The influence of soil moisture drought indices and water supply and demand on vegetation productivity and LULCC in Chile

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Central Chile has been the focus of research studies due to the persistent decrease in water supply, which is impacting the hydrological system and vegetation development. This persistent period of water scarcity has been defined as a megadrought. Our objective is to assess the impact of drought on LULCC (land use land cover change) over continental Chile using drought indices of water supply and demand, soil moisture, and their impact on vegetation productivity. The monthly ERA5-Land (ERA5L) variables for precipitation, temperature, and soil moisture were used. From 2001 to 2022, we used the land cover MODIS product MCD12Q1, and from 2000 to 2023, we used the NDVI (Normalized Difference Vegetation Index) product MOD13A3 collection 6.1. As drought indices, we compute the standardized anomaly of cumulative NDVI (zcNDVI), the Standardized Precipitation Evapotranspiration Index (SPEI), the Evaporative Demand Drought Index (EDDI), and the Standardized Soil Moisture Index (SSI). These indices were calculated for time scales of 1, 3, 6, 12, 24, and 36 months, except for zcNDVI, which was for 6 months. We analyze the trend for LULCC, vegetation productivity, and drought indices. Also, we analyzed the temporal correlation of SPI, SPEI, EDDI, and SSI with zcNDVI to gain insights into the impact of water supply and demand on vegetation productivity. Our results showed that LULCC was highest in “Centro,” “Sur,” and “Austral,” with 36%, 31%, and 34% of change in the surface type, respectively. The EDDI shows that water demand has increased for all zones, with a major increase in “Norte Grande.” The drought indices of water supply and soil moisture evidence a decreasing trend, which decreases at longer time scales, from “Norte Grande” to “Sur.” “Austral” is the only zone that shows an increase in supply. Vegetation productivity measures by zcNDVI present a negative trend in “Norte Chico” and “Centro.” On the other hand, forests seem to be the most resistant to drought. The types that show to be most affected by variation in climate conditions are shrublands, savannas, and croplands. The drought indices that have the capability of explaining to a major degree the variance in vegetation productivity are SSI-12, followed by SPEI-24 and SPEI-12 in “Norte Chico” and “Centro.” The results indicate that “Norte Chico” and “Zona Central” are the most sensitive regions to water supply deficits lasting longer than a year. Our results can help develop a robust vegetation productivity forecasting model for land cover classes in Chile.

# Introduction

The sixth assessment report (AR6) of the IPCC (Calvin et al. 2023) indicates that human-induced greenhouse gas emissions have increased the frequency and/or intensity of some weather and climate extremes, and the evidence has been strengthened since AR5 (IPCC 2013). There is a high degree of confidence that rising temperatures will increase the land area where droughts will occur more frequently and with greater severity (Seneviratne 2021). Even though Vicente-Serrano et al. (2022) analyzed the meterological drought trend, it showed that there is not a substatntial change at the global scale. Also, F. Kogan, Guo, and Yang (2020) indicates that for the main grain-producing countries, drought has not been intensified or extended. Nonetheless, drought increases tree mortality and triggers changes in land cover and, consequently, land use, thus impacting ecosystems (Crausbay et al. 2017). Likewise, there is a lack of understanding of how the alteration in water supply and demand is affecting land cover transformations. Which is of particular interest for Chile due to the megadrought (R. Garreaud et al. 2017)

The primary cause of drought is precipitation, and temperature makes it worse (Luo et al. 2017). Drought impacts soil moisture, hydrological regimes, and vegetation productivity. Initially, drought was commonly classified as meteorological, hydrological, and agricultural (Wilhite and Glantz 1985). Lately, Van Loon et al. (2016) and Amir AghaKouchak et al. (2021) have given an updated definition of drought for the Anthropocene, suggesting that it should be considered the feedback of humans’ decisions and activities that drives the anthropogenic drought. Even though it has been argued that those definitions do not fully address the ecological dimensions of drought, Crausbay et al. (2017) proposed the ecological drought definition 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.”. Moreover, many ecological studies have misinterpreted how to characterize drought, for example, sometimes considering “dry” conditions as “drought” (Slette et al. 2019). On the other hand, the 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. Then, there is a challenge in conducting drought research, especially to evaluate its impact on ecosystems.

