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Spatial Assessment of Future Drought Risk in Agricultural Lands: A CMIP6-Based Analysis

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ABSTRACT
The acceleration of climate change is intensifying drought severity. Increasing drought conditions pose significant risks to agricultural lands and food security. The aim of this study is to determine the spatial exposure rate of agricultural land classes to drought conditions based on climate scenarios and different projection periods. In this study, a spatial analysis based on the SSP2-4.5 and SSP5-8.5 scenarios was conducted using the HadGEM3-GC3.1, MIROC6, and MPI-ESM1-2-HR climate models. Assessments covering Türkiye's Central Anatolia Region were conducted within a geographic information system (GIS)-based spatial modeling framework and encompass projections for the near future (2025-2040) and the end of the century (2081-2100). The findings indicate that under the end of the century SSP5-8.5 scenario, approximately 83-90% of the region may become semi-arid. Model results suggest that, by end of the century, the spatial exposure rate of the most productive agricultural lands, classified as prime agricultural lands and specialty crop lands, may reach a minimum of 76% under the SSP2-4.5 scenario and exceed 90% under the SSP5-8.5 scenario. This situation reveals a substantial risk to agricultural production and food security in the region. The coefficient of variation values support that the multi-model results produce similar outcomes in terms of spatial distribution and consistency. These findings highlight the urgent need to rapidly develop drought-focused spatial strategies to ensure the sustainability of agricultural production in Central Anatolia Region. In this context, the scalable and transferable agricultural land class-drought oriented spatial exposure rate approach proposed in this study can be considered an important decision-support tool for policymakers.

Keywords: Climate scenarios, Drought, Aridity index, Spatial analysis, Agricultural land classes

1. Introduction

The global climate system has undergone pronounced changes over the past century because of accelerated temperature increases and irregularities in rainfall regimes, producing far-reaching impacts on natural ecosystems as well as human activities (IPCC 2021; Yavaşlı & Erlat 2023). The disruption of the delicate balance between temperature and precipitation reshapes the hydrological cycle, reduces water resources and leads to substantial losses in soil moisture regimes (Bannayan et al. 2010; IPCC 2014; 2022). One of the most evident outcomes of this transformation in the climate system is drought (Stagge et al. 2015; Straffelini & Tarolli 2023). Drought is a complex climate-related hazard that emerges not only from precipitation deficits but also from the combined effects of increased temperatures, enhanced evaporation, extended sunshine duration, abnormal rainfall fluctuations, declining soil moisture and alterations in hydrological flows (Lickley & Solomon 2018; Li et al. 2020; Pour et al. 2020; Zhou et al. 2020; Islam et al. 2021a,b,c; Jerin et al. 2021; Ullah et al. 2022). Drought is commonly classified into four main types: meteorological, agricultural, hydrological and socio-economic (Wilhite & Glantz 1985; Arabameri et al. 2022). This classification highlights that drought is a multidimensional phenomenon with not only physical but also economic and societal consequences.

The global increase in drought affected regions has intensified the significance of drought related research. Recent findings show that areas classified as drought prone zones constitute nearly 41% of the Earth's land surface (Lewin et al. 2024; Wen et al. 2025). Climate projections also indicate that the frequency and severity of drought will exhibit a more pronounced rise in future periods (Cook et al. 2018; Spinoni et al. 2018; Ghazi et al. 2025). The lasting impacts of drought impose long term pressures on the agricultural sector and generate cumulative effects that persist over many years (Tao et al. 2011; Miyamoto & Hackmann 2025). Therefore, drought is considered a critical risk factor for agricultural production, food security, and rural development (Dinç et al. 2016; Çelik & Yakar 2024).

Agricultural production is one of the sectors most sensitive to climate change (IPCC 2022). Increases in temperature, irregular precipitation patterns and higher evaporation reduce crop yields, increase water demand and cause shifts in planting and harvesting calendars (Bozoglu et al. 2019; Benli & Özdemir 2025; Demiral & Bahçekapılı 2025). The impacts of drought on agriculture are widely discussed at the global scale, and studies examining this interaction employ diverse methodological approaches (Mollema et al. 2012; Bocchiola et al. 2013; Andrade et al. 2021). Some studies analyze aridity conditions using climate-based indices and relate these indices to agricultural yield (Dietz et al. 2021; Oğuz et al. 2022; Miyamoto & Hackmann 2025). Other studies use projections derived from global climate models to evaluate how future drought scenarios may affect agricultural production (Sen et al. 2012; Leng & Hall 2019). Approaches based on crop growth simulations model plant development under drought and water stress to reveal changes in agricultural productivity (Wellens et al. 2013; Asseng et al. 2015). This diversity reflects the interdisciplinary nature of the drought agriculture relationship. However, two significant limitations stand out in the literature: the insufficient use of future climate scenarios, which leaves long term impacts uncertain, and the inability of low-resolution climate data to produce reliable results at the local scale. Studies based on Climatic Research Unit (CRU), Coupled Models Intercomparison Project Phase 3 (CMIP3) and Coupled Model Intercomparison Project Phase 5 (CMIP5) show that systematic biases in the models pose important constraints for regional aridity and drought analyses (Ullah et al. 2022; Ghazi et al. 2025).

Drought analysis indices are fundamental tools for assessing the spatial and temporal impacts of climate change on agriculture (Mishra & Singh 2011; Beguería et al. 2014; Afshar et al. 2022; Zhang et al. 2022; Bharambe et al. 2023; Abu Arra et al. 2024). The literature includes various methods such as the De Martonne aridity index (De Martonne 1926), the Emberger aridity index (Emberger 1930), the Erinç aridity index (Erinç 1965), the Pinna combinative aridity index (Zambakas 1992), and the United Nations Environment Programme (UNEP) aridity index (UNEP 1992). Among these, the De Martonne Aridity Index is one of the most widely used approaches because of its simple yet robust structure that jointly considers temperature and precipitation (Gebremedhin et al. 2018; Ullah et al. 2022). Its applicability at annual, seasonal, and monthly scales, together with its ability to be easily integrated into different climate scenarios, provides significant advantages for mapping drought prone areas (Quan et al. 2013; Moral et al. 2016; Andrade et al. 2021).

In future oriented climate projections, Coupled Model Intercomparison Project Phase 6 (CMIP6) models and Shared Socioeconomic Pathway (SSP) scenarios have become the primary reference point in contemporary literature (O'Neill et al. 2016; Seneviratne & Hauser 2020). CMIP6 provides more accurate projections compared to previous model generations, and when combined with SSP scenarios that represent different socioeconomic development pathways, it enables a more reliable assessment of future climate conditions (Hausfather 2019; Grose et al. 2020; Narsey et al. 2020; Ayugi et al. 2021). Global climate models simulate atmospheric, oceanic, and land surface processes in an integrated manner, making them one of the most critical tools for generating future climate projections (Eyring et al. 2016; Meehl et al. 2020). These models provide an essential scientific basis for identifying long term trends in temperature, precipitation, and drought, allowing decision makers to rely on more robust insights when developing adaptation strategies (Knutti & Sedláček 2013; IPCC 2021).

