Drought indices of water demand and supply, soil moisture, vegetation, and their impact on LULCC in continental 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 “Mega Drought”. Our objective is to examine the effects of drought on LULCC (land use land cover change) over continental Chile using drought indices of water supply and demand, soil moisture, and vegetation productivity. For the analysis, continental Chile was divided into five zones according to a latitudinal gradient: “Norte Grande,” “Norte Chico,” “Centro,” “Sur,” and “Austral.” 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. We estimated atmospheric evaporative demand (AED) using the Hargreaves-Samani equation with the ERA5L temperature. We used the Standardized Precipitation Index (SPI), the Standardized Precipitation Evapotranspiration Index (SPEI), the Evaporative Demand Drought Index (EDDI), the Standardized Soil Moisture Index (SSI), and the Standardized anomaly of cumulative NDVI (zcNDVI) as drought indicators. 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 were highest in “Centro,” “Sur,” and “Austral,” with 36%, 31%, and 34%, 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.” Showing to be the zones most impacted by climatic conditions, the years 2020 and 2022 suffered the most extreme drought. 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 longer than a year, potentially explained by a low capacity of water storage in those zones that should be further investigated.

# 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). Furthermore, drought increases tree mortality and triggers changes in land cover and, consequently, land use, thus impacting ecosystems (Crausbay et al. 2017). Nevertheless, there is a lack of understanding of how the alteration in water supply and demand is affecting land cover transformations.

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; 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. Following the same approach, Vicente-Serrano, Beguería, and López-Moreno (2010) incorporates into the SPI the effect of temperature through the use of potential evapotranspiration, thus proposing the SPEI (Standardized Precipitation Evapotranspiration Index). Similarly, to evaluate solely the evaporative demand driven by temperature, Hobbins et al. (2016) and McEvoy et al. (2016) came up with the Evaporative Demand Drought Index (EDDI). 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, (Kogan 1995)). From TWS, we can estimate the standardized terrestrial water storage index (STI) (Cui et al. 2021), a standardized anomaly that follows the methodology of the SPI, SPEI, EDDI, and zcNDVI. Thereby, we have drought indices for water supply, demand, and storage, which can help to make a comprehensive assessment of drought.

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 1981–2023/2001–2023; ii) to assess the LULC change for 2001–2021 and how it relates to drought indices; iii) to evaluate the relationship between zcNDVI, a measure of vegetation productivity, and drought indices for water demand and supply and soil moisture; and iv) to assess if the observed changes in the drought indices are linked to TWS.

# 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.” The south part of “Sur” and the north part of “Austral” are dominated by an oceanic climate (Cfb). 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).

## 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 of 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 validated the ERA5L variables for monthly mean temperature, total precipitation, and volumetric soil water content. For temperature and precipitation, we used the weather network from the Ministry of Agriculture of Chile (www.agromet.com). We used 266 stations located throughout Chile. For soil moisture, we select a soil network for water content and temperature, localized in the Aconcagua’s river basin (“Norte Chico”). This network corresponds to 53 sensors of the type Temperature Moisture Sensor (TMS) (**Wild2019?**).

### 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 . For supply, we used the index recommended by the World Meteorological Organization (WMO) for monitoring drought, the SPI (**Mckee1993?**). 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 as the other two years as prediction
3. calculate a confusion matrix with the classes extracted in the 1000 poitns 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

The time series of NDVI is affected by climatic conditions, vegetation development, seasonality, and changes in vegetation type. In this study, we want to analyze the variation in vegetation productivity in different land cover types and how it is affected by water demand, water supply, and soil moisture. 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.

Thus, we calculated a raster mask for IGBP MODIS considering the macroclasses that remain without change for more than 80% of the years (2001–2022) per pixel, which allows us to identify the areas with no land cover change for the macroclasses.

### 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 having vehetation: forest, cropland, grassland, savanna, and shrubland.