Chile has been facing a persistent rainfall deficit for more than a decade (R. Garreaud et al. 2017), which has impacted vegetation development (Zambrano 2023) and the hydrological system (Boisier et al. 2018). Current drought conditions have affected crop productivity (Zambrano et al. 2016, 2018), forest development (Miranda et al. 2020; Alejandro Venegas-González et al. 2018), forest fire occurrence (Urrutia‐Jalabert et al. 2018), land cover change (Fuentes et al. 2021), water supply in watersheds (Alvarez-Garreton et al. 2021), and have had economic impacts (Fernández et al. 2023). In 2019–2020, the drought severity reached an extreme condition in Central Chile (30–34°S) not seen for at least 40 years, and the evidence indicates that the impact is transversal to the land cover classes of forest, grassland, and cropland (Zambrano 2023). The prolonged lack of precipitation in Central Chile is producing changes in ecosystem dynamics that must be studied.

For the spatiotemporal assessment of drought impact (i.e., by water supply and demand) on land cover changes, we need climatic realiable variables such as precipitation, temperature, soil moisture, land cover, and vegetation status. For developing countries like Chile, the weather networks present several disadvantages, such as gaps, a short history, and low-quality data. Reanalysis data, as the ERA5-Land (ERA5L) (Muñoz-Sabater et al. 2021) provides hourly climatic information (precipitation, temperature, and soil moisture) without gaps since 1950 with global extension. ERA5L has already been used for drought assessment using the Standardized Precipitation-Evapotranspiration Index (SPEI) (Nouri 2023) and for flash drought (Wang et al. 2023) by analyzing soil moisture and evapotranspiration. On the other hand, satellite remote sensing (West, Quinn, and Horswell 2019; A. AghaKouchak et al. 2015) is the primary method to evaluate how drought impacts vegetation dynamics. The Moderate-Resolution Imaging Spectroradiometer (MODIS) can be used to get vegetation drought indices (VDI), which are often used as proxies for productivity (Paruelo et al. 2016; Schucknecht et al. 2017). Besides, land use and land cover (LULC) change can be driven by drought (Tran et al. 2019; Akinyemi 2021). To analyze these changes, multiple LULC products exist (Grekousis, Mountrakis, and Kavouras 2015). One of those that provides time series since 2001 is the MCD12Q1 (Friedl and Sulla-Menashe 2019) from MODIS. The variation in water supply and demand is finally reflected in the total water storage (TWS). The Gravity Recovery and Climate Experiment (GRACE), which allows analyzing changes in water availability at coarse resolution, can retrieve the TWS (Ahmed et al. 2014; Ma et al. 2017). We can find drought indices of supply (i.e., precipitation) and demand (i.e., temperature) using climatic reanalysis (ERA5L) and vegetation data (MODIS). This lets us figure out how drought changes LULC. Further, the TWS can be assessed with regard to the changes in water supply and demand to gain insight into the impact on water storage.

To evaluate meteorological drought (i.e., water supply), the World Meteorological Organization (WMO; WMO et al. (2012)) recommends the Standardized Precipitation Index (SPI; (**Mckee1993?**)), a multiscalar drought index that allows to monitor precipitation deficits from short- to long-term. In the same way, Vicente-Serrano, Beguería, and López-Moreno (2010) adds the effect of temperature to the SPI by using atmospheric evaporative demand (AED). The Standardized Precipitation Evapotranspiration Index (SPEI) was established in this manner. In a similar vein, Hobbins et al. (2016) and McEvoy et al. (2016) developed the Evaporative Demand Drought Index (EDDI) to evaluate evaporative demand that is solely dependent on AED. For vegetation, in a similar manner as the SPI, SPEI, and EDDI; Zambrano et al. (2018) proposed the zcNDVI, a standardized anomaly of the cumulative Normalized Difference Vegetation Index (NDVI), which could be acumulated over the growing season or any period (e.g., months), resulting in a multiscalar drought index. For soil moisture, several drought indices exist, such as the Soil Moisture Deficit Index (SDMI) a normalized index (Narasimhan and Srinivasan 2005) and the Soil Moisture Agricultural Drought Index (SMADI) (Souza, Ribeiro Neto, and Souza 2021) which is a normalized index using vegetation, land surface temperature, and a vegetation condition index (VCI, (F. N. Kogan 1995)). Thereby, today we have drought indices for water supply and demand, which can help to make a comprehensive assessment of drought and help to forecast it.

