The effects of drought on land cover change and vegetation productivity in continental Chile

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Chile has experienced a persistent decrease in water supply, which impacts the hydrological system and vegetation development. This persistent period of water scarcity has been defined as a mega-drought. There are few studies about the relationship between drought and ecosystem changes that can help with a better understanding of ecological drought. The aim of our study is to evaluate the interaction of drought, land cover change, and vegetation productivity over continental Chile. To assess drought, we used drought indices for atmospheric evaporative demand (AED), water supply, and soil moisture from short- (1, 3, 6 months) to long-term (12, 24, 36 months) time scales. We derived the drought indices using monthly ERA5-Land reanalysis data from 1981 to 2023. We used the Moderate-Resolution Imaging Spectroradiometer (MODIS) datasets to derive information on annual land cover and monthly vegetation productivity. Our results showed that except for the Austral part, Chile has a temporal decreasing trend in water supply, and across the whole country, there is an increase in AED. These trends become stronger over longer time scales. We found a negative trend in vegetation productivity in the north-central area, which is more prominent for shrubland and savanna as compared to croplands and forests. The anomaly in soil moisture over the past 12 months (SSI-12) is the most important variable explaining these changes, followed by anomalies in accumulated precipitation over one to two years (SPI-12 and SPI-24). The variable importance obtained by random forest models indicates that drought is explaining about 20–30% of the change in land cover surface across Chile for forest, grassland, shrubland, and savanna but has no relation to the changes in croplands. The increase in AED is the main variable associated with the change in land cover, followed by a reduction in precipitation and soil moisture. Our findings provide insightful information that could assist in developing adaptation measures for Chilean ecosystems to cope with climate change and drought. Also, this study could contribute to a better comprehension of ecological drought.

# 1. Introduction

Drought is often classified as 1) meteorological when precipitation in a specific period remains below the mean precipitation experienced in the same period during multiple years (more than 30 years usually), 2) hydrological when these anomalies last for long periods (months to years) and affect water systems, and 3) agricultural when the deficit negatively impacts plant health and leads to decreased productivity of crops or pastures (Wilhite and Glantz 1985). However, because drought is also influenced by human activities, Anne F. Van Loon et al. (2016) and Amir AghaKouchak et al. (2021) expanded the drought definition for the Anthropocene, indicating that the feedback of human decisions and activities should also be considered (i.e., anthropogenic drought). Droughts lead to increased tree mortality (Cheng et al. 2024) and induces alterations in land cover and land use, ultimately affecting ecosystems (Crausbay et al. 2017). Even though many ecological studies have at times mistakenly considered “dry” conditions as “drought” (Slette et al. 2019). Ecological drought can be defined as *“an episodic deficit in water availability that drives ecosystems beyond thresholds of vulnerability, impacts ecosystem services, and triggers feedback in natural and/or human systems”* (Crausbay et al. 2017). In light of current global warming, it is crucial to study the interaction between drought and ecosystems in order to understand their feedback and impact on future water security (Bakker 2012).

Global warming, as a result of human-induced greenhouse gas emissions, has increased the frequency and intensity of drought, according to the sixth assessment report (AR6) of the Intergovernmental Panel on Climate Change (IPCC) (Calvin et al. 2023). The evidence supporting this claim has been strengthened since AR5 (IPCC 2013). Recent studies, however, have produced contrasting findings, with some suggesting that drought has not exhibited a significant trend over the past forty years (Vicente-Serrano et al. 2022; Kogan, Guo, and Yang 2020). Vicente-Serrano et al. (2022) analyzed the trend in meteorological drought on a global scale, finding that only in a few regions an increase in the severity of drought was observed. Moreover, they attributed this increase solely to an increase in atmospheric evaporative demand (AED) due to higher temperatures, which in turn enhances vegetation water demand, with important implications for agricultural and ecological droughts. Also, they state that *“the increase in hydrological droughts has been primarily observed in regions with high water demand and land cover change, led by an increase in agricultural land”*. Similarly, Kogan, Guo, and Yang (2020) analyzed the drought trend using remotely-sensed vegetation health indicators, finding that for the globe and main grain-producing countries, drought has not expanded or intensified during the past 38 years. Nonetheless, Intergovernmental Panel On Climate Change (2023) suggests that there is a medium to high degree of confidence that rising temperatures will increase the extent, frequency, and severity of agricultural and ecological droughts. Also, AR6 (Calvin et al. 2023) predicts that many regions of the world will experience more severe agricultural and ecological droughts even if global warming stabilizes at 1.5°–2°C. To better evaluate the impact of drought trends on ecosystems, assessments that correlate meteorological and soil moisture variables to their effects on vegetation are much needed.

From 1960 to 2019, land use change has impacted around one-third of the Earth’s surface, which is four times more than previously thought (Winkler et al. 2021). Multiple studies aim to analyze and forecast changes in land cover globally (Winkler et al. 2021; Song et al. 2018) and regionally (Chamling and Bera 2020; Homer et al. 2020; Yang and Huang 2021; Schulz et al. 2010; Echeverría et al. 2012). Some seek to analyze the impact of land cover change on climate conditions such as temperature and precipitation (Luyssaert et al. 2014; Pitman et al. 2012). There is less research on drought and its relation to land cover change and vegetation productivity (Chen et al. 2022; Akinyemi 2021; Peng et al. 2017). Peng et al. (2017) utilized net primary productivity to examine the spatial and temporal variations in vegetation productivity at global level and assess to what extent drought influenced this variability by comparing the twelve-month Standardized Precipitation Evapotranspiration Index (SPEI) and land cover change. According to their findings, drought is responsible for 37% of the decline and accounts for 55% of the variability in vegetation productivity. Chen et al. (2022) instead found poor correlations (r<0.2) between the vegetation productivity trends against meteorological drought (SPEI of twelve months in December) and soil moisture at the global level. These studies mostly looked at how changes in land cover and vegetation productivity are related to a single drought index (SPEI) obtained for 12 month periods. SPEI takes into account the combined effect of precipitation and AED as a water balance, but it does not allow to know the contribution of each variable on its own. To better understand these contributions on land cover change and vegetation productivity the following questions may be asked: i) how do land cover and vegetation productivity respond to short- to long-term meteorological and soil moisture droughts? And ii) How is this response different between humid and arid climatic zones? Likewise, there is a lack of understanding of how the alteration in water supply and demand is affecting land cover transformations.