High spatial resolution climate data are a critical component, particularly in studies assessing the vulnerability of agricultural lands (Straffelini & Tarolli 2023). The WorldClim dataset, which is widely used across the globe, provides a spatial resolution of approximately 1 km (Fick & Hijmans 2017) and offers an essential foundation for evaluating the future conditions of agricultural areas at the local scale. Studies such as Beck et al. (2018), Straffelini & Tarolli (2023), and Yavaşlı & Erlat (2023) emphasize that high-resolution spatial datasets play a key role in identifying areas most affected by drought.

Although research on drought, drought indices, and agricultural lands in Türkiye has increased (Bakanoğulları et al. 2022; Çamalan & Çetin 2022; Tuğrul & Hınıs 2022; Baykal et al. 2023; Çamalan et al. 2023; Çetin & Kumanlıoğlu 2023; Yavaşlı & Erlat 2023), studies that simultaneously incorporate high spatial resolution datasets and multiple climate scenarios remain limited. Moreover, in most existing research, agricultural lands have not been examined in sufficient detail according to agricultural land productivity classes, which makes it difficult to comprehensively assess regional agricultural exposure to aridity and drought.

This study aims to address this gap by integrating agricultural land classes with spatial exposure to drought under different global climate models (HadGEM3 GC3.1, MIROC6, and MPI ESM1-2-HR), near future (2025-2040) and end of the century (2081-2100) projections, and the SSP2 4.5 and SSP5 8.5 scenarios, using high resolution evaluations at 1 km spatial resolution. The objective of the study is to assess future aridity and drought conditions in the Central Anatolia Region under varying climate scenarios and projection periods by employing CMIP6 climate model outputs together with the De Martonne Aridity Index, and to determine the spatial exposure levels of agricultural land classes to these changes. In line with this objective, a GIS-based spatial analysis framework was employed to integrate climate projections with agricultural land classes, enabling high-resolution mapping of aridity conditions and spatial exposure levels (Quan et al. 2013; Straffelini & Tarolli 2023). This framework allows for systematic overlay, classification, and quantification of drought risk across different agricultural productivity classes, thereby providing a methodological basis for evaluating spatial vulnerability patterns. The spatial analysis approach enabled the detailed identification of exposure levels and supported the development of a transferable methodological structure for future regional planning studies.

This approach is of critical importance considering the region's increasing water stress and growing pressures on agricultural production. By using the SSP2 4.5 and SSP5 8.5 scenario-based projections, the study presents future drought indices and integrates these results with agricultural lands, thereby reinforcing the contributions of the research.

This study provides two primary contributions to literature. These contributions are as follows: (i) establishing a spatial framework for examining the relationship between agricultural land classes and the aridity index and for determining their spatial exposure rate, and (ii) presenting comparable results for aridity index values and spatial exposure rates across different projection periods and scenarios using multiple global climate models.

The remainder of the paper is organized as follows. Section 2, Materials and Methods, describes the study area, the CMIP6-based climate datasets and SSP scenarios, the De Martonne Aridity Index, and the GIS-based spatial modeling framework used to integrate climate projections with agricultural land classes. Section 3, Results, presents the projected changes in temperature and precipitation and the corresponding spatial distribution of aridity conditions and exposure levels across agricultural land classes. Section 4, Discussion, interprets the findings in relation to the existing aridity and climate change literature and discusses their implications for agricultural sustainability and food security. Finally, Section 5, Conclusions, summarizes the main outcomes of the study and their relevance for regional planning and climate adaptation.

2. Material and Methods

2.1. Study Area

Türkiye, located in the Northern Hemisphere between 36-42° N latitudes and 26-45° E longitudes, is among the countries for which a pronounced increase in the frequency and severity of droughts is projected in the future (Önol & Ünal 2014; Türkeş et al. 2016; Türkeş et al. 2020; Yeşilköy & Şaylan 2022; Öztürk & Çolak 2024). A substantial proportion of existing studies focusing on Türkiye have been conducted at provincial or sub-regional scales (Kartal et al. 2025; Rotbeei et al. 2025; Selçuk et al. 2024; Şener & Davraz 2025). The study area encompasses the Central Anatolia Region of Türkiye, located between 37-41° N latitudes and 30-38° E longitudes. The Central Anatolia Region stands out as one of the region's most severely affected by drought conditions in Türkiye (Türkeş 2012; Gümüş et al. 2023). In addition, the region ranks among the leading areas in the country in terms of the extent and production of cereal-based agricultural systems (TÜİK 2025). The region, where agricultural production areas are extensive, is characterized by an agricultural land classification dominated by prime agricultural lands, specialty crop lands, and marginal agricultural lands (Figure 1).