In this research, we aim to analyze the impact of drought on different types of ecosystems (land cover classes) in continental Chile. Our specific goals are: i) to analyze the trend on multi-scalar drought indices for water demand and supply, soil moisture, and vegetation productivity for 1981–2023; ii) to assess the LULC change for 2001–2022 and how it relates to drought indices; and iii) to evaluate the relationship between vegetation productivity and drought indices for water demand and supply and soil moisture.

# Study area

Continetal Chile has a diverse climate condition from north to south and east to west (Aceituno et al. 2021) ([Figure 1](#fig-studyArea)), which determines its great ecosystem diversity ([Figure 2](#fig-LCprop)). The Andes Mountains are a main factor in latitudinal variation (R. D. Garreaud 2009). To describe the climate and ecosystem of Chile, we use the Koppen-Geiger release by Beck et al. (2023) and the land cover type persistance of 80% of times for 2001–2022, from the IGBP classification scheme (Friedl and Sulla-Menashe 2019) (see [Section 3.4](#sec-methods_lulc)). “Norte Grande” and “Norte Chico” 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). Mainly, the land is barren, with a minor surface of vegetation types such as shrubland and grassland. In the zones “Centro” and the north half of “Sur,” the main climate is Mediterranean, with warmer to hot summers (Csa and Csb). There is a significant amount (50%) of Chilean matorral (shrubland and savanna, (Fuentes et al. 2021)), then grassland (16%), forest (8%), and croplands (5%), in “Centro.” An oceanic climate (Cfb) predominates in the south of “Sur” and the north of “Austral.” Those zones are high in forest and grassland. The southern part of the country has a tundra climate, and in Patagonia, 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 |

# Materials and Methods

## Software and packages used

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, the suite {tidyverse} (Wickham et al. 2019) was used.

## Data

### Earth observation data

For water supply and demand variables, we used ERA5L (Muñoz-Sabater et al. 2021), a reanalys dataset that provides the evolution of land variables since 1950. It has a spatial resolution of 0.1°, hourly frequency, and global coverage. We selected the variables for total precipitation, 2 meter temperature maximum and minimum, and volumetric soil water layers between 0 and 100cm of depth (layer 1 to layer 3). The data was downloaded using the Copernicus Climate Data Store (CDS) Application Program Interface (API) implemented in {ecmfwr} (Hufkens, Stauffer, and Campitelli 2019).

To derive a proxy for vegetation productivity, we used the product MOD13A3 collection 6.1 from MODIS (Didan 2015). It provides vegetation indices (NDVI and EVI) at 1km of spatial resolution and monthly frequency. The MOD13A3.061 and MCD12Q1.061 were retrieved from the online Data Pool, courtesy of the NASA EOSDIS Land Processes Distributed Active Archive Center (LP DAAC), USGS Earth Resources Observation and Science (EROS) Center, Sioux Falls, South Dakota, https://lpdaa.usgs.gov/tools/data-pool/.

### Weather stations

We compared the ERA5L variables for monthly mean temperature, total precipitation, and volumetric soil water content against values retrieved by weather stations. For temperature and precipitation, we used the weather network from the Ministry of Agriculture of Chile (www.agromet.com) between 2015 and 2023. We used 277 stations located throughout Chile. For soil moisture, we select a private soil network that is owned by the agricultural enterprise Garces Fruit, which has 99 stations in Central Chile, located in cherry fruit crops. The sensors are installed at 30, 60, and 90m and are the model Teros 12 from MeterGroup. To avoid the effect of irrigation on soil moisture, which ERA5L hardly captures, we used daily data for the year 2022 and the months outside the growing season, May to September.

### Validation of ERA5L variables

To account for the performance of the ERA5L climatic variables regarding the values measured by the weather stations. We selected the following metrics:

: mean absolute error : bias : unbiassed root mean squared error : coefficient of correlation : value of the variable measure by the weather station : value of the variable measure by ERA5L

## Drought Indices

### Atmospheric Evaporative Demand (AED)

For the indices EDDI and SPEI that use water demand, first we have to calculate the AED. For this, we used the method of Hargreaves (George H. Hargreaves 1994; George H. Hargreaves and Samani 1985):

where is extraterrestrial radiation; , , and are mean, maximum, and minimum temperature . We calculate the centroid coordinates per pixel and use the latitude to estimate .

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 when the use of several climatic variables is limited (Vicente-Serrano et al. 2014).

### Non-parametric calculation of drought indices

We derived the drought indices of water supply and demand, soil moisture from the ERA5L dataset, and vegetation from the MODIS product, all at monthly frequency.