To address the previous questions over extensive regions, we can utilize gridded data on water availability, vegetation conditions, and the respective drought indices. For monitoring drought, the World Meteorological Organization recommends the SPI (Standardized Precipitation Index) (WMO et al. 2012). The SPI is a multi-scalar drought index that only uses precipitation to assess short- to long-term droughts. Vicente-Serrano, Beguería, and López-Moreno (2010) proposed the Standardized Precipitation Evapotranspiration Index (SPEI), which incorporates the temperature effect by subtracting AED from precipitation. SPEI allows for analyzing the combined effect of precipitation and AED. Since its formulation, it has been used worldwide for the study and monitoring of drought (Gebrechorkos et al. 2023; Liu et al. 2024). Recently, there has been more interest in using AED to track droughts separately to better disengage the effects of precipitation from temperature-dependent effects (Vicente‐Serrano et al. 2020). One of the reasons is that AED is linked to more flash droughts in limited water regions (Noguera, Vicente‐Serrano, and Domínguez‐Castro 2022). Hobbins et al. (2016) and McEvoy et al. (2016) developed the Evaporative Demand Drought Index (EDDI) to monitor droughts solely using the AED, and it has proven effective in monitoring flash droughts (H. Li et al. 2024; Ford et al. 2023). For soil moisture, several drought indices exist, such as the Soil Moisture Deficit Index (SDMI) (Narasimhan and Srinivasan 2005) and the Soil Moisture Agricultural Drought Index (SMADI) (Souza, Ribeiro Neto, and Souza 2021). Hao and AghaKouchak (2013) and A. AghaKouchak (2014) proposed the Standardized Soil Moisture Index (SSI), which has a similar formulation as the SPI, SPEI, and EDDI. Thus, many drought indices exist that allow for a comprehensive assessment of drought on short- to long-term scales and that allow for the use of single variables from Earth’s water balance (e.g., precipitation, AED, soil moisture). Climatic variability impacts vegetation development, with unfavorable conditions such as low precipitation and high temperatures usually promote a decrease in plant productivity. To monitor the response of vegetation for large areas, the common practice is to use satellite data. For example, the Normalized Difference Vegetation Index (NDVI) derived from frequent satellite observations of red and near infrared spectral reflectance, has been widely used as a proxy for biomass production (Camps-Valls et al. 2021; Paruelo et al. 2016; Helman et al. 2014). For Chile’s cultivated land, Zambrano et al. (2018) used the zcNDVI for assessing seasonal biomass production in response to drought. Comparing the various meteo-related and vegetation-based drought indices, we can further our understanding of the impact of drought on ecosystems.

Chile’s diverse climatic and ecosystem types (Beck et al. 2023; Luebert and Pliscoff 2022) make it an ideal natural laboratory for studying climate and ecosystems. Additionally, the country has experienced severe drought conditions that have had significant effects on vegetation and water storage. North-central Chile has faced a persistent precipitation deficit since 2010, defined as a mega-drought (R. Garreaud et al. 2017), which has impacted the Chilean ecosystem and consequently makes it highly vulnerable to climate change (Barría et al. 2021; Alvarez-Garreton et al. 2021). This mega-drought was defined by the annual time series of the Standardized Precipitation Index (SPI) at a time scale of twelve months at the end of each year (December) when having values below one standard deviation. Some studies have addressed how this drought affects single ecosystems in terms of forest growth (Miranda et al. 2020; Alejandro Venegas-González et al. 2018), forest fire occurrence (Urrutia‐Jalabert et al. 2018), and crop productivity (Zambrano 2023a; Zambrano et al. 2018, 2016). The term “mega-drought” is used in Chile to describe a prolonged water shortage that lasts for several years, resulting in a permanent deficit that impacts the hydrological system (Boisier et al. 2018). Therefore, it is crucial to evaluate temporal scales that consider the cumulative impact over a period of several years. In Chile, the relationship between drought and the environment remains poorly understood. Hence, we aim to contribute to understanding how climatic and soil moisture droughts influence ecosystem dynamics in order to provide useful information that helps for a better understanding of ecological droughts and, at the same time, helps to make well-informed decisions on adaptation strategies.

Here, we analyze the multi-dimensional impacts of drought across ecosystems in continental Chile. More specifically, we aim to assess: i) short- to long-term temporal trends in multi-scalar drought indices; ii) temporal changes in land-use cover and the direction and magnitude of their relationships with trends in drought indices; and iii) the trend in vegetation productivity and its relationship with drought indices across Chilean ecosystems.

# 2. Study area

Continental Chile has diverse climate conditions with strong gradients from north to south and east to west (Aceituno et al. 2021) ([Figure 1](#fig-studyArea)a), which determines its great ecosystem diversity (Luebert and Pliscoff 2022) ([Figure 1](#fig-studyArea)c). The Andes Mountains are a main factor in climate variation (R. D. Garreaud 2009). For an aggregated overview of the results of the study, we used the five Chilean macrozones: “Norte Grande,” “Norte Chico,” “Centro,” “Sur,” and “Asutral”. “Norte Grande” (17°34’–25°42’S) and “Norte Chico” (25°42’-32°8’S) predominate in an arid desert climate with hot (Bwh) and cold (Bwk) temperatures. At the south of “Norte Chico,” the climate changes to an arid steppe with cold temperatures (Bsk). In these two northern regions, the land is mostly bare, with a small surface of vegetation types such as shrubland and grassland. In the macrozones “Centro” (32°08’-36°12’S) and the northern half of “Sur,” (36°12’-43°48’S) the main climate is Mediterranean, with warm to hot summers (Csa and Csb). Land cover in “Centro” comprises a significant amount of shrubland and savanna (50%), grassland (16%), forest (8%), and croplands (5%). An oceanic climate (Cfb) predominates in the south of “Sur” and the north of “Austral” (43°48’-56°00’S) Those zones have a large areal extent of forest and grassland. The southern part of the country has a tundra climate, and in “Austral,” it is a cold semi-arid area with an extended surface of grassland, forest, and, to a lesser extent, savanna.