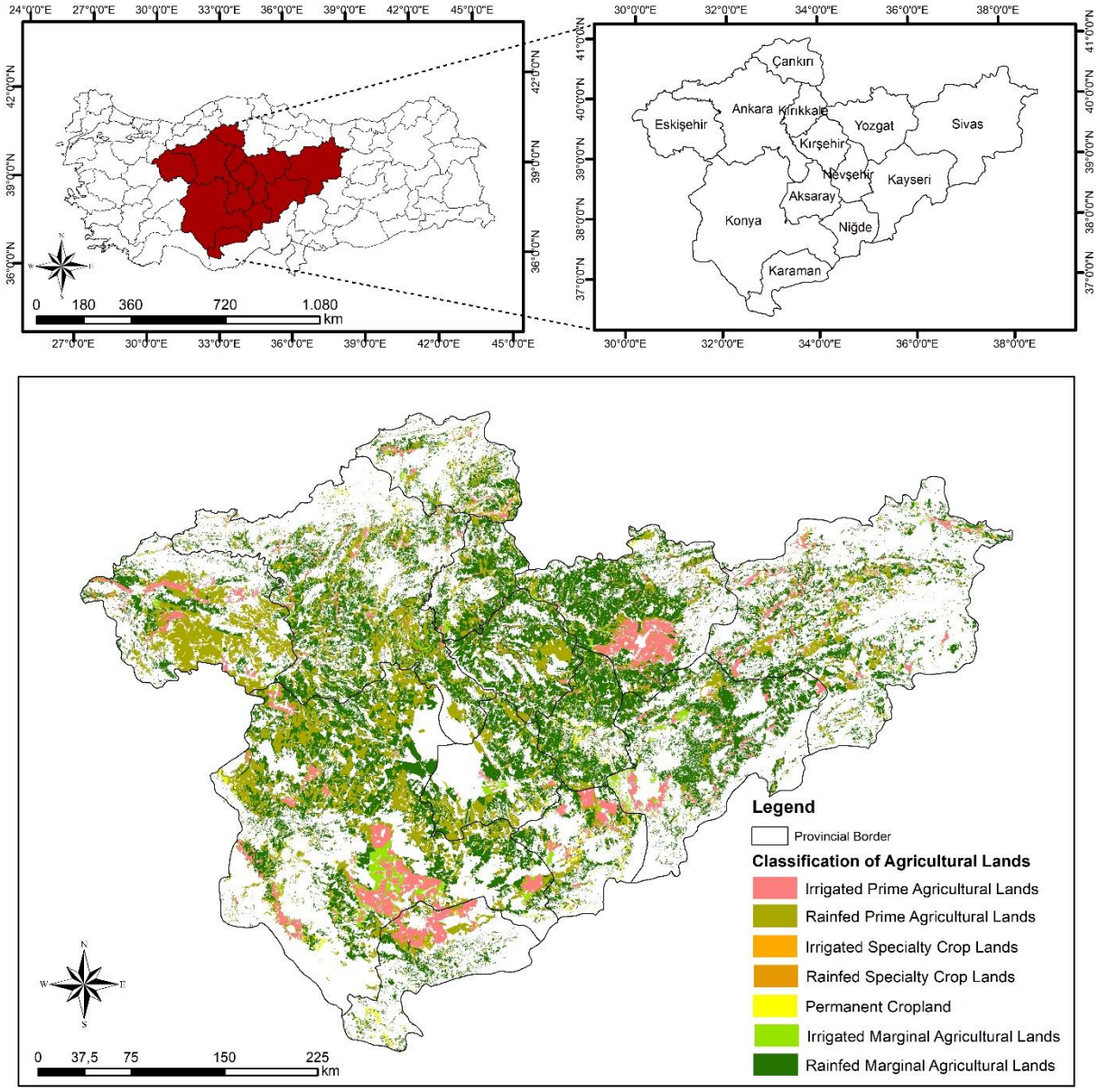


Figure 1- Study area and agricultural land classification

2.2. Selection of climate models and data processing

Climate models are fundamental tools used to investigate the response of climate systems to various forcings and to generate climate projections across different temporal scales (IPCC 2013). In this study, the selected climate models are based on the CMIP6 (Coupled Model Intercomparison Project Phase 6) dataset, which was developed in alignment with the assessment reports of the Intergovernmental Panel on Climate Change. CMIP6 provides projections with higher accuracy compared to previous model generations and offers improved capability in estimating the regional and global impacts of climate change (Narsey et al. 2020; Ayugi et al. 2021). To ensure robust and comparable results, three different models were employed rather than relying on a single model. The assessment therefore utilizes the HadGEM3 GC3.1, MIROC6 and MPI ESM1-2-HR climate models. HadGEM3 GC3.1, developed by the UK Met Office Hadley Centre, exhibits strong agreement with observational records and demonstrates high predictive performance (Roberts et al. 2019; Andrews et al. 2020). MIROC6, one of the leading Japanese climate models, performs strongly in representing mean climate, climate change and climate sensitivity, and has contributed substantially to the IPCC Assessment Reports (Tatebe et al. 2019). MPI ESM1-2-HR, developed by the Max Planck Institute for Meteorology, is recognized for its robust predictive capability, particularly for temperature related indicators (Mauritsen et al. 2019).

In this study, the potential impacts of climate change were assessed using the SSP scenarios defined within CMIP6, which represent different socioeconomic development pathways. Accordingly, near future projections for 2025 to 2040 and end of the century projections for 2081 to 2100 were analyzed under the SSP2 4.5 scenario, which reflects a continuation of current trends, and the SSP5 8.5 scenario, which represents high emission conditions. SSP2 4.5 corresponds to the continuation of current

trajectories and indicates an increase of 4.5 W/m^2 in radiative forcing. SSP5 8.5 represents a development pathway dominated by fossil fuel driven growth, leading to an increase of 8.5 W/m^2 in radiative forcing by the end of the century.

In this research, the temperature and precipitation variables derived from the HadGEM3 GC3.1, MIROC6 and MPI ESM1-2-HR climate models were obtained from the WorldClim database, which provides climate data at approximately 1 km spatial resolution (Fick & Hijmans 2017). The WorldClim platform presents current and projected future climate characteristics using multiple climate models and scenarios. These data enable the implementation of agriculture-based assessments (Çelik et al. 2025).

Geographic information systems provide an essential decision support framework for conducting analyses related to temperature, precipitation and drought under climate change. In this study, spatial mapping, modeling and calculations were performed using ArcGIS Pro, one of the GIS application platforms. Accordingly, the tiff formatted datasets were downloaded from the WorldClim database and projected into the WGS1984 UTM Zone 36N coordinate system. Another key dataset of the study concerns the spatial representation of agricultural lands. For this purpose, vector based agricultural land data were obtained through a data request from the Ministry of Agriculture and Forestry, General Directorate of Agricultural Reform, within the scope of the inventory maps produced for the Identification and Improvement of Problematic Agricultural Lands Project. The inclusion of land use information for areas larger than 1 hectare with high spatial detail is particularly important.

Since the methodological framework of this study is based on raster data processing, vector based agricultural land features were converted into raster format using the Euclidean distance tool. The agricultural land classification used in the study is based on the categories defined in the Soil Conservation and Land Use Law of Türkiye numbered 5403. In this classification, agricultural lands are categorized based on their natural characteristics and their importance for national agricultural production as prime agricultural lands, specialty crop lands, permanent cropland and marginal agricultural land. In the Soil Conservation and Land Use Law, these categories are defined as follows. Absolute agricultural land refers to land with high productivity that is currently used or suitable for agricultural production. Special product land refers to land outside absolute agricultural land where, due to soil and topographic limitations, regionally adapted special plant species can be cultivated. Perennial crop land refers to land outside the absolute and special product categories where perennial trees, shrubs and similar plant forms suitable for local ecological conditions are cultivated. Marginal agricultural land refers to land outside the other categories where only traditional soil-based agriculture can be practiced because of soil and topographic constraints.

Ensuring that all datasets have the same spatial resolution is critical for accurate mapping and calculations. Because the global climate models have an approximate spatial resolution of 1 km and the rasterized agricultural data have a spatial resolution of 50 meters, the climate model grids were first converted to 50 meters. This process was carried out by increasing the spatial resolution of the climate model grids through resampling using the bilinear interpolation method. It should be noted that no new information was generated in this process. The main purpose was to standardize spatial resolution across all datasets.

2.3. Calculation of the aridity index and spatial exposure rate

The final stage of the study involves determining the aridity index and the spatial exposure rate of agricultural lands to drought. In this study, the De Martonne index, defined as an aridity or humidity index, was used to assess drought variations (De Martonne, 1926). At the regional scale, the De Martonne aridity index, which is based on long-term temperature and precipitation indicators, is widely employed for evaluating aridity (Moral et al. 2016; Ullah et al. 2022; Moral et al. 2023). The simplicity of the De Martonne aridity index and the ease of access to the required data further enhance its applicability (Charalampopoulos et al. 2023). The De Martonne aridity index is calculated using Equation 1:

$$AI_{DM} = \frac{P_a}{T_a + 10} \quad \text{(Eq. 1)}$$

Where: AI_{DM}, De Martonne aridity index value; P_a, annual total precipitation based on long-term averages (mm); T_a, annual mean air temperature based on long-term averages (°C)

The index values provide important information on the aridity and humidity conditions of a region. In this study, the aridity index values were classified as follows: AI < 10: arid, 10 ≤ AI < 20: semi-arid, 20 ≤ AI < 24: Mediterranean, 24 ≤ AI < 28: semi-humid, 28 ≤ AI < 35: humid, 35 ≤ AI ≤ 55: very humid, AI > 55: extremely humid (Deniz et al. 2011; Moral et al. 2016; Charalampopoulos et al. 2023). This study adopts an AI ≤ 20 threshold as a critical value for assessing the spatial exposure rate of agricultural land classes, as it represents the boundary between semi-arid and arid conditions according to the De Martonne classification.

