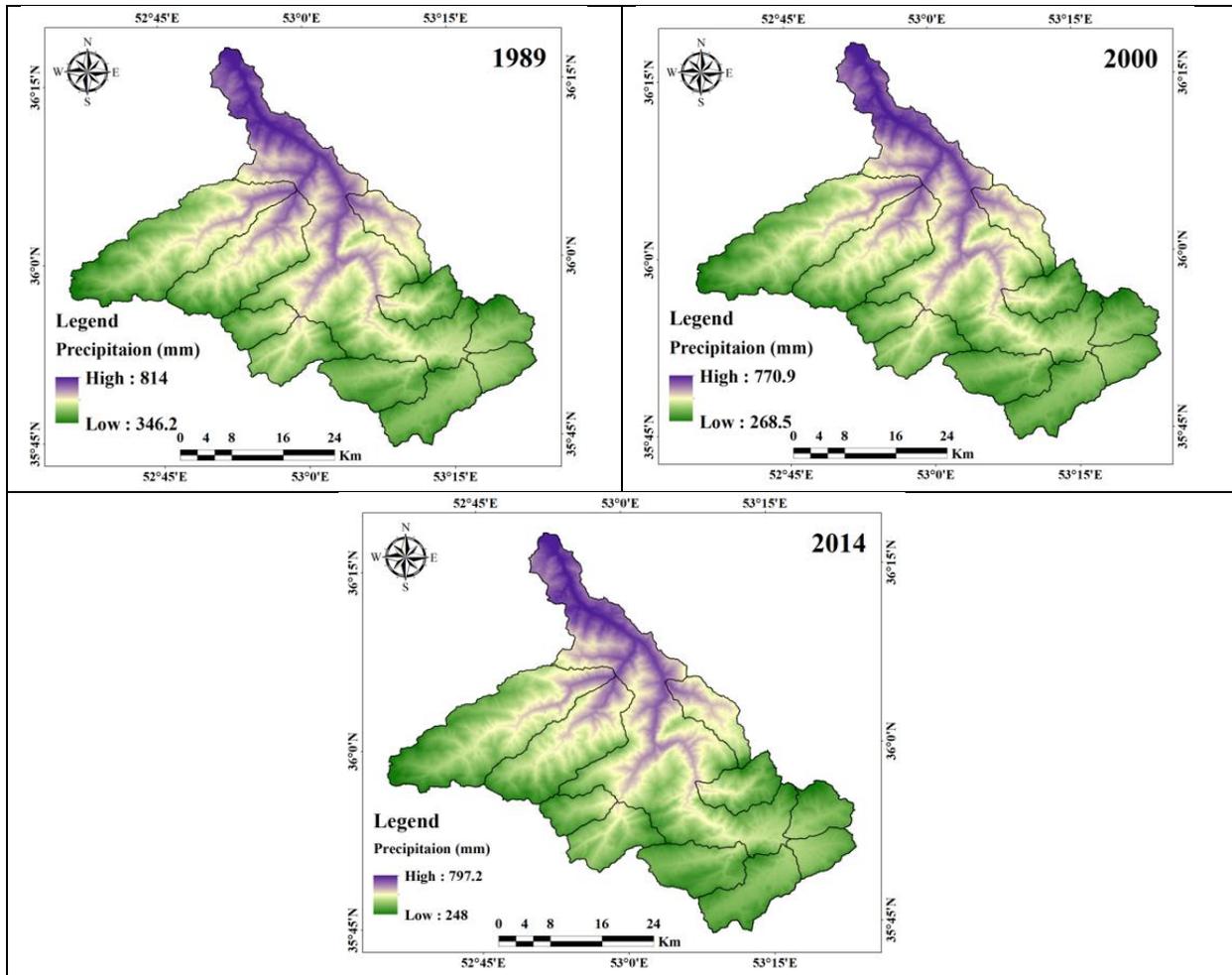
**Table 1.** Analysis of the relationship between elevation, precipitation, and temperature in the Talar Watershed during the study period

Variable	Year	R <sup>2</sup>	p-value	Relationship
Precipitation	1989	0.861	0.084	$P = 854.97 * e^{-0.00023H}$
	2000	0.605	0.038	$P = 818.94 * e^{-0.00028H}$
	2014	0.646	0.029	$P = 852.40 * e^{-0.00031H}$
Temperature	1989	0.748	0.026	$T = 18.494 * e^{-0.00064H}$
	2000	0.821	0.002	$T = 17.547 * e^{-0.00024H}$
	2014	0.899	0.000	$T = 18.03 * e^{-0.00027H}$

Note: H represents elevation (in meters) and P is precipitation (in mm), and T is temperature (in °C).