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| Figure 1: (a) Chile with the Koppen-Geiger climate classes and the five macrozones “Norte Grande”, “Norte Chico”, “Centro”, “Sur”, and “Austral”. (b) Topography reference map. (c) land cover classes for 2022. (d) Persistent land cover classes (> 80%) for 2001-2022 |

# 3. Materials and Methods

## 3.1 Data

### 3.1.1 Gridded meteorological and vegetation data

To analyze land cover change, we used the classification scheme by the IGBP (International Geosphere-Biosphere Programme) from the product MCD12Q1 Collection 6.1 from MODIS. The MCD12Q1 product is produced for each year from 2001 to 2022 and defines 17 classes (see Table S1). To maintain our focus on a large scale and follow the FAO classification (FAO 2022), we considered native and planted forests as “forests”, which represent ecosystems dominated by larger trees. To derive a proxy for vegetation productivity, we used the Normalized Difference Vegetation Index (NDVI) from the product MOD13A3 Collection 6.1 from MODIS (Didan 2015). MOD13A3 provides vegetation indices with 1km spatial resolution and monthly frequency. The NASA EOSDIS Land Processes Distributed Active Archive Center (LP DAAC), USGS Earth Resources Observation and Science (EROS) Center, Sioux Falls, South Dakota, provided the MOD13A3 and MCD12Q1 from the online Data Pool, accessible at https://lpdaa.usgs.gov/tools/data-pool/.

For soil moisture, water supply, and water demand variables, we used ERA5L (ECMWF Reanalysis version 5 over land) (Muñoz-Sabater et al. 2021), a reanalysis dataset that provides the evolution of atmospheric and land variables since 1950. It has a spatial resolution of 0.1° (9 km), hourly frequency, and global coverage. We selected the variables for total precipitation, maximum and minimum temperature at 2 meters, and volumetric soil water layers between 0 and 100 cm of depth (layer 1 to layer 3). shows a summary of the data and its main characteristics.

## 3.2 Short- to long-term drought trends

### 3.2.1 Atmospheric Evaporative Demand (AED)

To compute the drought indices that use water demand, it is necessary to first calculate the AED. To do this, we employed the Hargreaves method (George H. Hargreaves 1994; George H. Hargreaves and Samani 1985) by applying the following equation:

where is extraterrestrial radiation; , , and are mean, maximum, and minimum temperature at 2m. For calculating we used the coordinate of the latitud of the centroid of each pixel as follow:

where

: extraterrestrial radiation ,  
: solar constant = 0.0820 ,  
: inverse relative distance Earth-Sun,  
 sunset hour angle ,  
: latitude ,  
: solar declination .

We chose the method of Hargreaves to estimate AED because of its simplicity, which only requires temperatures and extrarrestrial radiation. Also, it has been recommended over other methods (e.g., Penman-Monteith) when the access to climatic variables is limited (Vicente-Serrano et al. 2014).

### 3.2.2 Non-parametric calculation of drought indices

To derive the drought indices of water supply and demand, soil moisture, and vegetation (i.e., the proxy of productivity), we used the ERA5L dataset and the MODIS product, with a monthly frequency for 1981–2023 and 2000–2023, respectively. The drought indices correspond to a historical anomaly of a variable (e.g., meteorological, vegetation, or soil moisture). To account for the anomaly, the common practice is to derive it following a statistical parametric method in which it is assumed that the statistical distribution of the data is known (Heim 2002). A wrong decision in the statistical distribution is usually the highest source of uncertainty (Laimighofer and Laaha 2022). In the case of Chile, due to its high degree of climatic variability, it is difficult to choose a proper distribution without previous research that could be applicable throughout Chile. Here, we follow a non-parametric method for the calculation of the drought indices, in a similar manner as the framework proposed by Farahmand and AghaKouchak (2015).

For the purpose of monitoring water supply drought, we used the well-known Standardized Precipitation Index (SPI), which relies on precipitation data. To evaluate water demand, we chose the Evaporative Demand Drought Index (EDDI), developed by Hobbins et al. (2016) and McEvoy et al. (2016), which is based on the AED. The United States currently monitors drought using the EDDI (https://psl.noaa.gov/eddi/) as an experimental index. To consider the combined effect of water supply and demand, we selected the SPEI (Vicente-Serrano, Beguería, and López-Moreno 2010). For SPEI, an auxiliary variable is calculated. Soil moisture is the main driver of vegetation productivity, particularly in semi-arid regions (W. Li et al. 2022). Hence, for soil water drought, we used the SSI (Standardized Soil Moisture Index) (Hao and AghaKouchak 2013). For the SSI, we used the average soil moisture from ERA5L at 1m depth. Finally, for the proxy of productivity, we used the zcNDVI (Zambrano et al. 2018), which was derived from the monthly time series of NDVI derived from MOD13A1. All the indices are multi-scalar and can be used for the analysis of short- to long-term droughts.

To derive the drought indices, we first calculate the sum of the variables with regard to the time scale(s). In this case, for generalization purposes, we will use , referring to variables , , , , and (Table ). We accumulated each over the time series of values (months), and for the time scales :

The corresponds to a moving window (convolution) that sums the variable for time scales . Start from the last month (n) and sum the variable for s months, then follow month by month until the first month in which it could sum for s months (n-s+1). For example, using as a variable the precipitation, a period of twelve months (n), and a time scale of three months (s), it will be:

Then, an inverse normal approximation (Abramowitz and Stegun 1968) obtains the empirically derived probabilities once the variable cumulates over time for the scale . Then, we used the empirical Tukey plotting position (Wilks 2011) over to derive the probabilities across a period of interest:

The drought indices , , , , and are obtained following the inverse normal approximation:

is referring to the drought index calculated for the variable (i.e., SPI, SPEI, EDDI, SSI, and zcNDVI). The values for the constats are: , , , , , and . For , W= , and for , replace with and reverse the sign of .