In this study, a spatial exposure assessment is conducted to determine the vulnerability ratio of agricultural lands located in areas with high aridity index values (AI ≤ 20). The spatial exposure assessment consists of a two-stage process that includes identifying agricultural land classes located in areas with high drought risk and quantifying their proportional extent. The Boolean logic approach is used to identify the intersection points between areas of high drought risk and the spatial exposure areas

corresponding to each agricultural land class. Within this approach, the integration of binary maps based on conditional functions is expressed as the fulfillment of conditions (1) and the non-fulfillment of conditions (0) (Bonham- Carter 1994). Boolean logic provides an important evaluative framework as a logical reasoning method used within geographic information system models (Gao et al. 2023). In this study, the Boolean intersect (AND operator) is applied to determine the intersection of spatially affected areas based on the drought index and agricultural land classification, thereby identifying areas that satisfy both conditions. These areas are identified for each agricultural land class as areas that meet the specified conditions within each grid cell (prime agricultural lands, specialty crop lands, permanent cropland, marginal agricultural lands). In determining these conditions, the following Boolean intersection formula is applied (Eq. 2):

$$\text{Spatial exposure area} = (\text{AI} \leq 20) \cap (\text{agricultural land class}) \quad \text{(Eq. 2)}$$

The spatial exposure rate was calculated using Equation 3. Equation 3 is applied separately for each agricultural land class. In this equation, the area of agricultural land represents the total amount of that specific class within the region, while *al* denotes the agricultural land class.

$$Spatial\ exposure\ rate_{al}(\%) = \frac{Spatial\ exposure\ \text{area}_{al}}{Area\ of\ the\ \ agricultural\ land\ class_{al}} * 100 \quad \text{(Eq. 3)}$$

In long term climate projections, uncertainties may increase depending on the use of different climate model systems. These uncertainties vary according to the complexity of GCM structures, underlying assumptions, initial conditions, and parameterizations. To enhance rationality in climate model evaluations and to enable robust comparisons, the use of a multi model approach based on multiple GCMs has emerged as a necessity (Sansom et al. 2021; Talukder et al. 2025). Multi model means derived from multiple climate models represent an important approach for reducing uncertainties (Xu et al. 2010; Tegegne et al. 2019). To reduce the systematic uncertainties that may arise from relying on a single climate model in future projections, the multi-model approach using HadGEM3 GC3.1, MIROC6 and MPI ESM1 2 HR was employed. The aridity index results from these models were combined to calculate the ensemble mean and ensemble standard deviation, and the coefficient of variation (CV) values were derived. The ensemble analysis in this study refers to the statistical evaluation of the consistency and similarity between the ensemble mean derived from multiple global climate models and individual single climate model outputs. To compare the degree and spatial distribution of discrepancies and uncertainties among the models, CV was calculated at the grid cell level and mapped spatially (Whelen & Siqueira 2018). The calculation of CV was performed using the following Equation 4:

$$CV\ (\%) = \frac{std(\sigma)}{mean\ (\sigma)} * 100 \quad \text{(Eq. 4)}$$

Where: CV, coefficient of variation; $an(\sigma)$, ensemble mean; $std(\sigma)$, ensemble standard deviation

CV values provide important insights into model consistency and uncertainty by comparing the spatial distribution and magnitude of the models. A CV value approaching %0 indicates low uncertainty and high consistency, whereas values approaching %100 are interpreted as indicating increased uncertainty and reduced consistency (Assamnew et al. 2025).

3. Results

3.1. Temperature and precipitation changes

Across Central Anatolia, all models indicate a clear increase in temperature under both SSP2-4.5 and SSP5-8.5 scenarios. Particularly under the high greenhouse gas emission SSP5-8.5 scenario, temperature increases are projected to reach significantly higher levels. End of the century projections reveal temperature anomalies approximately 2-3 times higher than those in the near future, indicating that climate change impacts related to temperature will accelerate markedly throughout the region.

In HadGEM3 GC3.1 results, the accelerated increases under SSP5-8.5 suggest very substantial temperature rises, with annual mean temperatures in the southern and central parts of the region reaching 23-24 °C. In areas with lower baseline temperatures, SSP2-4.5 scenarios indicate an increase of approximately +2.7 °C by the end of the century, while SSP5-8.5 projects increase up to +5.3 °C. In warmer areas, end of the century temperatures is projected to rise by +2.3 °C under SSP2-4.5 and +4 °C under SSP5-8.5 relative to the near future. Scenarios based on the MIROC6 model produce more moderate temperature increases for the near future, while suggesting that end of the century warming may be severe. Particularly in cooler areas, SSP5-8.5 scenarios anticipate temperature rises of +4.6 °C. The MPI ESM1-2-HR model projects more limited temperature changes compared to the other two models but still indicates significant warming in end of the century scenarios. For the end of the century SSP2-4.5 scenario, the temperature increase relative to the near future is +1.8 °C, whereas it reaches +3.9 °C under SSP5-8.5 (Figure 2). The results of all three models indicate that in regions with initially low temperatures, temperature increases of approximately 3.9-5.3 °C could occur under the SSP5-8.5 scenario. Considering the 1.5 °C global temperature threshold, this suggests that the region will exceed this threshold by a substantial margin by the end of the century.

Regarding annual total precipitation, the models suggest no significant changes in the near future, while SSP5-8.5 end of the century scenarios indicate a marked decrease. For all three models, precipitation changes under SSP2-4.5 are minimal and closely aligned. Under SSP5-8.5, the MPI ESM1-2-HR model projects the greatest reduction in precipitation, although HadGEM3 GC3.1 and MIROC6 show similar values, ranging approximately between 300 and 675 mm. Overall, the models consistently identify spatial patterns of high and low precipitation areas (Figure 2).