To evaluate water demand, we chose the (Hobbins et al. 2016; McEvoy et al. 2016) index, which uses the . We used the SPI (**Mckee1993?**), a drought monitoring index that the World Meteorological Organization (WMO) recommends. We calculated the SPEI, which used a balance between and , in this case, an auxiliary variable is used. In this study, we used the (standardized soil moisture index at 1 m) (Hao and AghaKouchak 2013; A. AghaKouchak 2014), which uses soil moisture at 1m depth. Finally, for the proxy of productivity, , we used the NDVI. Before using the NDVI, it was smoothed using a locally weighted polynomial regression, following the procedure described in Zambrano et al. (2018) and Zambrano et al. (2016).

All the indices are multi-scalar and were calculated for time scales of 1, 3, 6, 12, 24, and 36 months, except for zcNDVI, which was calculated for 6 months. The goal is to be able to evaluate short- and long-term droughts in water demand and supply and soil moisture. This is particularly important for central Chile because it has suffered from a prolonged decrease in precipitation for more than 12 years (René D. Garreaud et al. 2020; Boisier et al. 2018; R. Garreaud et al. 2017).

To calculate the drought indices, first we must calculate the accumulation of the variable. In this case, for generalization purposes, we will use , referring to , , , , and (Table ). We cumulated each over the time series of values, and for the time scales :

It corresponds to a moving window (convolution) that sums the variable for starting for the last month until the month, which could sum for months (n-s+1). Once the variable is cumulated over time for the scale , we used a nonparametric approach following Hobbins et al. (2016) to derive the drought indices. Thus, the empirically derived probabilities are obtained through an inverse normal approximation (Abramowitz and Stegun 1968). 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 . The values for the constats are: , , , , , and . For , W= , and for , replace with and reverse the sign of .

## LULC change for 2001-2022 and its relation with water supply and demand, and soil moisture

### Land cover macroclasess and validation

To analyze the LULCC, we use the IGBP scheme from the MCD12Q1 collection 6.1 from MODIS. This product has a yearly frequency from 2001 to 2022. The IGBP defines 17 classes; from these, we regrouped into ten macroclasses, as follows: classes 1-4 to forest, 5-7 to schrublands, 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 classes for 2001 and 2023.

To validate the land cover obtained, we compare the macroclasses with the ones of a more detailed land cover map made by Zhao et al. (2016) for Chile with samples acquired in the years 2013–2014 (LCChile). The later has a spatial resolution of 30 m and three levels of defined classes; from those, we used level 1, which fits with the macroclasses land cover. We chose the years 2013 (IGBP2013) and 2014 (IGBP2014) from land cover macrolcasses to validate with LCChile.

We follow the next procedure:

1. resampled LCChile to the spatial resolution (500m) of the land cover macroclasses using the nearest neighbor method,
2. took a random sample of 1000 points within continental Chile and extracted the classes that fell within each point for LCChile, IGBP2013, and IGBP2014; we considered the point extracted from LCChile as the truth and the values from the other two years as predictions.
3. calculate a confusion matrix with the classes extracted from the 1000 points for LCChile, IGBP2013, and IGBP2014. Calculate the performance metrics of accuracy and F1.

where and refer to true positive and false negative, correctly classified classes; and to true negative and false positive, wrongly classified classes.

### Land cover persistence mask 2001-2022

Climate, vegetation development, seasonality, and changes in vegetation type all have an impact on the time series of NDVI. In this study, we want to examine the variation in vegetation productivity across various land cover types and how water demand, water supply, and soil moisture affect it. In order to avoid changes due to a change in the land cover type that will wrongly impact NDVI, we will develop a persistence mask for land cover for 2001–2023. Thereby, we reduce an important source of variation on a regional scale.

Therefore, we generated a raster mask for IGBP MODIS per pixel using macroclasses that remain constant for at least 80% of the years (2001–2022). This enables us to identify regions where the land cover of the macroclasses has remained constant.