The drought indices were calculated for time scales of 1, 3, 6, 12, 24, and 36 months at a monthly frequency for 1981–2023 in order to be used for short- to long-term evaluation of drought.

For the proxy of vegetation productivity, we chose the time scale that best correlates with annual net primary productivity (NPP) across continental Chile. For this purpose, we calculated the zcNDVI for time scales of 1, 3, 6, and 12 months in December and compared it with the annual NPP. We used the NPP from the MOD17A3HGF (Running and Zhao 2019) dataset (MODIS). We choose to use six months because the r-squared of zcNDVI with NPP highly increases from one to six months, but from six to 12 months has a lower improvement. We obtained an r-squared of 0.31 for forest and 0.72 for shrubland (refer to the supplementary material in Section S5). Then, we chose the proxy of vegetation productivity for six months, which we will name zcNDVI hereafter. It was calculated at a monthly frequency for 2000–2023.

### 3.2.3 Trend of drought indices

To estimate if there are significant positive or negative trends for the drought indices, we used the non-parametric test of Mann-Kendall (Kendall 1975). To determine the magnitude of the trend, we used Sen’s slope (Sen 1968). Some of the advantages of applying this methodology are that the Sen’s slope is not affected by outliers unlike regular regressions does, and it is a non-parametric method that is not influenced by the distribution of the data. We applied the Mann-Kendall test to see if the trend was significant and Sen’s slope to estimate the magnitude of the trend. We did this for the indices SPI, EDDI, SPEI, and SSI using the six time scales with data from 1981 to 2023 (monthly frequency), resulting in 24 trends (per index and time scale). Then, we extracted the trend aggregated by each of the five macrozones: “Norte Grande” to “Asutral,” and per land cover type: grassland, forest, cropland, shrubland, savanna, and barren land ([Figure 1](#fig-studyArea)d).

## 3.3 Interaction of land cover and drought

### 3.3.1 Land cover change

To analyze the land cover change, we use the IGBP scheme from the MCD12Q1 collection 6.1 from MODIS. This product has been previously used for studies of drought and land cover in Chile (Fuentes et al. 2021; Zambrano et al. 2018). We regrouped the 17 classes into ten macroclasses, as follows: classes 1-4 to forest, 5-7 to shrublands, 8-9 to savannas, 10 as grasslands, 11 as wetlands, 12 and 14 to croplands, 13 as urban, 15 as snow and ice, 16 as barren, and 17 to water bodies. Thus, we have a land cover raster time series with the ten macroclasses for 2001 and 2023. We validate the land cover macroclasses regarding a highly detailed (30 m of spatial resolution) land cover map made for Chile by Zhao et al. (2016) for 2013-2014. Our results showed a global accuracy of ~0.82 and a F1 score of ~0.66. Section S2 in the Supplementary Material shows the procedure for validation.

We calculated the surface occupied per land cover class into the five macrozones (“Norte Grande” to “Austral”) per year for 2001–2023. After that, we calculated the trend’s change in surface per land cover type and macroclass. We used Mann-Kendall for the significance of the trend (Kendall 1975) and Sen’s slope to calculate the magnitude (Sen 1968).

To assess how water demand and supply, and soil moisture affect the variation in vegetation productivity across various land cover types, we avoid analyzing areas that have major land cover changes for 2021–2022. To assess how zcNDVI varied irrespective of land cover change, we developed a persistence mask for land cover, which only retains pixels for which the macroclass remained the same for at least 80% of the years (2001–2022) ([Figure 1](#fig-studyArea)d).

### 3.3.2 Relationship between land cover and drought trends

The goal of this section is to identify which drought indices and time scales have a major impact on changes in land cover type. We examined the relationship between the trend in land cover classes and the trend in drought indices. To have more representative results, we conducted the analysis over sub-basins within continental Chile. We used 469 basins, which have a surface area between 0.0746 and 24,000 km2 and a median area of 1,249 km2. For each basin, we calculated the trend per land cover type, considering the proportion of the type relative to the total surface of the basin. Then, we extracted per basin the average trend (Sen’s slope) of the drought indices SPI, SPEI, EDDI, SSI, and all their time scales 1, 3, 6, 12, 24, and 36. Also, we extracted the average trend in the proxy of vegetation productivity (zcNDVI)

Random forest (Ho 1995) employs multiple decision trees, allowing for classification and regression. Some advantages include the ability to find non-linear relationships, reduce overfitting, and derive variable importance. We used the regression random forest to model the trends in land cover per macroclass, using drought indices as predictors. This included the four drought indices per six time scales and the zcNDVI, totaling 25 predictors. As a result, we created six random forest models, one per trend in land cover macroclass. We trained 1000 forests in a resampled scheme to obtain more reliable results regarding variable importance. We resampled by creating ten folds, running a random forest per fold, and calculating the r-squared (rsq), root mean square error (RMSE), and variable importance. The variable importance helps for a better understanding of the relationships by finding which variable has a higher contribution to the model. Thus, we calculate the variable’s importance by permuting out-of-bag (OOB) data per tree and computing the mean standard error in the OOB. After permuting each predictor variable, we repeated the process for the remaining variable. We repeated this process ten times (per fold) to obtain the performance metrics (rsq, RMSE, and variable importance).

Finally, we visually explore the connection between the SPI, EDDI, and SSI drought indices for short- and long-term changes in land cover. To do this, we compare the relative changes in land cover surface (in terms of the total surface area per land cover type and macrozone) with the drought indices of six (short-term) and thirty-six months (long-term). We created a scatterplot in which the x-axis shows drought indices trends and the y-axis shows land cover change trends.