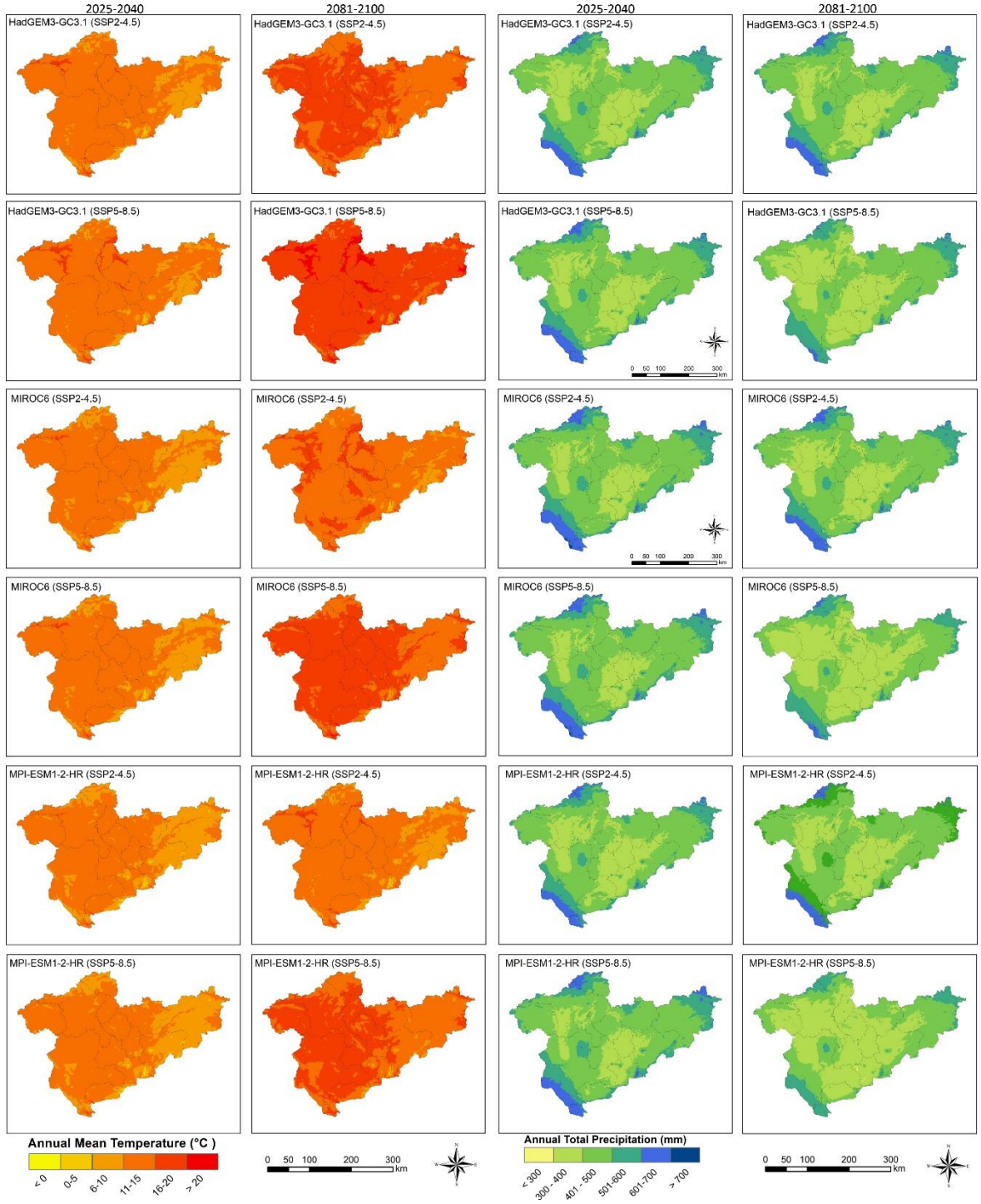


Figure 2- Changes in mean temperature and annual total precipitation under different models and projection scenarios

3.2. Determination of the spatial exposure rate of agricultural land classes based on the aridity index

In the De Martonne aridity index, values approaching zero indicate increasing drought severity. Values within the range of 0-20 are classified as arid and semi-arid, and all models indicate that Central Anatolia will predominantly exhibit a semi-arid climate. In the HadGEM3 GC3.1 model, the aridity index is 13.9 under the SSP2-4.5 scenario, decreasing to 12.4 by the end of the century, suggesting an intensification of drought severity. The increase in aridity in the model results shows a parallel trend with decreasing moisture conditions. Particularly, large areas of Ankara, Eskişehir, Aksaray, Niğde, central and northern Konya,

Nevşehir, and most of Kırıkkale are projected to experience widespread semi-arid conditions in both the near-future and end of the century projections. In the MIROC6 model, the index value is 14.6 for the near future, decreasing to 13.2 by the end of the century, indicating an increase in drought severity. Under the SSP5-8.5 scenario, a pronounced and extensive increase in the spatial distribution of semi-arid areas is observed. The MPI ESM1-2-HR model produces index values and spatial patterns similar to those of the other two models (Figure 3).

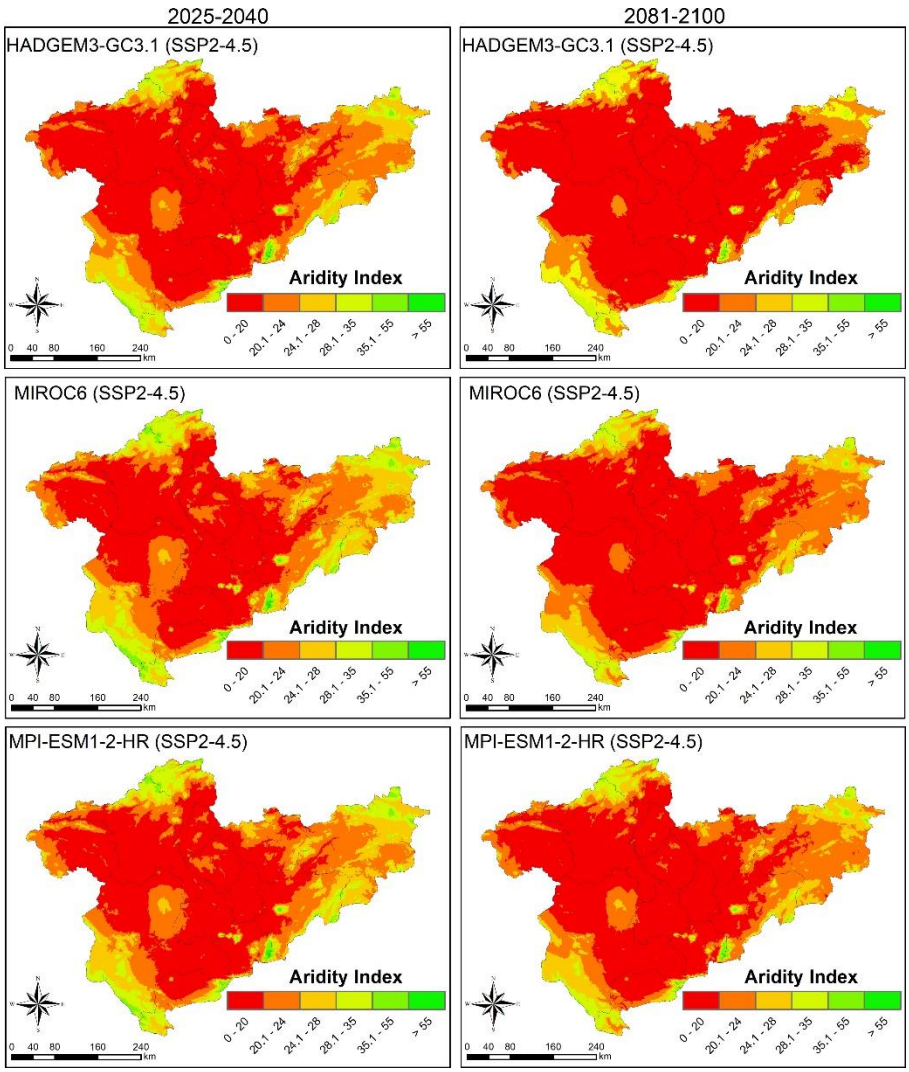


Figure 3- Aridity index under the SSP2-4.5 scenario

Under the SSP5-8.5 scenario, semi-arid climate conditions are projected to become dominant across Central Anatolia, particularly by the end of the century. At the end of century De Martonne aridity index values are calculated as 10.7 for the HadGEM3-GC3.1 model, 10.9 for the MIROC6 model, and 11.3 for the MPI-ESM1-2-HR model. These values indicate a significant increase in drought severity across the region, while relatively humid areas observed in the near-future scenario are projected to shrink considerably (Figure 4). Both SSP2-4.5 and SSP5-8.5 scenario results emphasize an overall increase in aridity across all three models, while the limited humid areas are expected to decline sharply by the end of the century. Furthermore, the similarity of index values and spatial distribution across the three models supports the consistency and reliability of the results.