Based on the results presented in Table 1, precipitation decreased exponentially with increasing elevation across all study years (1989, 2000, and 2014). In 1989, this relationship showed a relatively high coefficient of determination ( $R^2 = 0.861$ ), though it was not statistically significant ( $p = 0.084$ ). In 2000 and 2014, the relationship was statistically significant with moderate determination coefficients ( $R^2 =$

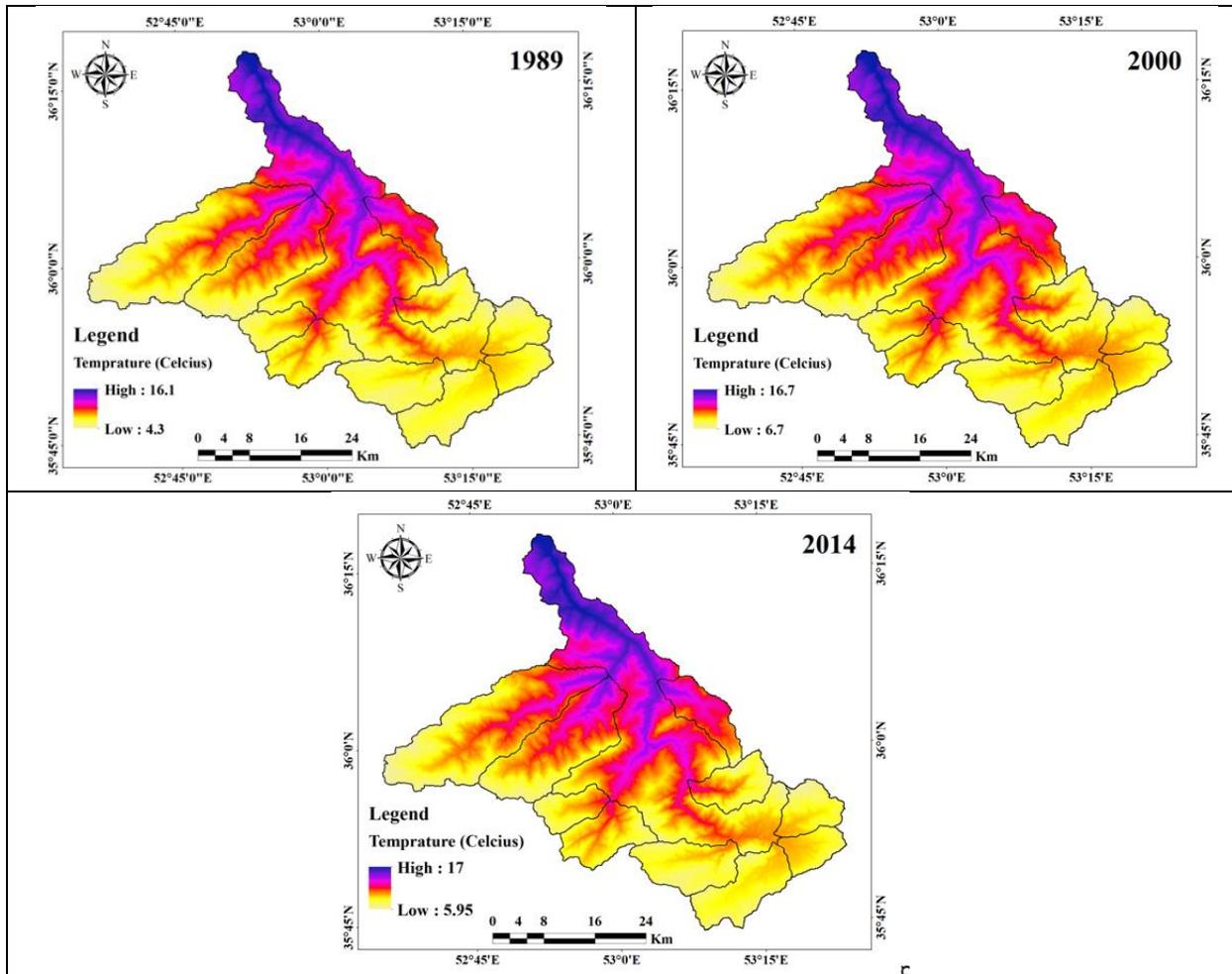
$0.605$  and  $R^2 = 0.646$ , respectively;  $p < 0.05$ ). Air temperature also decreased exponentially with elevation in all years, showing an inverse relationship. This relationship was statistically significant in each year, with the coefficient of determination increasing from  $0.748$  in 1989 to  $0.899$  in 2014, indicating a strengthening correlation between elevation and temperature over the study period.