## 3.4 Drought impacts on vegetation productivity

For each land cover macroclass, we analyzed the trend of vegetation productivity over the unchanged land cover macroclasses. To achieve this, we used the persistent mask of land cover macroclasses , thus reducing the possibility of evaluating productivity trends that are due to year-to-year variation in land cover. We used the zcNDVI as a proxy of vegetation productivity. To assess productivity in Chile’s cultivated land, Zambrano et al. (2018) used the zcNDVI for assessing seasonal biomass production in relation to climate.

We examine the drought indices of water demand, water supply, and soil moisture and their correlation with vegetation productivity. The objective is to determine to what extent soil moisture and water demand and supply affect vegetation productivity, thus addressing three main questions: 1) Which of the drought variables—supply, demand, or soil moisture—helps most in explaining the changes in vegetation productivity? How do the short- to long-term time scales of the drought variable affect vegetation productivity in Chile? 2) How strong is the relationship between the variables and the drought index? And finally, 3) how does the correlation vary per-land cover type? Answering these questions should advance our understanding of how climate is affecting vegetation, considering the impact on the five land cover types: forest, cropland, grassland, savanna, and shrubland.

We conducted an analysis on the linear correlation between the indices SPI, SPEI, EDDI, and SSI over time periods of 1, 3, 6, 12, 24, and 36 months with zcNDVI. We used a method similar to that used by Meroni et al. (2017) which compared the SPI time-scales with the cumulative fAPAR (fraction of Absorbed Photosynthetically Active Radiation). We performed a pixel-to-pixel linear correlation analysis for each index within the persistent mask of land cover macroclasses. We first compute the Pearson coefficient of correlation for each of the six time scales. A time scale is identified as the one that attains the highest correlation (p < 0.05). We then extracted the Pearson correlation coefficient corresponding to the time scales where the value peaked. As a result, for each index, we generated two raster maps: 1) containing the raster with values of the time scales and drought index that reached the maximum correlation, and 2) having the magnitude of the correlation obtained by the drought index at the time scales.

## 3.5 Software

For the downloading, processing, and analysis of the spatio-temporal data, we used the open source software for statistical computing and graphics, R (R Core Team 2023). For downloading ERA5L, we used the {ecmwfr} package (Hufkens, Stauffer, and Campitelli 2019). For processing raster data, we used {terra} (Hijmans 2023) and {stars} (Pebesma and Bivand 2023). For managing vectorial data, we used {sf} (Pebesma 2018). For the calculation of AED, we used {SPEI} (Beguería and Vicente-Serrano 2023). For mapping, we use {tmap} (Tennekes 2018). For data analysis and visualization, the suite {tidyverse} (Wickham et al. 2019) was used. For the random forest modeling, we used the {tidymodels}(Kuhn and Wickham 2020) and {ranger}(Wright and Ziegler 2017) packages.

# 4. Results

## 4.1 Short- to long-term drought trends

[Figure 2](#fig-trendDI) shows the spatial variation of the trend for the drought indices from short- to long-term scales. The white space on the maps indicates a not significant trend. SPI and SPEI have a decreasing trend from “Norte Chico” to “Sur.” However, there is an increasing trend in “Austral.” The degree of the trend is stronger at higher time scales. The SSI indicates that in “Norte Grande,” there are surfaces that have increased in the southwest and in the northeast have decreased, and are shown for all time scales. Similar to SPI and SPEI, SSI decreases at higher time scales. EDDI showed a positive trend for the whole of continental Chile, with a higher trend toward the north and a descending gradient toward the south. The degree of trend increases at higher time scales.

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| |  |  |  |  | | --- | --- | --- | --- | | |  | | --- | | (a) SPI (Standardized Precipitation Index) | | |  | | --- | | (b) SPEI (Standardized Precipitation Evapotranspiration Index) | |  |  |  | | --- | --- | | |  | | --- | | (c) EDDI (Evaporative Demand Drought Index) | |   Figure 2: Linear trend of the drought index (\*) at time scales of 1, 3, 6, 12, 24, and 36 months for 1981-2023 |

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| Figure 3: Trend per decade for the drought indices SPI, EDDI, SPEI, and SSI aggregated by macrozone. |

The [Figure 3](#fig-trendDIMacro) displays the averaged aggregation per macrozone, the drought index, and the timescale. The macrozones that reached the lowest trend for SPI, SPEI, and SSI are “Norte Chico” and “Centro,” where the indices also decrease at longer time scales. This may potentially be explained by the prolonged reduction in precipitation that has affected the hydrological system in Chile. At 36 months, it reaches trends between -0.03 and -0.04 (z-score) per decade for SPI, SPEI, and SSI. For “Sur,” the behavior is similar, decreasing at longer scales and having between -0.016 and -0.025 per decade for SPI, SPEI, and SSI. “Norte Grande” has the highest trend at 36 months for EDDI (0.042 per decade), and “Centro” has the lowest for SPI and SPEI. In “Norte Grande” and “Norte Chico,” which are in a semi-arid climate, it is evident that the EDDI has an effect on the difference between the SPI and SPEI index, which is not seen in the other macrozones. Contrary to the other macrozones, “Austral” showed an increase in all indices, being the highest for EDDI at 36 months (0.025) and the lowest for SSI, which shows only a minor increase in the trend.

## 4.2 Interaction of land cover and drought

### 4.2.1 Land cover change

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| Figure 4: Proportion of land cover class from the persistent land cover for 2001-2022 (>80%) per macrozone and land cover macroclass. |

For vegetation, we obtained and used hereafter five macroclasses of land cover from IGBP MODIS: forest, shrubland, savanna, grassland, and croplands. [Figure 1](#fig-studyArea)c shows the spatial distribution of the macroclasses through Chile for the year 2022. [Figure 1](#fig-studyArea)d shows the macroclasses of land cover persistence (80%) during 2021–2022, respectively (Table ). Within continental Chile, barren land is the land cover class with the highest surface area (277,870 ). The largest type of vegetation, with 137,085 , is forest. Grassland has 74,247 , savanna 55,206 , shrubland 25,341 , and cropland 3,146 (Table ). The macrozones with major changes for 2001–2022 were “Centro,” “Sur,” and “Austral,” with 36%, 31%, and 34% of their surface changing the type of land cover, respectively ([Figure 1](#fig-studyArea) and Table ). [Figure 4](#fig-LCprop) shows the summary of the proportion of surface per land cover class and macrozone, derived from the persistence mask over continental Chile.