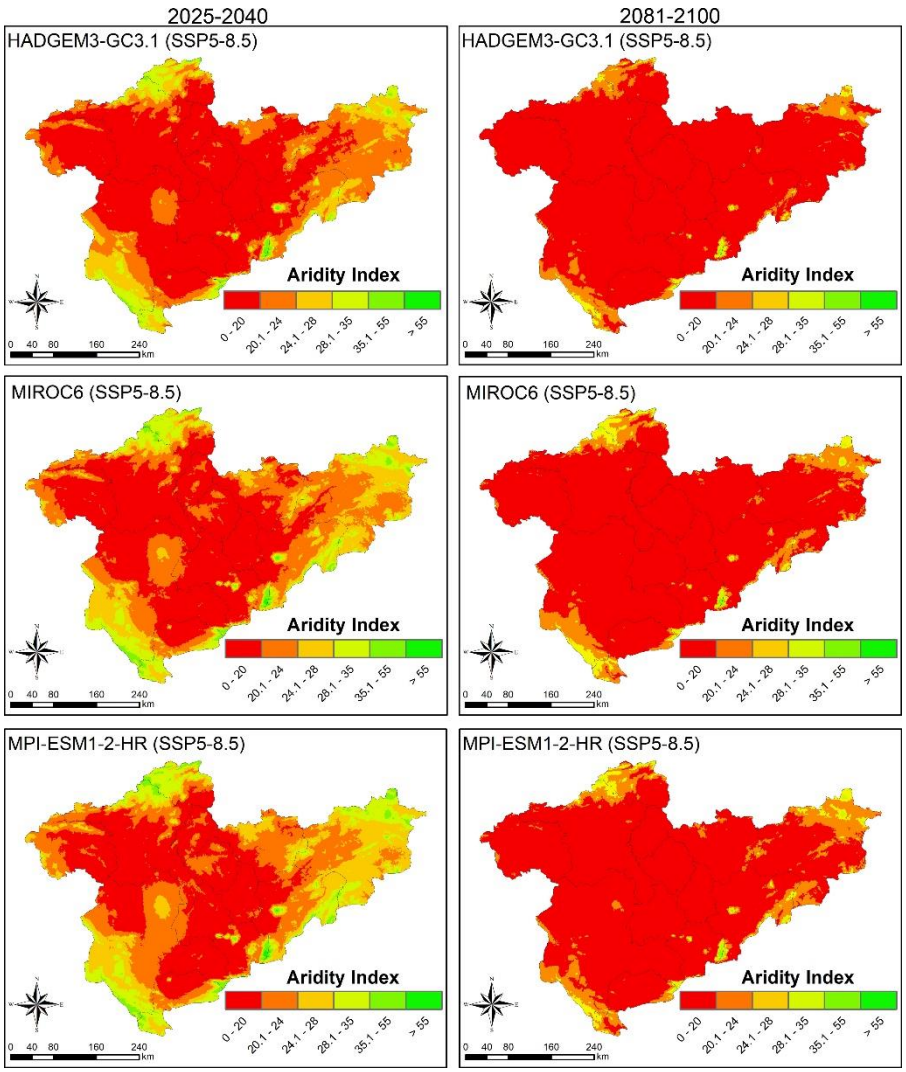


Figure 4- Aridity index under the SSP5-8.5 scenario

According to the De Martonne aridity index results, semi-arid areas constitute the largest spatially distributed class across the region. The HadGEM3-GC3.1 model under the SSP2-4.5 scenario indicates that approximately 55.73% of the total area will fall under the semi-arid class in the near future, increasing to 73.59% by the end of the century. The MIROC6 model projects that 46.45% and 62.62% of the total area will exhibit semi-arid spatial distribution in the near and far future, respectively. The MPI-ESM1-2-HR model forecasts 48.46% in the near future and 57.22% by the end of the century. Under the SSP5-8.5 scenarios, semi-arid areas are projected to cover approximately 83-90% of the total area. By the end of the century, this proportion reaches 90.75% in the HadGEM3-GC3.1 model, 85.80% in the MIROC6 model, and 83.67% in the MPI-ESM1-2-HR model (Figure 5). The model results indicate that under the SSP5-8.5 scenario, the extensive semi-arid areas will exert significant pressure on agricultural land classes. This highlights the necessity of considering the interrelationships between water resources, agriculture, and cropping patterns simultaneously at the regional scale.