To assess how water demand and supply and soil moisture are related to vegetation productivity (zcNDVI), we analyze the linear correlation between the indices SPI, SPEI, EDDI, and SSI for 1, 3, 6, 12, 24, and 36-month time scales against zcNDVI. We followed a similar approach to that used by Meroni et al. (2017) when using the SPI for meteorological drought against the cumulative FAPAR (Fraction of Absorbed Photosynthetically Active Radiation) as a proxy for vegetation productivity. We made a pixel-to-pixel linear correlation analysis per index. First, we calculate the Pearson coefficient of correlation for the six time scales and let the time scale that reaches the maximum correlation be significant (p < 0.05). Then, we extracted the Pearson correlation value corresponding to the time scales that reached the maximum value. Thus, we derived two raster maps per index, the first with the time scales and the second with 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 temperature: , , and . For precipitation, $MAE=28.1\nmm$, , and .

## 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 highest surface with 135,00 , followed by grassland (73,176 ), savanna (54,410 ), shrubland (24,959 ), and cropland (3,100 ) (). 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 condition (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’. |

Regarding vegetation productivity aggregated through the macrozones in the five land cover macroclasses, in “Norte Grande,” there is an increase trend of 0.02 (z-index) per decade, related to types of grassland and shrubland. 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 appears to be the region most affected by a negative trend in vegetation (Fuentes et al. 2021).

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

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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| |  |  |  |  | | --- | --- | --- | --- | | |  | | --- | | (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 |

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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, LULCC, and climate conditions

1.- Respecto a lo que indica Vicente-Serrano et al. (2018), de que el aumento en la tendencia en severidad de la sequía (hidrológica) tiene que ver más con un aumento de la demanda de agua (ej, LULCC, amazonas) que a una tendencia en las condiciones climáticas (SPI-12). ¿Qué pasa en Chile?

## land cover types most impacted by drought throughout Chile

2.- Sobre los tipos de land cover más afectados por los indicadores de sequía. Asociación con el matorral chileno (Fuentes et al. 2021). Diferencia entre el Norte Chico, Centro y lo que pasa hacía el sur (Miranda et al. (2023))

## Drought indices of water demand and supply, soil moisture to predict changes in vegetation productivity

1. Como podrían servir estos resultados para desarrollar o mejorar un predictor de productividad de la vegetación.

* Los datos ERA5L están casi en tiempo real, 7 dias; MODIS también.
* EL SSI se ve como un poderoso indicador que explica la variabilidad en la productividad de la vegetación.

## Future outlook

4.- Qué se podría hacer mejor en futuras investigaciones del tema. - mejorar la resolución y calidad de los datos climáticos -

# Conclusion

# References

Abramowitz, Milton, and Irene A Stegun. 1968. *Handbook of Mathematical Functions with Formulas, Graphs, and Mathematical Tables*. Vol. 55. US Government printing office.

Aceituno, Patricio, Juan Pablo Boisier, René Garreaud, Roberto Rondanelli, and José A. Rutllant. 2021. “Climate and Weather in Chile.” In *Water Resources of Chile*, edited by Bonifacio Fernández and Jorge Gironás, 8:7–29. Cham: Springer International Publishing. <http://link.springer.com/10.1007/978-3-030-56901-3_2>.

AghaKouchak, A. 2014. “A Baseline Probabilistic Drought Forecasting Framework Using Standardized Soil Moisture Index: Application to the 2012 United States Drought.” *Hydrology and Earth System Sciences* 18 (7): 2485–92. <https://doi.org/10.5194/hess-18-2485-2014>.

AghaKouchak, A., A. Farahmand, F. S. Melton, J. Teixeira, M. C. Anderson, B. D. Wardlow, and C. R. Hain. 2015. “Remote Sensing of Drought: Progress, Challenges and Opportunities.” *Reviews of Geophysics* 53 (2): 452–80. <https://doi.org/10.1002/2014RG000456>.

AghaKouchak, Amir, Ali Mirchi, Kaveh Madani, Giuliano Di Baldassarre, Ali Nazemi, Aneseh Alborzi, Hassan Anjileli, et al. 2021. “Anthropogenic Drought: Definition, Challenges, and Opportunities.” *Reviews of Geophysics* 59 (2): e2019RG000683. <https://doi.org/10.1029/2019RG000683>.

Ahmed, Mohamed, Mohamed Sultan, John Wahr, and Eugene Yan. 2014. “The Use of GRACE Data to Monitor Natural and Anthropogenic Induced Variations in Water Availability Across Africa.” *Earth-Science Reviews* 136 (September): 289–300. <https://doi.org/10.1016/J.EARSCIREV.2014.05.009>.