From the trend analysis in Table , we can indicate that the “Norte Chico” shows an increase in barren land of 111 and a reduction in the class savanna of 70 . In the “Centro” and “Sur,” there are changes with an important reduction in savanna with 136 and 319 , respectively, and an increase in shrubland and grassland, showing a change for more dense vegetation types. The area under cultivation (croplands) appears to be shifting from the “Centro” to the “Sur.” Also, there is a high increase in forest (397 ) in the “Sur,” seemingly replacing the savanna lost (Table ).

### 4.2.2 Relationship between drought indices and land cover change

The random forest models for estimating the land cover trend based on the trends in drought indices reach an between 0.32 and 0.39 for the land cover types (Table ) excluding cropland. It is more likely that short- and medium-term increases in AED (EDDI-6 and EDDI-12) and short-term precipitation deficits (SPI-6 and SPEI-6) are associated to changes in grassland and bare land. The short-term increase of AED (EDDI-3 and EDDI-6) and the longer duration of the precipitation deficit (SPI-24, SPI-36, and SPEI-36) were the most important variables that correlated with changes in shrubland. The changes in savanna are associated with a short- and long-term increase in AED and a three-year precipitation deficit (SPI-36). The increase in cumulative AED from 12 to 36 months is the strongest associated variable that contributes to changes in forests, followed by the reduction of soil moisture over six and 36 months. The supplementary material in Section S3 provides further details about the variable’s importance.

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| Figure 5: Relationship between the trend in land cover change (y-axis) and the trend in drought indices (x-axis) for the five macrozones. Vertical panels correspond to 1, 3, 6, 12, 24, and 36 months of the time scale by drought index. Horizontal panels show each drought index |

[Figure 5](#fig-TrendsLandDrought) shows the connection between the SPI, EDDI, and SSI drought indices and changes in land cover. Forest in the “Sur,” shrubland and grassland in “Centro,” barren land in “Norte Chico,” and savanna in “Austral” showed an increase in land cover extent, which was associated with an increase in EDDI. Savanna in “Centro,” “Sur,” and “Norte Chico” decreases with the increase in EDDI. The SPI and SSI showed similar behavior regarding the trend in land cover type. A decrease in SPI and SSI is associated with an increase in the surface in shrubland and grassland in “Centro,” forest in “Sur,” and barren land in “Norte Chico,” as well as a decrease trend in savanna in “Norte Chico,” “Centro,” and “Sur.”

## 4.3 Drought impacts on vegetation productivity within land cover

### 4.3.1 Trends in vegetation productivity

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| Figure 6: (a) Map of the linear trend of the index zcNDVI for 2000–2023. Greener colors indicate a positive trend; reder colors correspond to a negative trend and a decrease in vegetation productivity. Grey colors indicate either no vegetation or a change in land cover type for 2001–2022. (b) Temporal variation of zcNDVI aggregated at macrozone level within continental Chile. Each horizontal panel corresponds to a macrozone from ‘Norte Grande’ to ‘Austral’. |

The temporal variation within the macrozones is shown in [Figure 6](#fig-zcNDVI_var)b. There is a negative trend in “Norte Chico” with -0.035 and “Centro” with -0.02 per decade. Vegetation reached its lowest values for 2019-2022, with an extreme condition in early 2020 and 2022 in the “Norte Chico” and “Centro”. The “Sur” and “Austral” show a positive trend of around 0.012 and 0.016, respectively, per decade ([Figure 6](#fig-zcNDVI_var)).

In [Figure 6](#fig-zcNDVI_var) it is showed the spatial map of trends in zcNDVI ([Figure 6](#fig-zcNDVI_var)a). In “Norte Grande,” vegetation productivity, as per the z-index, exhibits a yearly increase of 0.027 for grassland and 0.032 for shrubland. In the “Norte Chico,” savanna has the lowest trend of -0.062, cropland -0.047, shrubland -0.042, and grassland -0.037. In “Centro,” shrubland reaches -0.07, savanna -0.031, cropland -0.024, forest -0.017, and grassland -0.005 per decade. This decrease in productivity could be associated either with a reduction in vegetation surface, a decrease in biomass, or browning.

### 4.3.2 Correlation between vegetation productivity and drought indices

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| Figure 7: Time scales per drought index that reach the maximum coefficient of determination. White spaces indicate no significant correlation. |

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| Figure 8: Pearson correlation value for the time scales and drought index that reach the maximum coefficient of determination. White spaces indicate no significant correlation. |

[Figure 7](#fig-corTimeScale) shows the highest coefficient of determination (r-squared, or rsq) found in the regression analysis between zcNDVI and different drought indicators over time scales of 1, 3, 6, 12, 24, and 36 months. The spatial variation of time scales reached per index is mostly for time scales above 12 months. In the case of SSI, the predominant scales are 6 and 12 months. For all indices, to the north, the time scales are higher and diminish toward the south until the south part of “Austral,” where they increase. In [Figure 8](#fig-corPerson), the map of Pearson correlation values (r) is shown. The EDDI reached correlations above 0.5 between “Norte Chico” and “Sur.” The correlation changes from negative to positive toward the Andes Mountains and to the sea, just as in the northern part of “Austral.” The SPI and SPEI have similar results, with the higher values in “Norte Chico” and “Centro” being higher than 0.6. Following a similar spatial pattern as EDDI but with an opposite sign. The SSI showed to be the index that has a major spatial extension with a higher correlation. It has a similar correlation to SPI and SPEI for “Norte Chico” and “Sur,” but has improvements for “Sur.”