**Figure 4.** Spatial distribution of annual precipitation in the Talar Watershed during the study years

Overall, the spatial variation of rainfall in the Talar watershed (Figure 4) indicates that the highest precipitation occurred in the northern and northeastern parts, with amounts gradually decreasing towards the central and southern areas, signifying lower rainfall in these regions. This spatial pattern reflects the influence of elevation and geographical features on rainfall

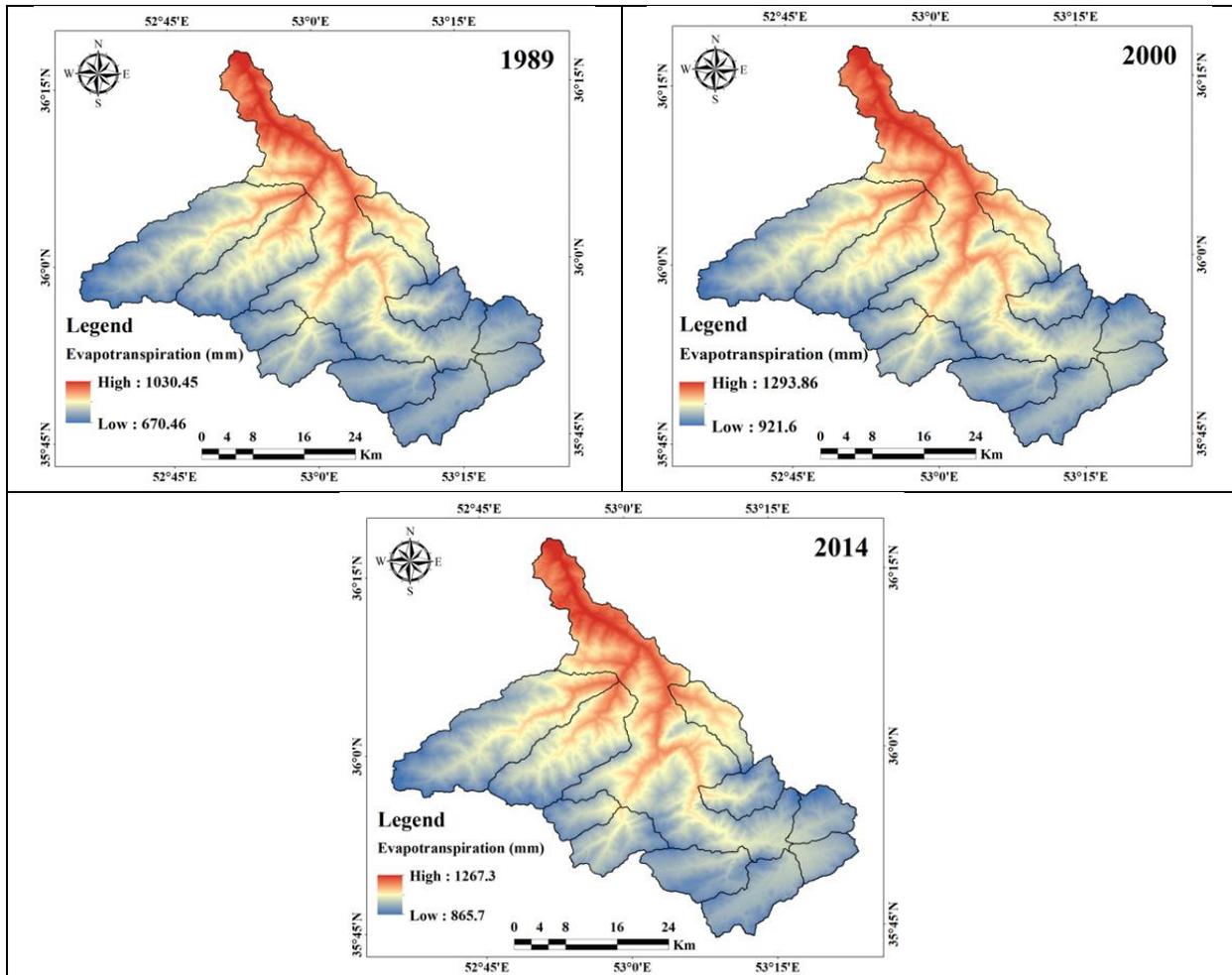
distribution and precipitation type, resulting in higher rainfall across the elevated northern zones and lower rainfall in the low-lying southern areas. Concurrently, the average annual rainfall for the years 1989, 2000, and 2014 was 552.6 mm, 479.8 mm, and 472.8 mm respectively, demonstrating a declining trend over the study period.