### Land cover trend and drought indices

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; we used the Sen’ slope (Sen 1968) based on Mann-Kendall (Kendall 1975). This way, we obtain a matrix of trends of 5 x 5 (macrozones x land cover). The aim is to later explore if the trend in land cover classes is associated with a trend in the drought indices. For this, we will use the techniques of regresion and regularization of Lasso (Tibshirani et al. 2010) and Ridge (Hoerl and Kennard 1970). Also, we will test random forests for this purpose (Ho 1995). We will choose the trend of land cover surface per macroclass and macrozone as the response variable and the trend of the drought indices (SPI, SPEI, EDDI, and SSI for time scales 1, 3, 6, 12, 24, and 36 months) as the predictor variables. With this analysis, we expect to gather insights regarding whether there is a pattern of climatic influence along Chile or if what is happening in Central Chile has to do with more localized climatic conditions.

## Trend of drought indices for water demand and supply, soil moisture, and vegetation productivity

### Mann-Kendall and Sen’s slope

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 as regular regression does, and it is a non-paramteric method that is not affected by the distribution of the data. We applied both to the six time scales from 1981 to 2023 (monthly frequency) and the indices SPI, EDDI, SPEI, and SSI. In the case of zcNDVI (six months) was for 2000 to 2023. Thus, we have 31 trends. Also, we extracted the trend aggregated by macrozone and land cover class, obtaining a table of 31x5x5 (drought indices trends x macrozone x land cover class). We will use this data in [Section 3.4](#sec-methods_lulc) to analyze if there is a strong relationship between the trends of drought indices and land cover surface within continental Chile.

### Trend in vegetation productivity without land cover change

Vicente-Serrano et al. (2022) made a global analysis of the drought’s severity trend using SPI, SPEI, and the Standardized Evapotranspiration Deficit Index (SEDI; Vicente-Serrano et al. (2018)) to evaluate AED. They indicate that the increase in hydrological drought has been due to anthropogenic effects rather than climate change. This is because the global increase in AED did not explain the change in the spatial pattern of the hydrological drought. Also, they state that *“the increase in hydrological droughts has been primarily observed in regions with high water demand and land cover change”*. We will contrast this hypothesis with what is occurring in Chile. To achieve this, we will use the land cover class type that remains more than 80% of types for 2001–2022 to evaluate the trend on zcNDVI and use this as a mask where there are low changes.

## Impact for water supply and demand, and soil moisture in vegetation productivity within land cover types

We analyze the drought indices of water demand and supply and soil moisture against vegetation to address: i) if short- or long-term time scales are most important in impacting vegetation through Chile; and ii) the strength of the correlation for the variable and the time scale. Then, we will summarize for each land cover class and macrozone. Thus, we will be able to advance in understanding how climate is affecting vegetation, considering the impact on the five macroclasses of vegetation: forest, cropland, grassland, savanna, and shrubland.

An analysis is conducted on the linear correlation between the indices SPI, SPEI, EDDI, and SSI over time periods of 1, 3, 6, 12, 24, and 36 months, and zcNDVI. The objective is to determine the impact of soil moisture and water demand and supply on vegetation productivity. We implemented a methodology similar to that of Meroni et al. (2017) when comparing the SPI for meteorological drought to the cumulative FAPAR (Fraction of Absorbed Photosynthetically Active Radiation), which served as an indicator for vegetation productivity. A pixel-to-pixel linear correlation analysis was performed for each index. To begin, the Pearson coefficient of correlation is computed for each of the six time scales. A significant time scale is identified as the one that attains the highest correlation (p < 0.05). Subsequently, the Pearson correlation coefficient corresponding to the time scales at which the value peaked was extracted. As a result, for each index, we generated two raster maps: one containing the time scales and the other the correlation value.

# Results

## Data

### Validation of ERA5L variables

The average metrics of performance of ERA5L over the 266 weather stations were in the case of monthly temperature: , , and , showing a good agreement, low error, and low overestimation. For cumulative monthly precipitation, , , and , showing a high correlation and a 93% bias and being overestimated by ERA5L. In the case of the 97 soil moisture stations, we averaged for the three depths (30, 60, and 90m) and then compared it with volumetric water content at 1m derived from ERA5L. For this case, we made a daily comparison, having a , , , and . The ERA5 soil moisture overestimate is 74%, but it has a kind of good correlation. For more detailed information, consult the supplementary material (SSX).

## LULC change for 2001-2022 and its relation with water supply and demand, and soil moisture

### Land cover macroclasess and validation

For vegetation, we obtained and use 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. The validation of IGBP2013 and IGBP2014 with LCChile reached near the same metrics of performance, having an accuracy of ~0.82 and a F1 score of ~0.66 (see SS1).