In Table , we aggregate per macrozone and land cover the correlation analysis presented in [Figure 7](#fig-corTimeScale) and [Figure 8](#fig-corPerson). According to what is shown, forests seem to be the most resistant to drought. Showing that only “Centro” is slightly (rsq = 0.25) impacted by a 12-month soil moisture deficit (SSI-12). In the “Norte Chico” and to a lesser extent in the “Norte Grande,” it is evident that a SSI-12 with a rsq = 0.45 and a decrease in water supply (SPI-36 and SPEI-24 with rsq = 0.28 and 0.34, respectively) have an impact on grasslands. However, this type was unaffected by soil moisture, water supply, or demand in macrozones further south. The types that show to be most affected by variation in climate conditions are shrublands, savannas, and croplands. For savannas in “Norte Chico,” the SSI-12 and SPI-24 reached an rsq of 0.74 and 0.58, respectively. This value decreases to the south, but the SSI-12 is still the variable explaining more of the variation in vegetation productivity (rsq = 0.45 in “Centro” and 0.2 in “Sur”). In the case of croplands, the SPEI-12, SPI-36, and SSI-12 explain between 45% and 66% of the variability in “Norte Chico.” The type of land most impacted by climatic variation was shrubland, where soil moisture explained 59% and precipitation, 37%, in “Norte Chico” and “Centro,” with SSI-12 being the most relevant variable, then SPI-36 in “Norte Chico” and SPI-24 in “Sur.”

# 5. Discussion

## 5.1 Vegetation water demand and its relation to drought

In our study, we took into account the variation in vegetation productivity in Chile, specifically in areas without any changes in land cover, to prevent any misleading conclusions about the increase in water demand due to land cover change. Our results show a contrasting perspective regarding the evidence provided by Vicente-Serrano et al. (2022) on a global scale, who indicates that the increase in drought is led by an increase in agricultural land, which in turn increases water demand.

Our results indicate that except for the southern part of the country, the SPI, SPEI, and SSI (water supply) showed declining trends, while the EDDI (water demand) increased across continental Chile. The trends in water demand and supply were stronger as the time scales increased, indicating a long-term reduction in water supply (except for the southern part) and an increase in water demand by the atmosphere. Also, we found that there has been a significant declining trend in vegetation productivity (zcNDVI) since 2000 for the north-central part of the country, which reached its lowest level between 2020 and 2022 and has impacted natural and cultivated land. Further, croplands showed a decrease in surface area for the north-central region, while barren land increased. We link these changes to a decrease in the water demand from vegetation because, despite the increase in AED, the surface area for water-demanding vegetation is declining as well as the biomass production. However, some questions arise regarding what is occurring with the cultivated land. Evidence suggests that higher-water-demanding crops have replaced croplands in the Petorca basin (central Chile), leading to an increase in water abstraction (Muñoz et al. 2020; Duran-Llacer et al. 2020). Nonetheless, at this scale of analysis, the effect of higher crop water demand on drought is minor compared to the decrease in water supply and increase in AED over all land cover types.

The long-scale trends (e.g., 36 months) demonstrate the impact of human-induced climate change on water availability in Chile, potentially due to an intense hydrological drought stemming from the ongoing precipitation deficit and rising AED. But it is likely that in zones most affected by drought, the main cause is not an increase in vegetation water demand due to an intensification of cultivated land (e.g., an increase in irrigated crops) like in other parts of the globe (Vicente‐Serrano et al. 2020). North-central Chile has experienced a decline in vegetation productivity across land cover types, which is primarily attributable to variations in water supply and soil moisture. An increase in water demand, led by an increase in the surface area of irrigated crops or the change to more water-demanding crops, could strengthen this trend, however, it escapes the scope of this study. Future work should focus on the regions where the drought has been more severe and has a high proportion of irrigated crops to get insight on the real impact of irrigation on ecosystems in those zones.

## 5.2 Sensitivity of land cover vegetation to short- and long-term drought

We analyzed the time series of drought indices and vegetation productivity per land cover type. Our results indicate that forest is the type most resistant to drought, and shrublands, savannas, and croplands have higher sensitivity.

In their study in the Yangtze River Basin in China, Jiang et al. (2020) analyzed the impact of drought on vegetation using the SPEI and the Enhanced Vegetation Index (EVI). They found that cropland was more sensitive to drought than grassland, showing that cropland responds strongly to short- and medium-term drought (< SPEI-6). In our case, the SPEI-12 was the one that most impacted the croplands in “Norte Chico” and “Centro.” In general, most studies show that croplands are most sensitive to short-term drought (< SPI-6) (Zambrano et al. 2016; Potopová et al. 2015; Dai et al. 2020; Rhee, Im, and Carbone 2010). Short-term precipitation deficits have an impact on soil water, so less water is available for plant growth. However, we found that in “Norte Chico,” an SPI-36 and SPEI-12 had a higher impact, which are associated with long-term water deficit, and in “Centro,” an SPI-12 and SPEI-12. Thus, we hypothesize that this impact could be attributed to the hydrological drought that has decreased groundwater storage (Taucare et al. 2024), which in turn is impacted by long-term deficits, and consequently, the vegetation is more dependent on groundwater. In “Sur” and “Austral,” the correlations between drought indices and vegetation productivity decrease, as do the time scales that reach the maximum r-squared. The possible reason for this is that the most resistant types, forest and grassland, predominate south of “Centro.” Also, drought episodes have been less frequent and intense and have had a lower impact on water availability for vegetation.

According to Senf et al. (2020), severe drought conditions in Europe are a significant cause of tree mortality. However, we discovered that forests are the most resilient land cover class to drought, with less variation in drought indices. Supporting this is Fathi-Taperasht et al. (2022), who assert that Indian forests are the most drought-resistant and recover rapidly. Similarly, the work of Wu et al. (2024), who analyzed vegetation loss and recovery in response to meteorological drought in the humid subtropical Pearl River basin in China, indicates that forests showed higher drought resistance. Using Vegetation Optical Depth (VOD), kNDVI, and EVI, Xiao et al. (2023) tested the resistance of ecosystems and found that ecosystems with more forests are better able to handle severe droughts than croplands. They attribute the difference to a deeper rooting depth for trees, a higher water storage capacity, and different water use strategies between forest and cropland (Xiao et al. 2023).