**Figure 5.** Mean annual temperature variations across the Talar Watershed during the study period

Based on Figure 5, in the Talar watershed, spatial temperature variations are primarily controlled by topography, with the northern highlands exhibiting lower temperatures (around 5.95°C in 2014) and the lower-lying central and southern areas experiencing higher temperatures (up to 17°C in 2014). The north-to-south thermal gradient reveals a decrease of approximately 11°C, demonstrating the significant influence of elevation differences on the regional

microclimate. This pattern unequivocally confirms the inverse relationship between elevation and temperature: as altitude increases, temperatures decrease markedly. The mean annual temperatures in the Talar watershed of Mazandaran Province for the study years 1989, 2000, and 2014 were 8.92°C, 11.07°C, and 10.6°C, respectively. This suggests a general warming trend that corresponds with observed reductions in precipitation over the same period.

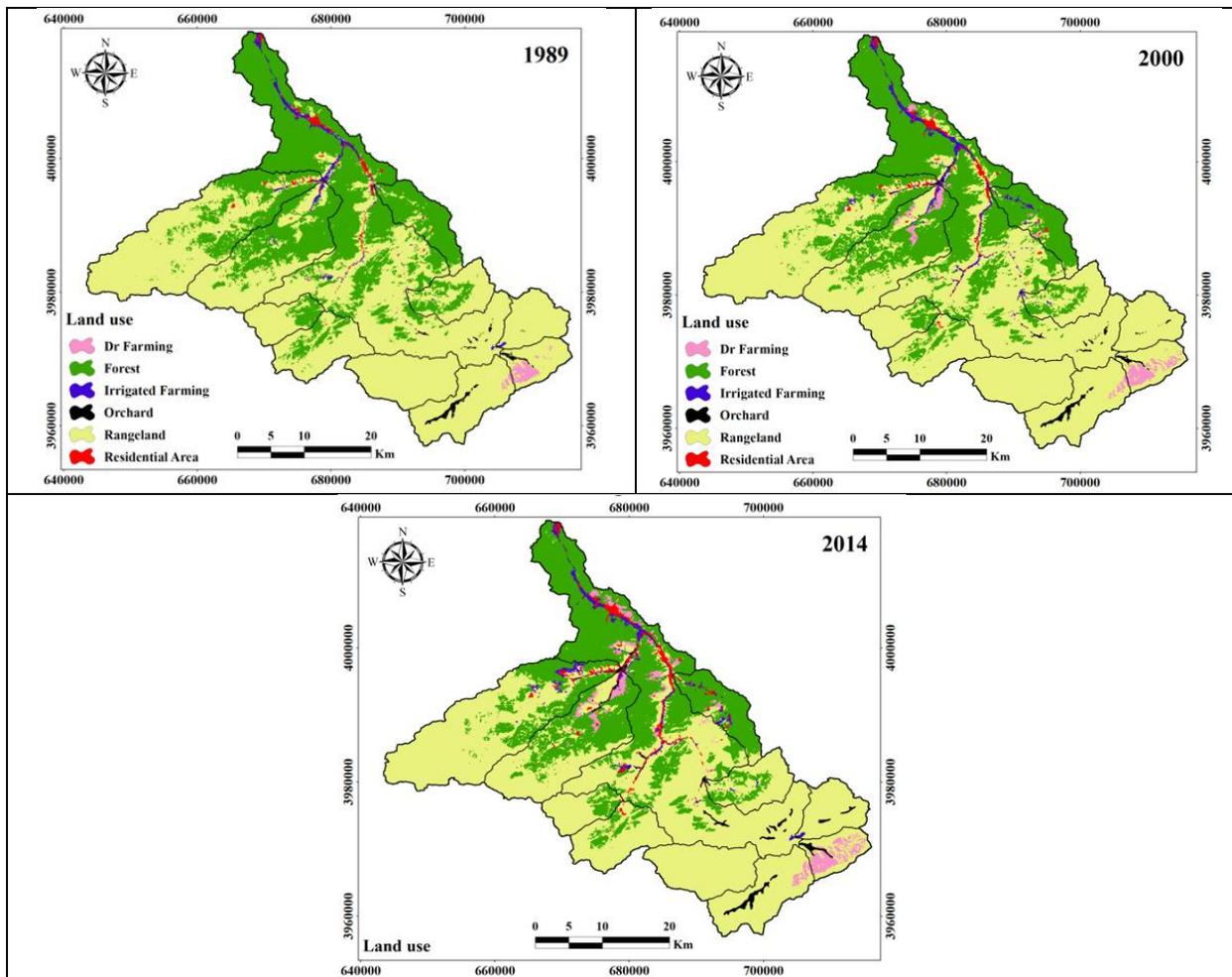


**Figure 6.** Annual evapotranspiration patterns in the Talar Watershed over the study period

As shown in Figure 4, the reference evapotranspiration ( $ET_0$ ) in 2014 in the Talar watershed exhibited a clear spatial pattern of decrease from the lowland northern areas toward the elevated southern regions. This pattern is mainly influenced by lower temperatures and the type of vegetation cover in the higher southern

areas. The annual average  $ET_0$  for the years 1989, 2000, and 2014 was 812.1 mm, 1083.0 mm, and 1035.0 mm, respectively.

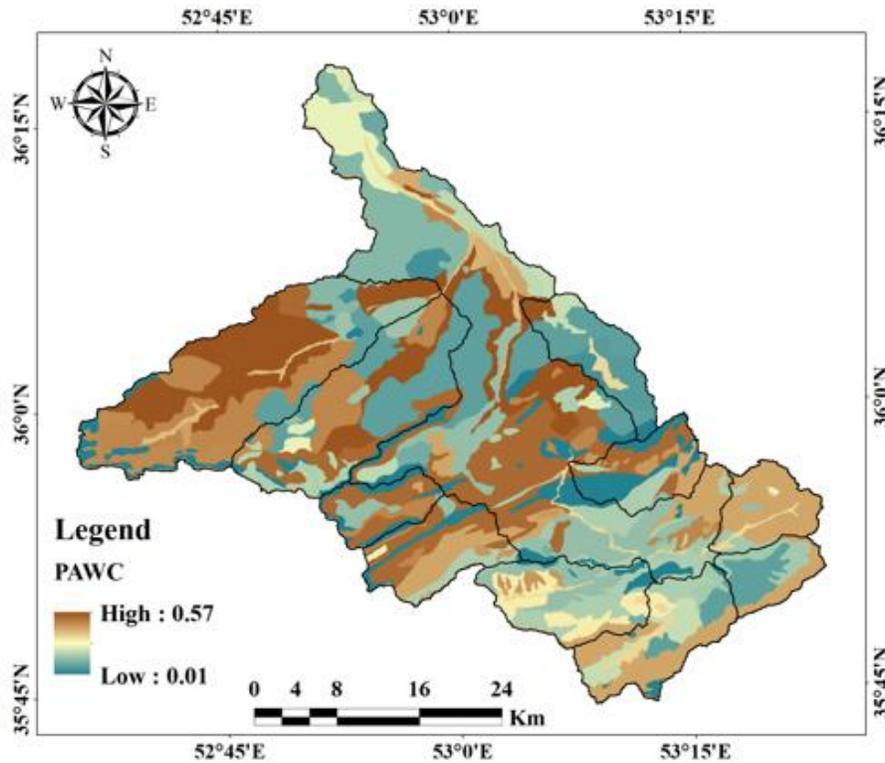