Akinyemi, Felicia O. 2021. “Vegetation Trends, Drought Severity and Land Use-Land Cover Change During the Growing Season in Semi-Arid Contexts.” *Remote Sensing 2021, Vol. 13, Page 836* 13 (5): 836. <https://doi.org/10.3390/RS13050836>.

Alvarez-Garreton, Camila, Juan Pablo Boisier, René Garreaud, Jan Seibert, and Marc Vis. 2021. “Progressive Water Deficits During Multiyear Droughts in Basins with Long Hydrological Memory in Chile.” *Hydrology and Earth System Sciences* 25 (1): 429–46. <https://doi.org/10.5194/hess-25-429-2021>.

Beck, Hylke E., Tim R. McVicar, Noemi Vergopolan, Alexis Berg, Nicholas J. Lutsko, Ambroise Dufour, Zhenzhong Zeng, Xin Jiang, Albert I. J. M. van Dijk, and Diego G. Miralles. 2023. “High-Resolution (1 Km) Köppen-Geiger Maps for 1901–2099 Based on Constrained CMIP6 Projections.” *Scientific Data* 10 (1). <https://doi.org/10.1038/s41597-023-02549-6>.

Beguería, Santiago, and Sergio M. Vicente-Serrano. 2023. *SPEI: Calculation of the Standardized Precipitation-Evapotranspiration Index*. <https://CRAN.R-project.org/package=SPEI>.

Boisier, Juan P., Camila Alvarez-Garreton, Raúl R. Cordero, Alessandro Damiani, Laura Gallardo, René D. Garreaud, Fabrice Lambert, Cinthya Ramallo, Maisa Rojas, and Roberto Rondanelli. 2018. “Anthropogenic Drying in Central-Southern Chile Evidenced by Long-Term Observations and Climate Model Simulations.” *Elementa* 6 (1): 74. <https://doi.org/10.1525/elementa.328>.

Calvin, Katherine, Dipak Dasgupta, Gerhard Krinner, Aditi Mukherji, Peter W. Thorne, Christopher Trisos, José Romero, et al. 2023. “IPCC, 2023: Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, H. Lee and J. Romero (Eds.)]. IPCC, Geneva, Switzerland.” Intergovernmental Panel on Climate Change (IPCC). <https://www.ipcc.ch/report/ar6/syr/>.

Crausbay, Shelley D., Aaron R. Ramirez, Shawn L. Carter, Molly S. Cross, Kimberly R. Hall, Deborah J. Bathke, Julio L. Betancourt, et al. 2017. “Defining Ecological Drought for the Twenty-First Century.” *Bulletin of the American Meteorological Society* 98 (12): 2543–50. <https://doi.org/10.1175/BAMS-D-16-0292.1>.

Cui, Aihong, Jianfeng Li, Qiming Zhou, Ruoxin Zhu, Huizeng Liu, Guofeng Wu, and Qingquan Li. 2021. “Use of a Multiscalar GRACE-Based Standardized Terrestrial Water Storage Index for Assessing Global Hydrological Droughts.” *Journal of Hydrology* 603 (December): 126871. <https://doi.org/10.1016/j.jhydrol.2021.126871>.

Didan, K. 2015. “MOD13Q1 MODIS/Terra Vegetation Indices 16-Day L3 Global 250m SIN Grid V006.” NASA EOSDIS Land Processes DAAC. https://doi.org/<http://dx.doi.org/10.5067/MODIS/MOD13Q1.006>.

Fernández, Francisco J., Felipe Vásquez-Lavín, Roberto D. Ponce, René Garreaud, Francisco Hernández, Oscar Link, Francisco Zambrano, and Michael Hanemann. 2023. “The Economics Impacts of Long-Run Droughts: Challenges, Gaps, and Way Forward.” *Journal of Environmental Management* 344 (October): 118726. <https://doi.org/10.1016/j.jenvman.2023.118726>.

Friedl, M, and D Sulla-Menashe. 2019. “MCD12Q1 MODIS/Terra+Aqua Land Cover Type Yearly L3 Global 500m SIN Grid V006 [Data Set]. NASA EOSDIS Land Processes DAAC.” <https://doi.org/10.5067/MODIS/MCD12Q1.006>.