In central Chile, A. Venegas-González et al. (2023) observed a significant decline in the overall growth of sclerophyllous moist forests (mediterranean forests), which they attributed to increased drought conditions. In another study, Fuentes et al. (2021) evaluated water scarcity and land cover change in Chile between 29° and 39° south latitude. They used the one-month SPEI for drought evaluation, which resulted in misleading results. For instance, they failed to identify a temporal trend in the SPEI, but they still observed a decline in water availability and a rise in AED, trends that should have been detectable if they were using longer SPEI time scales. Thus, according to the results presented in this study, for the assessment of drought, it is necessary to consider drought indices on a short- to long-scale basis.

## 5.3 Vegetation productivity and drought

We found that the 12-month soil moisture deficit affected plant productivity in all land cover types in Chile. The main external factors that affect biomass production by vegetation are actual evapotranspiration and soil moisture, and the rate of ET in turn depends on the availability of water storage in the root zone. Thus, soil moisture plays a key role in land carbon uptake and, consequently, in the production of biomass (Humphrey et al. 2021). The study results showed that the soil moisture-based drought index (SSI) was better at explaining vegetation productivity across land cover macroclasses than meteorological drought indices like SPI, SPEI, and EDDI. According to (Chatterjee et al. 2022) in the early growing season and especially in irrigated rather than rainfed croplands, soil moisture has better skills than SPI and SPEI for estimating gross primary production (GPP) . Also, Zhou et al. (2021) indicate that the monthly scaled Standardized Water Deficit Index (SWDI) can accurately show the effects of agricultural drought in most of China. Nicolai-Shaw et al. (2017) also looked at the time-lag between the SWDI and the Vegetation Condition Index (VCI). They found that there was little to no time-lag in croplands but a greater time-lag in forests.

In our case, there is strong spatial variability throughout Chile and between classes, mainly attributable to climate heterogeneity, hydrological status, or vegetation resistance to water scarcity. The semi-arid “Norte Chico” and the Mediterranean “Centro” were where SSI had the best performance. In Chile, medium-term deficits of 12 months are more relevant in the response of vegetation for all land cover types, which decreases to the south, and in the case of croplands, they seem to react in a shorter time, with six months (SSI-6) in “Centro.” This variation for croplands could be related to the fact that in “Norte Chico,” the majority of crops are irrigated, but to the south there is a higher proportion of rainfed agriculture, which is most dependent on the short-term availability of water. Rather, in “Norte Chico,” the orchards are more dependent on irrigation, which in turn depends on the availability of storage water in dams of groundwater reservoirs, which are affected by long-term drought (e.g., SPI-36).

## 5.4 Drought information to aid in adaptation

Our findings present valuable information for policymakers in developing adaptation strategies for droughts. Our results show that the different climate components, such as AED, water supply, soil moisture, and their impact on vegetation, should be considered when evaluating the multi-dimensional nature of drought. Also, for a better understanding of drought propagation (A. F. Van Loon, Van Huijgevoort, and Van Lanen 2012) from meteorological to agricultural and ecological drought, we should consider the climatic response at different time scales, ranging from short to long. Additionally, the spatiotemporal characteristics of our results allow us to distinguish distinct geographical contexts, recognizing the diversity in climate, but also shedding light on agricultural practices (ranging from irrigated to dryland farming), technological advancements in irrigation efficiency, and the region-specific capabilities for drought adaptation, including groundwater management and reservoir water storage. This information, combined with agricultural information and statistics, could provide a strong foundation for the development of science-based adaptation policies.

In a commitment to fostering informed and dynamic adaptation efforts, our results are disseminated publicly and continually updated via the Drought Observatory for Agriculture and Biodiversity of Chile (ODES) (<https://odes-chile.org/app/unidades>) (Zambrano 2023b; Kunst and Zambrano 2023). This initiative ensures the availability of extensive climate data, facilitating the development of adaptive strategies that are both responsive to the realities of different regions and grounded in the latest scientific understanding. The proactive sharing and updating of such data underscores its key role in enabling policymakers to craft adaptive measures that are finely tuned to the diverse and evolving landscapes of drought impacts. Furthermore, the recently promulgated law about climate change in Chile (Law 21.455, https://www.bcn.cl/leychile/navegar?idNorma=1177286), which aims to implement sectoral adaptation plans for agriculture, forests, and biodiversity, could benefit from this information.

# 6. Conclusion

We found a significant trend toward decreasing water supply (SPI, SPEI, and SSI) in most of the Chilean territory, with the exception of the southern region. The trend is the strongest in the north-central zone. The whole country showed an increase in water demand (AED) due to increasing temperatures. The magnitude of the trends is stronger for longer time scales, which is evidence that there is a prolonged precipitation shortage and a prolonged increase in AED. The trend in vegetation productivity in the north-central area is affecting shrubland and savanna to a greater degree, followed by croplands and forests.

We model about 20–30% of the trends in land cover types, such as forest, grassland, shrubland, and savanna, based on drought indicators across Chile. There is no evidence that drought alters cropland surface area. The increase in AED is the most important variable explaining the variability in the change in land cover, followed by a reduction in precipitation and soil moisture.

The trends in drought indices are accompanied by multiple land cover changes in the country, most notably an increase of forest in “Sur,” of shrubland and grassland in “Centro,” and of savanna in “Centro” and “Sur.” In “Norte Chico” and “Centro,” the croplands have been declining in surface, whereas in “Sur,” there is an increase in cultivated land.

The change in vegetation productivity has been severe in the north-central part of the country for all land cover types, particularly savanna, shrubland, and croplands. The anomaly in soil moisture over the past 12 months is the main variable explaining these changes, followed by anomalies in accumulated precipitation over one to two years. The variation in AED seems to intensify the drought impact on vegetation productivity.

The results of this study provide insightful information that would assist in developing adaptation measures for Chilean ecosystems to cope with climate change and drought. Information that could be used in the scope of the national law on climate change, which seeks to implement adaptation strategies for agriculture, forests, and biodiversity.

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