The land use maps of the Talar watershed for the study years are presented in Figure 7, and the Plant Available Water Content (PAWC) based on land units is shown in Figure 8.



**Figure 7.** Land use maps of the study area for the research years

The results of land use classification accuracy for the years 1989, 2000, and 2014 indicate an overall improvement in accuracy and the Kappa coefficient over the study period. The average overall accuracy increased from approximately 79.51% in 1989 to 85.52% in 2014, reflecting enhanced classification precision. Forest and rainfed agriculture classes consistently showed the highest users' and producers' accuracies,

while orchard and residential areas exhibited lower accuracy compared to other classes. Additionally, the reduction in omission and commission errors over the years confirms the improvement in classification quality. These findings demonstrate that the classification process has become more reliable and precise over time.



**Figure 8.** Geographic distribution of Plant Available Water Content (PAWC) in the study area

Plant Available Water Content (PAWC) in the Talar watershed, as shown in Figure 8, ranges from 0.01 to 0.57, reflecting significant variability in the region's soil physical properties. The lowest PAWC values (0.01 to 0.1) are mainly found in the southern areas with steep slopes, shallow and rocky soils, and are often associated

with rangeland cover. In contrast, the highest values (0.4 to 0.57) occur in the northern regions, where deep clay-loam soils and forest cover dominate, indicating high water retention capacity. This spatial pattern is directly influenced by the watershed's lithological and geomorphological conditions.