### Land cover persistence mask 2001-2022

[Figure 1](#fig-studyArea) d, shows the macroclasses of land cover persistance (80%) during 2021-2022, respectively (). Within continental Chile, forest is the vegetation type with the highest surface area at 135,00 , followed by grassland (73,176 ), savanna (54,410 ), shrubland (24,959 ), and cropland (3,100 ) (Table ). The macrozones with major LULCC for 2001–2022 were “Centro,” “Sur,” and “Austral” with 36%, 31%, and 34%, respectively ([Figure 1](#fig-studyArea) and Table ); of its surface that changes the type of land cover. [Figure 2](#fig-LCprop) shows the summary of the proportion of surface per land cover class and macrozone, derived from the persistance mask over continental Chile.

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| Figure 2: Proportion of land cover class from the persistent land cover for 2001-2022 (>80%) per macrozone |

### Land cover trend and drought indices

The “Norte Chico” shows an increase in barrend land of 111 and a reduction in the class savanna of 70 . In the “Centro” and “Sur,” there are changes in the Chilean matorral, with an important reduction in savanna (136 to 318 ), and an increase in shrubland and grassland. Showing a change for more dense vegetation types. It appears to be a shift in the area of cropland from the “Centro” to the “Sur.” Also, there is a high increase in forest (397 ) in the “Sur,” replacing the savanna lost.

Further, we want to address whether the trend in land cover change for 2001–2023 is associated with trends in drought indices of water demand and supply and/or soil moisture for macrozone and land cover macroclasses. From the three methods tested, Ridge, Lasso, and Random Forest, neither gives significant results regarding whether the trend in a drought index for any time scale explains the trend in land cover change. Nevertheless, in “Norte Chico” and “Centro,” there is a decrease in croplands and savanna and an increase in barren land, which is associated with the variation in drought indices. Mainly for a decrease in water supply (SPI and SSI) and an increase in water demand (EDDI). However, due to the high variability from north to south in Chile, the climatic conditions (arid, semi-arid, and humid), and the land cover type, we believe that only in those zones could the LULCC be driven to some degree by drought.

## Trend of drought indices for water demand and supply, soil moisture, and vegetation productivity

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| Figure 3: (a) Map of the linear trend of the index zcNDVI-6 for 2001–2023. 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-6 aggregated at macrozone level within continental Chile. Each horizontal panel corresponds to a macrozone from ‘Norte Grande’ to ‘Austral’. |

In “Norte Grande,” vegetation productivity, as per the z-index, exhibits a yearly increase of 0.02 in the five land cover macroclasses, with respect to grassland and shrubland categories. There is a negative trend in “Norte Chico” with -0.04 and “Centro” with -0.02 per decade. In the “Norte Chico,” savanna (-0.05) has the lowest trend, and the rest of the types are around -0.04. In “Centro,” shrubland reaches -0.06, grassland -0.05, and croplands and savanna -0.01 per decade. This could be associated either with a reduction in vegetation surface, a decrease in biomass, or browning (Miranda et al. 2023). Vegetation reached its lowest values since the year 2019, reaching an extreme condition in early 2020 and 2022 in the “Norte Chico” and Centro” (Mega Drought). The “Sur” and “Austral” show a positive trend of around 0.016 per decade ([Figure 3](#fig-zcNDVI_var)). Despite the croplands suffering from drought just as badly as the native vegetation in “Norte Chico,” the Chilean matorral (Fuentes et al. 2021) appears to be the region most affected by a negative trend in vegetation productivity.

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| Figure 4: Trend per decade for the drought indices SPI, EDDI, SPEI, and SSI aggregated by macrozone. |

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| |  |  |  |  | | --- | --- | --- | --- | | |  | | --- | | (a) SPI (Standardized Precipitation Index) | | |  | | --- | | (b) SPEI (Standardized Precipitation Evapotranspiration Index) | |  |  |  |  |  | | --- | --- | --- | --- | | |  | | --- | | (c) EDDI (Evaporative Demand Drought Index) | | |  | | --- | | (d) SSMI (Standardized Soil Moisture Index) | |   Figure 5: Linear trend of the drought index (\*) at time scales of 1, 3, 6, 12, 24, and 36 months for 1981-2023 |

Analyzing the water supply, the macrozones that have the lowest trend are “Norte Chico” and “Centro,” where the SPI, SPEI, and SSI show that it decreases at longer time scales due to the prolonged reduction in precipitation. At 36 months, it reaches trends between -0.03 and -0.04 (z-score) per decade for SPI, SPEI, and SSI ([Figure 5](#fig-trendDI)). 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. On the other hand, all macrozones show an increase in the trend in all the drought indices, with “Norte Grande” having the highest at 36 months (0.042 per decade). Because of this, the SPEI (which uses AED) reached its lowest value in “Norte Grande,” with -0.03 at 36 months. Despite 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 ([Figure 5](#fig-trendDI) and [Figure 4](#fig-trendDIMacro)).