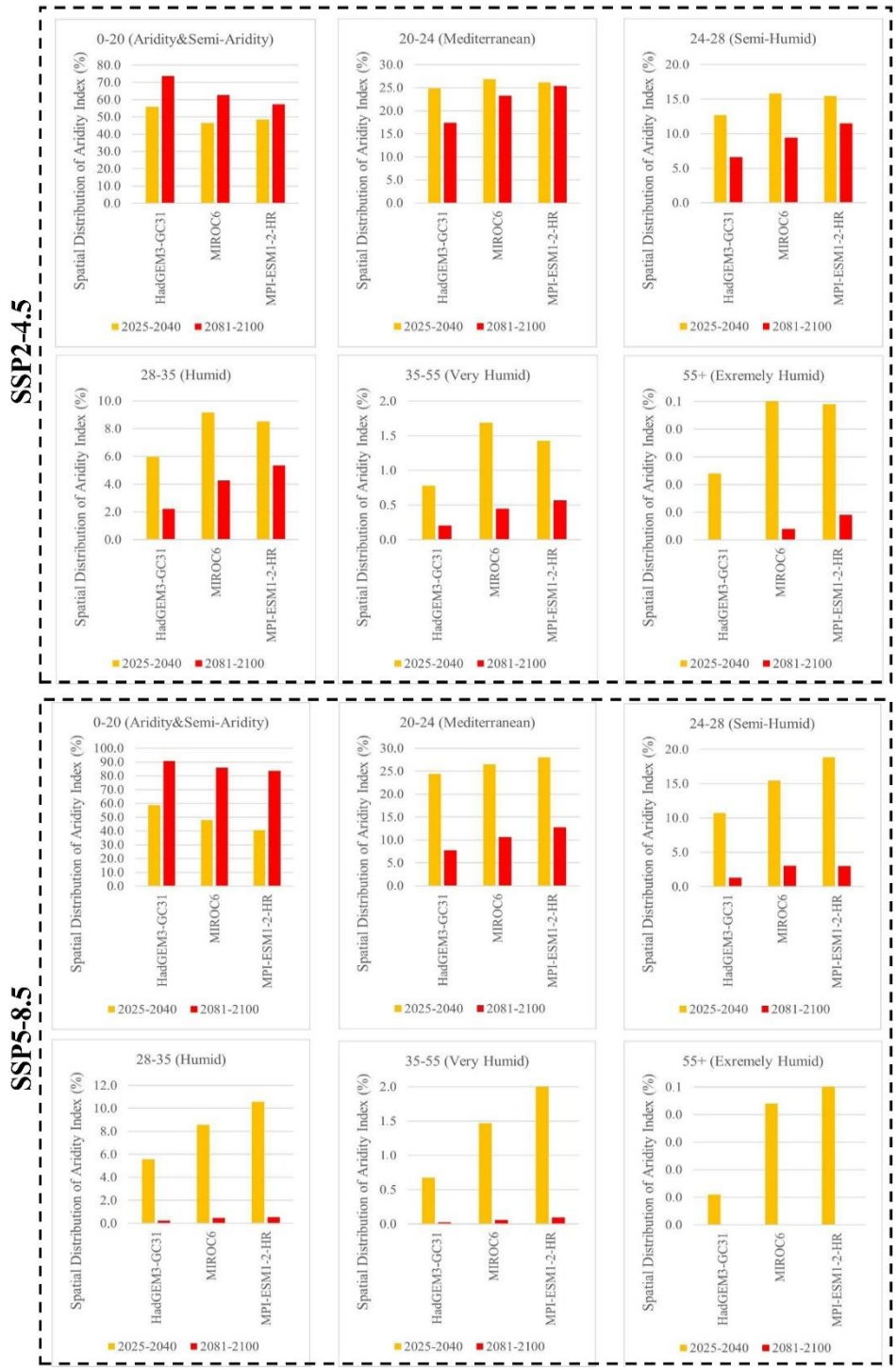


Figure 5- Spatial exposure rate of the aridity index under different scenarios

Multi-model ensemble results based on HadGEM3-GC3.1, MIROC6, and MPI-ESM1-2-HR demonstrate a high degree of consistency in CV values for SSP2-4.5 and SSP5-8.5 across different projection years. The low CV values for both the near future SSP2-4.5 and the end of the century SSP5-8.5 scenarios indicate that the models produce similar aridity index values and spatial patterns (Table 1).

Table 1- Coefficient of variation values of the multi-model

Period	*Scenario*	*Mean (min-max)*	*Std (min-max)*	*CV (min-max)*
2025-2040	SSP2-4.5	14.32-71.26	0.11-2.73	%0.62-%5.32
	SSP5-8.5	14.41-70.68	0.37-5.86	%1.70-%8.43
2081-2100	SSP2-4.5	13.06-58.55	0.28-4.82	%1.83-%8.34
	SSP5-8.5	10.97-44.32	0.08-2.73	%0.60-%6.32

The results indicate that all agricultural classes are likely to face increasing drought risk (Table 2). Under the SSP2-4.5 scenario, the spatial exposure rate of prime agricultural lands shows the highest increase in the HadGEM3-GC3.1 model, rising from 75.31% in the near future to 87.24% by the end of the century. Under the SSP5-8.5 scenario, this rate reaches 93.48%, indicating a substantial risk. Similarly, MIROC6 and MPI-ESM1-2-HR models project that over 91% of permanent croplands could be exposed to drought under the SSP5-8.5 scenario.

Although specialty crop areas occupy a smaller portion of the region compared to other agricultural lands, they emerge as the class with the highest spatial exposure rate. Under the SSP2-4.5 scenario, the spatial exposure rate ranges from 83.13% to 90.59% in the near future, increasing to 88.94%-94.06% by the end of the century. Under the SSP5-8.5 scenario, this risk intensifies, with the spatial exposure rate exceeding 95% across all models by the end of the century.

Permanent cropland areas will exhibit lower spatial exposure rates in the near future. Under SSP2-4.5, these areas show exposure rates of 52.30%-63.15% in the near future, rising to 62.18%-70.28% by the end of the century. Under SSP5-8.5, exposure rates reach 79.72%-89.78%, suggesting decreased climate resilience.

Marginal agricultural lands show spatial exposure rates of 54.44%-64.49% in the near future and 66.78%-82.91% by the end of the century under SSP2-4.5. Under SSP5-8.5, exposure rates rapidly increase to 90.04%-92.88% by the end of the century, indicating that the sustainability of production in marginal lands could be severely compromised.

Table 2- Spatial exposure rate of agricultural lands to aridity risk

Scenario	***Agricultural Land***	*Spatial Exposure Rate* ***(%)***	
		2025-2040	***2081-2100***
SSP2-4.5	Prime agricultural lands	75.31	87.24
		65.89	81.64
		68.71	76.59
SSP5-8.5		78.07	93.48
		68.37	91.98
		57.61	91.74
SSP2-4.5	Specialty crop lands	90.59	94.06
		83.13	90.69
		84.19	88.94
SSP5-8.5		88.60	95.84
		82.83	95.84
		82.44	96.77
SSP2-4.5	Permanent cropland	63.15	70.28
		52.30	65.21
		54.19	62.18
SSP5-8.5		62.03	89.78
		53.21	79.72
		49.35	86.10
SSP2-4.5	Marginal Agricultural Lands	64.49	82.91
		54.44	72.32
		56.89	66.78
SSP5-8.5		68.44	92.88
		56.00	91.23
		48.09	90.04
	HadGEM3-GC3.1	MIROC6	MPI-ESM1-2-HR

Overall, the findings suggest that the high and widespread aridity in Central Anatolia will result in spatial exposure rates exceeding 90% in the most productive permanent croplands and specialty crop areas under SSP5-8.5 by the end of the century, posing severe threats to agricultural production and food security. Even under SSP2-4.5, the exposure rate in highly productive agricultural areas exceeds 76.59% in the model, reporting the lowest rate, highlighting the vulnerability of fertile soils to drought. While numerical differences exist among model results, the spatial distribution, degree of risk, and long-term increasing trend of all agricultural classes show a high level of consistency. Exposure rates exceeding 90% in multiple agricultural classes by the end of the century signal a critical threat to food security and agricultural productivity.

4. Discussion

The findings of this study indicate that under both SSP2-4.5 and particularly SSP5-8.5 scenarios, temperature increases in Central Anatolia are projected to rise well above the global warming threshold, and concurrently, areas classified as semi-arid based on the De Martonne aridity index are expected to expand. These results are generally consistent with CMIP6-based projections suggesting significant aridification in the Mediterranean basin and semi-arid interior regions by the end of the century (Ghazi et

al. 2025; Trenberth et al. 2015; Eyring et al. 2016; Narsey et al. 2020; Seneviratne & Hauser 2020). Specifically, the dominance of semi-arid conditions in Central Anatolia under SSP5-8.5 supports previous studies highlighting the expansion of arid areas in the Mediterranean region (Feng & Fu 2013; Huang et al. 2016; Lewin et al. 2024; Wen et al. 2025).