**Table 2.** Biophysical characteristics and water consumption of land uses in the Talar watershed over the study years

Land Use Type	Vegetation Cover	Evapotranspiration Coefficient	Root Depth (Cm)			Water Consumption (M <sup>3</sup> )		
			1989	2000	2014	1989	2000	2014
Rainfed Farming	Yes	0.65	35.00	35.00	35.00	1,657,710	4,291,790	7,463,770
Forest	Yes	1.00	105.50	106.90	107.70	–	–	–
Irrigated Farming	Yes	0.65	30.00	30.00	30.00	11,924,419	15,892,762	17,385,739
Orchard	Yes	0.70	94.30	89.60	97.70	2,813,380	3,455,600	5,597,420
Rangeland	Yes	0.65	40.00	40.00	40.00	–	–	–
Residential Area	No	0.30	0.00	0.00	0.00	6,392,355	7,750,942	7,932,680

Based on the findings presented in Table 2, the Talar watershed shows that all land uses, including rainfed farming, forest, irrigated farming, orchard, and rangeland, have vegetation cover, whereas residential areas do not. The evapotranspiration coefficient is highest for forests (1.00) and lowest for residential areas (0.30). Root depth is greater in forests and orchards compared to other land uses, indicating a need for deeper water sources. Water

consumption in irrigated farming is the highest, increasing from about 11.9 million cubic meters (MCM) in 1989 to 17.4 MCM in 2014. Water use in rainfed farming and orchards has also significantly increased, from 1.6 million to 7.5 million and from 2.8 to 5.6 MCM, respectively. Residential water consumption has risen from 6.4 to 7.9 MCM over the same period. Water consumption for forests and rangelands is not reported, likely due to the absence of irrigation.

These data indicate growing water demand in agricultural and urban land uses, leading to increasing pressure on the watershed's water resources.

### 3.2 Sub-watershed prioritization based on specific water yield

Based on the results of water yield simulation using the InVEST ecosystem service model and the conducted assessments of the spatial distribution of annual water yield in the Talar watershed, it can be stated that the sub-watersheds located in the southern and eastern parts of the study area have the lowest water yield. Correspondingly, moving from south to north and from east to west, the annual water yield increases. The highest annual water yield

was calculated in the internal zone and Alasht sub-watersheds, with values of 68.5 and 27.1 MCM per year, respectively. The large area and higher precipitation due to the geographical location of these sub-watersheds can be considered as reasons for their high water yield. The lowest annual water yield was estimated in the Nizva sub-watershed with 3 MCM per year. It is noteworthy that the spatial variation of water yield is influenced by the distribution of precipitation, which is the most important factor in modeling the hydrological service of water yield (Terrado et al., 2014; Belete et al., 2020), evapotranspiration (Fu et al., 2017), as well as soil depth in the Talar watershed.