## Impact for water supply and demand, and soil moisture in vegetation productivity

According to what is shown in [Figure 6](#fig-corTimeScale), [Figure 7](#fig-corPerson), and Table , forest seems to be the most resistant type 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 “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.”

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| --- |
| Figure 6: Time scales per drought index that reach the maximum coefficient of determination |

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| Figure 7: Pearson correlation value for the time scales and drought index that reach the maximum coefficient of determination |

# Discussion

## Drought trend and attribution to LULCC

Vicente-Serrano et al. (2022), in a study at the global scale of drought trends, indicates that there have not been significant trends in meteorological drought since 1950. Also, state that the increase in hidrological trend in some parts of the globe (northeast Brazil and the Mediterranean region) is related to changes in land cover and specifically to the rapidly increasing irrigated area, which consequently increases water extraction. F. Kogan, Guo, and Yang (2020) analyzed the agricultural drought impact globally and in the main grain producer countries, finding that *“since 1980, the Earth warming has not changed the drought area or intensity”*.

In our study, we considered the variation in vegetation productivity in Chile for areas without changes in land cover macroclasses (see [Section 4.2.2](#sec-persistence_mask)), to avoid misleading conclusions that could be related to the increase in water demand due to LULCC. Our results show a contrasting perspective. There has been a significant trend in the decline of vegetation productivity (zcNDVI) since 2000 for “Norte Chico” and “Centro,” which has been extreme between 2020 and 2022, seemsly due to an intense hydrological drought due to the persistance of the Mega Drought (R. Garreaud et al. 2017). Despite using the persistance mask for vegetation’s trend analysis, cropland, which is the most water-demand type, showed a decrease trend in “Norte Chico” and “Centro.” Also, there was an increase in barren land for both types. These changes are associated with a decrease in water demand from vegetation. Nonetheless, we used the persistant land cover to ensure that the pixel has the same class; in the case of croplands, it could happen that some areas had changed crops for others with higher water consumption. But this effect should be minor compared to the results from ladcover macroclasses.

On the other hand, for “Norte Chico” and “Centro,” our results show a decrease in trends of water supply (SPI and SSI), which are higher at larger time scales and consequently impact the hydrological system. We claim that what occurred in central Chile defies findings made at the global level (Vicente-Serrano et al. 2022; F. Kogan, Guo, and Yang 2020), demonstrating that a constant decrease in water supply rather than an increase in water demand (i.e., irrigated crops) is the main cause of the hydrological drought. Finally, central Chile has shown a diminishment in vegetation productivity for all macroclasses, mainly attributed to variation in water supply, i.e., precipitation, which could be strengthened by an increase in water demand by, for example, an increase in the surface area of irrigated crops.

## Land cover types and their impact by drought

We found that shrubland, savannas (Chilean matorral), and croplands are the most sensitive to climate conditions. Being most affected by the 12-month soil moisture deficit. In a study in the Yangtze River Basin in China, Jiang2020 analyzed the impact of drought on vegetation using the SPEI and the Enahanced Vegetation Index (EVI). They found that cropland was more sensitive to drought than cropland, 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 impact soil water, and thus 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 hydrological drought (long-term), and in “Centro,” an SPI-12 and SPEI-12. Thus, we attribute this impact 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 (). What can be explained is that, south of “Centro,” predominate forest and grassland, the most resistant types. Also, drought episodes have been less frequent and intense. The drought episodes have had a lower impact on water availability for vegetation.

Extreme drought conditions are an important driver of tree mortality, as shown by Senf et al. (2020) in Europe. However, we found that forest is the type of land cover macroclass less affected by variation in drought indices, being the most resistant land cover class to drought. Supporting this is Fathi-Taperasht et al. (2022), who asserts 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), tests the resistance of ecosystems and finds that ecosystems with more forests are better able to handle severe droughts than croplands. They attribute the difference to a deeper rooting depth of trees, a higher water storage capacity, and different water use strategies between forest and cropland (Xiao et al. 2023).