Fuentes, Ignacio, Rodrigo Fuster, David Avilés, and Willem Vervoort. 2021. “Water Scarcity in Central Chile: The Effect of Climate and Land Cover Changes on Hydrologic Resources.” *Hydrological Sciences Journal* 66 (6): 1028–44. <https://doi.org/10.1080/02626667.2021.1903475>.

Garreaud, R. D. 2009. “The Andes Climate and Weather.” *Advances in Geosciences* 22 (October): 3–11. <https://doi.org/10.5194/adgeo-22-3-2009>.

Garreaud, René D., Juan P. Boisier, Roberto Rondanelli, Aldo Montecinos, Hector H. Sepúlveda, and Daniel Veloso‐Aguila. 2020. “The Central Chile Mega Drought (2010–2018): A Climate Dynamics Perspective.” *International Journal of Climatology* 40 (1): 421–39. <https://doi.org/10.1002/joc.6219>.

Garreaud, René, Camila Alvarez-Garreton, Jonathan Barichivich, Juan Pablo Boisier, Duncan Christie, Mauricio Galleguillos, Carlos LeQuesne, James McPhee, and Mauricio Zambrano-Bigiarini. 2017. “The 2010-2015 Mega Drought in Central Chile: Impacts on Regional Hydroclimate and Vegetation.” *Hydrology and Earth System Sciences Discussions* 2017: 1–37. <https://doi.org/10.5194/hess-2017-191>.

Grekousis, George, Giorgos Mountrakis, and Marinos Kavouras. 2015. “An Overview of 21 Global and 43 Regional Land-Cover Mapping Products.” *International Journal of Remote Sensing* 36 (21): 5309–35. <https://doi.org/10.1080/01431161.2015.1093195>.

Hao, Zengchao, and Amir AghaKouchak. 2013. “Multivariate Standardized Drought Index: A Parametric Multi-Index Model.” *Advances in Water Resources* 57 (July): 12–18. <https://doi.org/10.1016/j.advwatres.2013.03.009>.

Hargreaves, George H. 1994. “Defining and Using Reference Evapotranspiration.” *Journal of Irrigation and Drainage Engineering* 120 (6): 1132–39. <https://doi.org/10.1061/(ASCE)0733-9437(1994)120:6(1132)>.

Hargreaves, George H, and Zohrab A Samani. 1985. “Reference Crop Evapotranspiration from Temperature.” *Applied Engineering in Agriculture* 1 (2): 96–99.

Hijmans, Robert J. 2023. *Terra: Spatial Data Analysis*. <https://CRAN.R-project.org/package=terra>.

Ho, Tin Kam. 1995. “Random Decision Forests.” In *Proceedings of 3rd International Conference on Document Analysis and Recognition*, 1:278–82. IEEE.

Hobbins, Michael T., Andrew Wood, Daniel J. McEvoy, Justin L. Huntington, Charles Morton, Martha Anderson, and Christopher Hain. 2016. “The Evaporative Demand Drought Index. Part I: Linking Drought Evolution to Variations in Evaporative Demand.” *Journal of Hydrometeorology* 17 (6): 1745–61. <https://doi.org/10.1175/JHM-D-15-0121.1>.

Hoerl, Arthur E., and Robert W. Kennard. 1970. “Ridge Regression: Biased Estimation for Nonorthogonal Problems.” *Technometrics* 12 (1): 55–67. <https://doi.org/10.1080/00401706.1970.10488634>.

Hufkens, Koen, Reto Stauffer, and Elio Campitelli. 2019. “The Ecwmfr Package: An Interface to ECMWF API Endpoints.” <https://bluegreen-labs.github.io/ecmwfr/>.

IPCC. 2013. *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, UK; New York, USA: Cambridge University Press. <https://doi.org/10.1017/CBO9781107415324>.

Kendall, Mann. 1975. *Rank Correlation Methods (4th Ed*. 2d impression). Griffin.

Kogan, F. N. 1995. “Application of Vegetation Index and Brightness Temperature for Drought Detection.” *Advances in Space Research* 15 (11): 91–100. <https://doi.org/10.1016/0273-1177(95)00079-T>.

Luo, Lifeng, Deanna Apps, Samuel Arcand, Huating Xu, Ming Pan, and Martin Hoerling. 2017. “Contribution of Temperature and Precipitation Anomalies to the California Drought During 2012–2015.” *Geophysical Research Letters* 44 (7): 3184–92. <https://doi.org/10.1002/2016GL072027>.