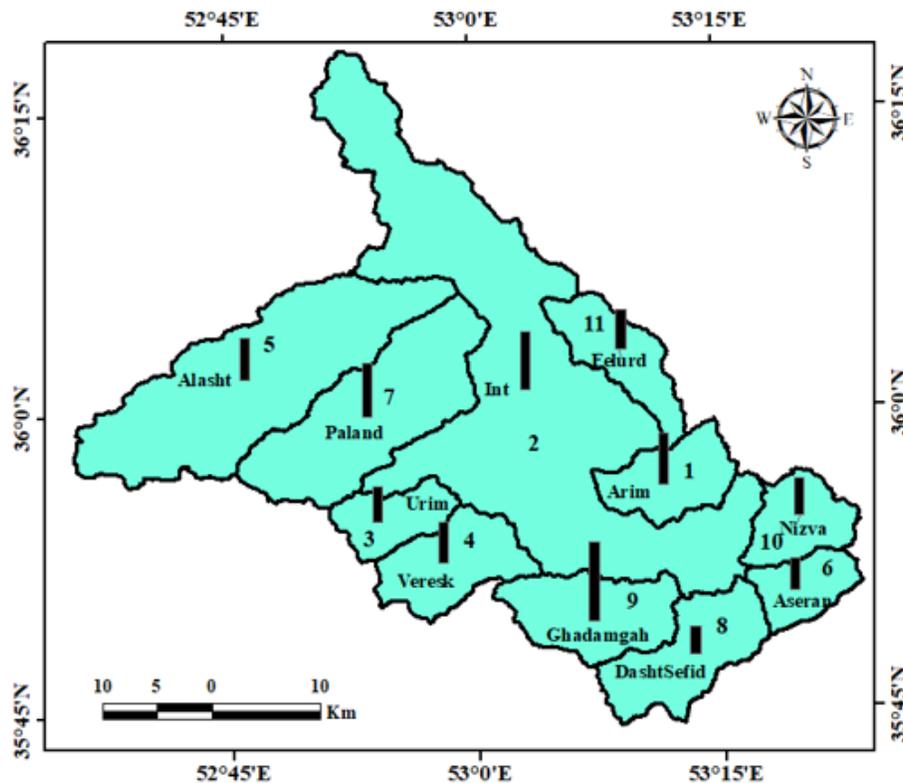


Figure 9. Ranking of sub-watersheds according to specific water yield

Prioritizing sub-watersheds based on water yield, as one of the hydrological ecosystem services, is essential for developing management strategies and implementing conservation measures. To identify critical sub-watersheds (those with the lowest water yield), and based on the findings shown in Figure 9, the Felurd and Nizva sub-

watersheds have the lowest specific water yield in the Talar watershed, with values of 533.8 and 610  $\text{m}^3\text{ha}^{-1}\text{year}^{-1}$ , respectively. Regarding the Felurd sub-watershed, although its annual precipitation is 530 mm, water loss due to evapotranspiration (477 mm) is high because of the dominant forest land use and high infiltration

caused by deep soil (1015 mm). The high ratio of evapotranspiration (335 mm) to precipitation (382 mm) in the Nizva sub-watershed also leads to significant water loss, making it critical in terms of specific water yield. The Arim sub-watershed ranks as the highest in specific water yield, with 1504 m<sup>3</sup>/ha, and is considered the least critical regarding water yield conditions in the study area. This is attributed to its higher precipitation and dominant rangeland land use, which results in lower evapotranspiration. Additionally, the lowest average soil depth (306 mm) and the highest average slope (57.2%) in the Arim sub-watershed contribute to its maximum specific water yield. The internal zone, as the largest sub-watershed with an area of approximately 640 square kilometers, has a specific water yield of 1088 m<sup>3</sup>ha<sup>-1</sup>year<sup>-1</sup>.

### 3.3 Quantifying the Contribution of Input Factors to Water Yield

Quantifying the contribution of input factors to water yield plays a crucial role in understanding and managing water resources. This process helps identify the key factors affecting watershed water output and enables optimal planning for sustainable conservation and utilization of water resources. Additionally, by recognizing the potential changes in each factor, it becomes possible to better predict the impacts of climate change and land use alterations. The contribution of changes in input factors to variations in water yield between 1989 and 2014 in the Talar watershed is presented in Table 3.

**Table 3.** Contribution of Input Factor Changes to Variations in Water Yield (1989-2014) in the Talar Watershed

Variable	Estimated Value (m <sup>3</sup> )		Change (%)
	Before Change	After Change	
Precipitation	1,478,516,480	1,225,222,500	52.33
Reference Crop Evapotranspiration	-	1,881,256,850	27.23
Land use	-	1,394,278,030	-5.69
Seasonal Factor	-	726,737,990	-50.84

According to the results of the analysis of input factor impacts on the InVEST water yield model (Table 3), precipitation had the greatest influence on the hydrological service in the Talar watershed, accounting for a 52.33% change in water yield over the 25-year study period (1989-2014). This finding aligns with reports by Boithias et al. (2014), Terrado et al. (2014), and Lian et al. (2020), which emphasize the critical role of precipitation in modeling water yield using the InVEST ecosystem services model. Furthermore, the findings indicate that other climatic variables, such as the seasonal factor and evapotranspiration, had a greater impact on water yield than land use in the Talar watershed. Land use, as one of the model's inputs, influences water yield through alterations in the hydrological cycle, particularly evapotranspiration and infiltration. In this regard, land use changes in the Talar watershed during the 25 years led to only a 5.7% increase in water yield, showing a relatively minor impact compared to climatic variables. Joorabian Shooshtari et al. (2018) also reported a greater influence of climatic factors over land use

in simulating river discharge using the SWAT model in the Nekarood watershed, Mazandaran Province. Similarly, Belete et al. (2020) found a 6% effect of land use on water yield over 14 years (2003-2017) using the InVEST model, consistent with the present study. Yang et al. (2019) in China also highlighted the limited role of land use in water yield estimation using InVEST and noted that this minimal influence might hinder accurate evaluation of land use change impacts on hydrological service performance. Based on the current findings, the seasonal factor and evapotranspiration contributed to 50.8% and 27.2% of the changes in water yield in the Talar watershed between 1989 and 2014. The strong impact of the seasonal factor may be attributed to its relationship with precipitation, which plays a dominant role in water yield modeling in this watershed

### 3.4 Sensitivity analysis of model inputs

Sensitivity analysis of model inputs is essential for identifying which factors most influence model outcomes, improving model reliability,

and guiding effective resource management decisions. The sensitivity analysis of the water

yield model to variations in input factors in the Talar watershed is presented in Table 4.