The results align with previous research conducted for Central Anatolia. Yavaşlı and Erlat (2023), using PCI, Erinç, and UNEP AI indices along with CMIP6 projections, identified Central Anatolia as one of the driest regions in both current and future conditions across Turkey. Similarly, Çamalan & Çetin (2022), using the SPEI index, reported that Central Anatolia experiences some of the most intense short-term aridity events.

Studies from other regions of Türkiye further corroborate the trend of increasing aridity. Yeşilköy & Şaylan (2022) observed rising aridity in Thrace, while Çelik & Yakar (2024) reported similar trends in Mersin using different aridity indices. Meteorological drought analyses in the Eğirdir Lake Basin (Şener & Davraz 2025) and meteorological and hydrological aridity assessments in the Gediz River Basin (Çetin & Kumanlıoğlu 2023) also indicate increasing pressures on water resources. These studies demonstrate that similar aridification trends occur even under diverse climatic and topographic conditions, supporting the results obtained for Central Anatolia in this study.

A key contribution of this study lies in the classification-based analysis of agricultural lands. The findings suggest that all agricultural classes face progressively increasing aridity risk. Under high-emission scenarios, a substantial share of high-productivity agricultural lands is projected to experience persistent semi-arid conditions, indicating that drought risk will increasingly concentrate in regions producing water-intensive and high-value crops. This pattern implies a structural shift in the region's agricultural vulnerability profile, as the most productive and economically valuable lands are also those most exposed to future climatic stress. Such concentration of aridity risk within core production zones heightens the likelihood of cascading impacts on regional food supply chains and rural livelihoods.

Even under the more moderate SSP2-4.5 scenario, a large proportion of high-productivity agricultural areas remains exposed, highlighting the magnitude of future risks to agricultural production potential. Given the structure of agricultural production in the region, this aridity risk could have long-term implications for crop yield and food security. These results align with previous studies discussing the impacts of aridity on agricultural productivity (Dinç et al. 2016; Straffelini & Tarolli 2023). While Çelik & Yakar (2024) and Şener & Davraz (2025) emphasize that declining precipitation will increase pressures on agricultural lands over the long term, Dietz et al. (2021) and Asseng et al. (2015) underline that aridity stress reduces both crop yield and quality. Croplands dependent on irrigation and high-value crop areas are particularly vulnerable to aridity shocks. This suggests that future production losses may not be evenly distributed across space but instead may disproportionately affect the most strategically important agricultural zones, thereby amplifying food security risks beyond what aggregate yield declines alone would indicate.

Another significant finding of this study is that, although numerical differences exist among climate models, the spatial distribution and long-term upward trends of aridity exposure across agricultural land classes exhibit a high degree of consistency. Previous studies based on CMIP3 and CMIP5 emphasized the limitations of model uncertainty (Ullah et al. 2022; Ghazi et al. 2025). By using three different CMIP6 global climate models, this study reduces such uncertainties, providing a more robust assessment of the potential aridity risks facing agricultural lands in Central Anatolia. The convergence of spatial patterns across models increases confidence that the identified high-risk agricultural zones reflect real vulnerability rather than model-specific anomalies.

The spatial analyses conducted within a GIS-based spatial modeling framework enabled the integrated assessment of aridity projections with agricultural land classes and enhanced the study's relevance for regional planning. The resulting spatial database provides a detailed representation of the distribution of aridity-related exposure across agricultural lands, facilitating spatially explicit identification of priority zones for adaptation interventions in land use planning, agricultural production strategies, and water management policies. This spatial framework allows not only the evaluation of current exposure rates of agricultural areas but also the assessment of potential impacts of future land use changes on regional water resources and food production capacity. The flexibility of the spatial modeling structure permits the method to be reapplied in different regions, with different land classes or alternative datasets, making the study a transferable methodological framework. Therefore, this study is valuable not only for its findings but also for its analytical structure, which can be integrated into spatial planning processes to guide decision-makers and policymakers in developing regional adaptation strategies.

This study has some limitations and provides avenues for future research. Agricultural land classes were integrated into projections under the assumption that they will remain unchanged in the future. Future studies could use spatial simulations of agricultural land-use changes and other land-use dynamics to determine exposure rates more accurately. Additionally, integrating these changes with climate scenarios would allow for more precise and reliable results for planning and policy development. Furthermore, in this study, exposure rates were assessed based on agricultural land classification. Differences in temperature and precipitation tolerance among crops may alter exposure levels. Specifically, crops with high drought tolerance may show different exposure rates. Therefore, future research could produce risk mapping and spatial exposure assessments tailored to the region or specific crop types, providing product-based insights.

5. Conclusions

This study demonstrates that the Central Anatolia Region is entering a pronounced aridification trajectory under climate change, with substantial implications for long-term agricultural sustainability and food security. Under the high-emission SSP5-8.5 scenario, large portions of the region are projected to shift toward semi-arid climatic conditions by the end of the century, signaling a structural transformation of the regional hydroclimatic regime.

The most productive agricultural classes, namely permanent croplands and specialized crop areas, show the highest vulnerability to aridity across all scenarios. In pessimistic scenarios, the spatial exposure of these areas exceeds 90%, posing serious threats to regional and national food security. Even under the more moderate SSP2-4.5 scenario, the exposure of high-productivity agricultural areas remains above 76%, highlighting the degree of risk to the region's future agricultural production potential. These findings indicate that climate-driven aridity may progressively undermine the reliability of agricultural output in one of Türkiye's most important food-producing regions.

One of the study's novel contributions is the detailed, spatially explicit assessment of aridity risk not only at the regional scale but also at the level of agricultural land classes. Although some quantitative differences exist among the CMIP6 models used, the high spatial consistency (low CV values) strengthens the reliability of the projections. This multi-model convergence enhances confidence that the identified high-risk agricultural zones reflect structurally vulnerable areas rather than model-specific artifacts. The GIS-based analytical approach allows for high-resolution spatial representation of aridity risk, providing a transferable methodological framework for both climate and regional planning research.

Considering the identified risks, there is a clear need to develop spatially targeted adaptation strategies to sustain agricultural production in the Central Anatolia Region. High-productivity agricultural areas expected to experience severe aridity should have water management plans and irrigation infrastructure revised according to climate projections. The spatial exposure patterns revealed in this study offer a scientific basis for prioritizing adaptation investments, optimizing water allocation policies, and redesigning regional agricultural planning frameworks. Policies should be developed to reduce water dependency and promote resilient drought crops in areas of high aridity risk to ensure the sustainability of regional agricultural production. In this respect, the study contributes not only to the scientific understanding of future aridity dynamics but also to evidence-based policy formulation aimed at safeguarding food security under intensifying climate stress.

This spatial approach provides a significant contribution to the understanding of the aridity-agriculture relationship in the region and establishes a foundation for developing more targeted, region specific and actionable strategies in response to drought conditions that are expected to intensify in the future. In addition, the spatial framework employed in this study, supported by GIS based data integration and scenario-oriented assessment, offers a transferable guideline for decision makers and policymakers that can be applied to different regions, various agricultural land classes or alternative aridity index calculations.

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