Ma, Siyu, Qianxin Wu, Jie Wang, and Shiqiang Zhang. 2017. “Temporal Evolution of Regional Drought Detected from GRACE TWSA and CCI SM in Yunnan Province, China.” *Remote Sensing 2017, Vol. 9, Page 1124* 9 (11): 1124. <https://doi.org/10.3390/RS9111124>.

McEvoy, Daniel J., Justin L. Huntington, Michael T. Hobbins, Andrew Wood, Charles Morton, Martha Anderson, and Christopher Hain. 2016. “The Evaporative Demand Drought Index. Part II: CONUS-Wide Assessment Against Common Drought Indicators.” *Journal of Hydrometeorology* 17 (6): 1763–79. <https://doi.org/10.1175/JHM-D-15-0122.1>.

Meroni, Michele, Felix Rembold, Dominique Fasbender, and Anton Vrieling. 2017. “Evaluation of the Standardized Precipitation Index as an Early Predictor of Seasonal Vegetation Production Anomalies in the Sahel.” *Remote Sensing Letters* 8 (4): 301–10. <https://doi.org/10.1080/2150704X.2016.1264020>.

Miranda, Alejandro, Antonio Lara, Adison Altamirano, Carlos Di Bella, Mauro E. González, and Jesus Julio Camarero. 2020. “Forest Browning Trends in Response to Drought in a Highly Threatened Mediterranean Landscape of South America.” *Ecological Indicators* 115 (August): 106401. <https://doi.org/10.1016/j.ecolind.2020.106401>.

Miranda, Alejandro, Alexandra D. Syphard, Miguel Berdugo, Jaime Carrasco, Susana Gómez-González, Juan F. Ovalle, Cristian A. Delpiano, et al. 2023. “Widespread Synchronous Decline of Mediterranean-Type Forest Driven by Accelerated Aridity.” *Nature Plants* 9 (11): 1810–17. <https://doi.org/10.1038/s41477-023-01541-7>.

Muñoz-Sabater, Joaquín, Emanuel Dutra, Anna Agustí-Panareda, Clément Albergel, Gabriele Arduini, Gianpaolo Balsamo, Souhail Boussetta, et al. 2021. “ERA5-Land: A State-of-the-Art Global Reanalysis Dataset for Land Applications.” *Earth System Science Data* 13 (9): 4349–83. <https://doi.org/10.5194/essd-13-4349-2021>.

Narasimhan, B., and R. Srinivasan. 2005. “Development and Evaluation of Soil Moisture Deficit Index (SMDI) and Evapotranspiration Deficit Index (ETDI) for Agricultural Drought Monitoring.” *Agricultural and Forest Meteorology* 133 (1-4): 69–88. <https://doi.org/10.1016/j.agrformet.2005.07.012>.

Nouri, Milad. 2023. “Drought Assessment Using Gridded Data Sources in Data-Poor Areas with Different Aridity Conditions.” *Water Resources Management* 37 (11): 4327–43. <https://doi.org/10.1007/s11269-023-03555-4>.

Paruelo, José M., Marcos Texeira, Luciana Staiano, Matías Mastrángelo, Laura Amdan, and Federico Gallego. 2016. “An Integrative Index of Ecosystem Services Provision Based on Remotely Sensed Data.” *Ecological Indicators* 71 (December): 145–54. <https://doi.org/10.1016/J.ECOLIND.2016.06.054>.

Pebesma, Edzer. 2018. “Simple Features for R: Standardized Support for Spatial Vector Data.” *The R Journal* 10 (1): 439–46. <https://doi.org/10.32614/RJ-2018-009>.

Pebesma, Edzer, and Roger Bivand. 2023. *Spatial Data Science: With Applications in R*. London: Chapman; Hall/CRC. <https://r-spatial.org/book/>.

R Core Team. 2023. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. <https://www.R-project.org/>.

Schucknecht, Anne, Michele Meroni, Francois Kayitakire, Amadou Boureima, Anne Schucknecht, Michele Meroni, Francois Kayitakire, and Amadou Boureima. 2017. “Phenology-Based Biomass Estimation to Support Rangeland Management in Semi-Arid Environments.” *Remote Sensing* 9 (5): 463. <https://doi.org/10.3390/rs9050463>.