In contrast to what we obtained, A. Venegas-González et al. (2023), who studied Cryptocarya alba and Beilschmiedia miersii (both from the Lauraceae family) that live in sclerophyllous forests in Chile, found that the trees’ overall growth had slowed down. This could mean that the natural dynamics of their forests have changed. They attributed it to the cumulative effects of the unprecedented drought (i.e., hydrological drought). Thus, we attribute that forest to being the most resistant to drought, due to the fact that most of the species comprising it are highly resilient to water scarcity compared to the other land cover classes. Nonetheless, if we want to go deep in our analysis, we should use earth observation data that is able to capture a higher level of detail. For example, when we used MOD13A3 with a 1km spatial resolution to measure vegetation condition, it took the average condition of 1 square kilometer. Then, to study how a type of forest (e.g., sclerophyllous forest) changes in response to drought on a local level using remote sensing, we should use operational products with higher spatial resolutions, such as those from Landsat or Sentinel.

## Soil moisture, vegetation productivity, and agricultural drought.

The main external factors that affect biomass production by vegetation are ET and SM, 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). Moreover, Zhang et al. (2022) indicates there is a bidirectional causality between soil moisture and vegetation productivity. Lastly, some studies have redefined agricultural drought as soil moisture drought from an hydrological perspective (Van Loon et al. 2016; Samaniego et al. 2018). Even though soil moisture is the external factor most determinant of vegetation biomass, there are multiple internal factors, such as species, physiological characteristics, and plant hydraulics, that would affect vegetation productivity. Because of that, we believe that agricultural drought, referring to the drought that impacts vegetation productivity, is the most proper term, as originally defined by Wilhite and Glantz (1985).

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. 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), according to Chatterjee et al. (2022)’s evaluation of the SPI and SPEI and their correlation with GPP in the CONUS. Also, Zhou et al. (2021) indicates that the monthly scaled Standardized Water Deficit Index (SWDI) can accurately show the effects of agricultural drought in most of China. Complementary, Nicolai-Shaw et al. (2017) analyzed the time-lag between SWDI and the Vegetation Condition Index (VCI), and they state that there was no or little time-lag with croplands but a significant time-lag in the case of 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, 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 the “Norte Chico,” the orchards are more dependent on the storage of water in dams of groundwater reservoirs, which are affected by long-term drought (e.g., SPI-36).

## Early drought forecasting for vegetation productivity

We analyzed the correlation between meteorological and soil moisture drought indices with zcNDVI. From our findings, we could further use the drought indices and time scales that have the highest r-squared to develop a combined model to forecast vegetation productivity in Chile. Despite the fact that SSI was the best-performing index, the rest of the indices should help to enhance predictability. Zambrano et al. (2018) proposed a prediction model for cropland surface in Chile at administrative units with a 1- to 6-month lead time using zcNDVI from MODIS and climate oscilation indices. The results given were r-squared, ranging from 0.95 at a 1-month lead time to 0.37 at a 6-month lead time. Thus, incorporating the results of this study with those made by Zambrano et al. (2018), we could develop a combined forecasting model at the pixel level for the macroclasses in Chile based on drought indices of water demand and supply and soil moisture.

## Future outlook (to complete)

# Conclusion

There is a trend toward decreasing water supply in most parts of Chile, less in the “Austral,” which is stronger in the “Centro” and “Norte Chico.” The whole country showed an increase in water demand. Vegetation productivity only showed a decrease in the “Norte Chico” and “Centro,” being highest for shrubland and croplands. Forest is the land cover most resistant to drought, and shrubland and cropland are the most sensitive.

A soil moisture deficit of 12 months (SSI-12) is highly correlated with vegetation productivity for the land cover classes of shrubland, savannas, croplands, and forest in “Norte Chico” and “Centro.” For the southern part of the country with humid conditions, the correlation with SSI decreases. Soil moisture overcomes the capacity to explain vegetation productivity over the supply and demand drought indices in the entire territory.

The variation in vegetation productivity appears to be associated with climate variation rather than anthropogenic factors (e.g., an increase in water demand by irrigated crops). Even though switching to more demanding crops on the land could increase the impact of drought on vegetation, this would need to be more thoroughly investigated, for instance at the watershed level.

The results of this study could help in the development of a robust forecasting system for land cover classes in Chile., helping to improve preparedness for climate change impacts on vegetation.

# Supplementary material

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