**Table 4. Sensitivity Analysis of Water Yield Model to Input Factor Variations in the Talar Watershed**

Variable Factor	Change Amount (%)	Relative Sensitivity Coefficient
Precipitation	+14.44	0.407
	-14.44	-0.454
Reference Evapotranspiration	+27.33	-0.222
	-27.33	0.372
Seasonality Factor	+14.44	-0.061
	-14.44	0.053

According to the results of the sensitivity analysis of the water yield model presented in Table 4, precipitation, with a relative sensitivity coefficient of approximately 0.42, was identified as the most sensitive factor in the hydrological water yield service model in the Talar watershed. The sensitivity coefficients indicate the direction and magnitude of the water yield response to increases or decreases in each input. This finding aligns with and confirms the results of Sánchez Canales et al. (2012), Marquès et al. (2013), and Hamel and Guswa (2015). Furthermore, Yang et al. (2019) in southern China also highlighted precipitation as the most sensitive factor in estimating water yield using the InVEST model, reporting a 138% increase in water yield with a 46% increase in precipitation. Correspondingly, a 14% decrease and an increase in precipitation resulted in a 43.5% decrease and 56.8% increase in water yield in the Talar watershed. Evapotranspiration and the seasonality factor ranked next in sensitivity, with relative sensitivity coefficients of 0.29 and 0.057, respectively, in the InVEST water yield model. It should be noted that, according to Redhead et al. (2016), the sensitivity of the water yield model to changes in precipitation and evapotranspiration depends on the specific watershed studied. Despite possible uncertainties associated with the seasonality parameter due to its wide numerical range, which may cause uncertainty in water yield estimates, the relatively low sensitivity of the model to seasonality compared to other variables is another result of this study, consistent with findings by Sánchez Canales et al. (2012) in Spain and Hamel and Guswa (2015) in the United States. It is

important to note that the model's sensitivity to the seasonality parameter may vary in each watershed depending on the amount and temporal distribution of precipitation. Therefore, the influence of seasonality on water yield is moderated by the availability of water content and precipitation amount, both of which exhibit spatial variability. Accordingly, the seasonality parameter can account for local precipitation characteristics as reflected in the model used (Yang et al., 2019). Overall, this sensitivity analysis emphasizes the dominant role of precipitation in water yield fluctuations, the important but opposite effect of evapotranspiration, and the relatively minor influence of seasonal changes. These insights are critical for effective water resource management and climate impact assessments.

#### 4. Conclusions

This study assessed the sensitivity of key climatic factors, precipitation, reference evapotranspiration, and seasonality index, on water yield modeling in the Talar watershed using the InVEST model and a 25-year data series. Sensitivity analysis revealed that precipitation had the strongest influence on model outputs, followed by evapotranspiration and seasonality, underscoring the dominant role of climate in shaping water yield dynamics. In contrast, land use change accounted for only about 6% of the variation in water yield over the study period, suggesting a relatively limited impact compared to climatic drivers. Spatial analysis identified the northern and northeastern sub-watersheds as high-yield zones, while Felurd and Nizva

emerged as critical low-yield areas due to high evapotranspiration and deep soils. Prioritizing sub-watersheds based on their water yield potential provides a practical framework for ecosystem-based resource management, including targeted conservation, vegetation restoration, and sustainable land use planning. Although the InVEST model simplifies hydrological processes, its accessibility and ecosystem service perspective make it suitable for other mountainous regions with similar climates. Future research should integrate RCP climate scenarios and process-based models such as SWAT or WEAP to improve the understanding of water resource dynamics under land use and climate change.

#### Author Contributions:

**Mohsen Zabihi:** Conceptualization, methodology, formal analysis and investigation, visualization, resources, writing-original draft preparation.

**Hamidreza Moradi:** Conceptualization, supervision, formal analysis and investigation.

**Abdulvahed Khaledi Darvishan:** Conceptualization, methodology, formal analysis and investigation, manuscript editing.

**Mehdi Gholamalifard:** Conceptualization, methodology, formal analysis and investigation.

#### Conflicts of interest

The authors of this article declared no conflict of interest regarding the authorship or publication of this article.

#### Data availability statement:

All data generated or analyzed during this study are included in this published article.

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