Sen, Pranab Kumar. 1968. “Estimates of the Regression Coefficient Based on Kendall’s Tau.” *Journal of the American Statistical Association* 63 (324): 1379–89. <https://doi.org/10.1080/01621459.1968.10480934>.

Seneviratne, X and Adnan, S and Zhang. 2021. *Weather and Climate Extreme Events in a Changing Climate*. Edited by P. Zhai Masson-Delmotte V., C. Péan A. Pirani S. L. Connors, and T. K. Maycock Lonnoy J. B. R. Matthews. Cambridge University Press. In Press.

Slette, Ingrid J., Alison K. Post, Mai Awad, Trevor Even, Arianna Punzalan, Sere Williams, Melinda D. Smith, and Alan K. Knapp. 2019. “How Ecologists Define Drought, and Why We Should Do Better.” *Global Change Biology* 25 (10): 3193–3200. <https://doi.org/10.1111/gcb.14747>.

Souza, Alzira Gabrielle Soares Saraiva, Alfredo Ribeiro Neto, and Laio Lucas De Souza. 2021. “Soil Moisture-Based Index for Agricultural Drought Assessment: SMADI Application in Pernambuco State-Brazil.” *Remote Sensing of Environment* 252 (January): 112124. <https://doi.org/10.1016/j.rse.2020.112124>.

Tibshirani, Robert, Jacob Bien, Jerome Friedman, Trevor Hastie, Noah Simon, Jonathan Taylor, and Ryan J. Tibshirani. 2010. “Strong Rules for Discarding Predictors in Lasso-Type Problems.” arXiv. <http://arxiv.org/abs/1011.2234>.

Tran, Hoa Thi, James B. Campbell, Randolph H. Wynne, Yang Shao, and Son Viet Phan. 2019. “Drought and Human Impacts on Land Use and Land Cover Change in a Vietnamese Coastal Area.” *Remote Sensing 2019, Vol. 11, Page 333* 11 (3): 333. <https://doi.org/10.3390/RS11030333>.

Urrutia‐Jalabert, Rocío, Mauro E. González, Álvaro González‐Reyes, Antonio Lara, and René Garreaud. 2018. “Climate Variability and Forest Fires in Central and South‐central Chile.” *Ecosphere* 9 (4): e02171. <https://doi.org/10.1002/ecs2.2171>.

Van Loon, Anne F., Tom Gleeson, Julian Clark, Albert I. J. M. Van Dijk, Kerstin Stahl, Jamie Hannaford, Giuliano Di Baldassarre, et al. 2016. “Drought in the Anthropocene.” *Nature Geoscience* 9 (2): 89–91. <https://doi.org/10.1038/ngeo2646>.

Venegas-González, Alejandro, Fidel Roig Juñent, Alvaro G. Gutiérrez, and Mario Tomazello Filho. 2018. “Recent Radial Growth Decline in Response to Increased Drought Conditions in the Northernmost Nothofagus Populations from South America.” *Forest Ecology and Management* 409 (February): 94–104. <https://doi.org/10.1016/j.foreco.2017.11.006>.

Vicente-Serrano, Sergio M., Cesar Azorin-Molina, Arturo Sanchez-Lorenzo, Jesús Revuelto, Juan I. López-Moreno, José C. González-Hidalgo, Enrique Moran-Tejeda, and Francisco Espejo. 2014. “Reference Evapotranspiration Variability and Trends in Spain, 1961–2011.” *Global and Planetary Change* 121 (October): 26–40. <https://doi.org/10.1016/j.gloplacha.2014.06.005>.

Vicente-Serrano, Sergio M., Santiago Beguería, and Juan I. López-Moreno. 2010. “A Multiscalar Drought Index Sensitive to Global Warming: The Standardized Precipitation Evapotranspiration Index.” *Journal of Climate* 23 (7): 1696–1718. <https://doi.org/10.1175/2009JCLI2909.1>.

Vicente-Serrano, Sergio M., Diego G. Miralles, Fernando Domínguez-Castro, Cesar Azorin-Molina, Ahmed El Kenawy, Tim R. McVicar, Miquel Tomás-Burguera, Santiago Beguería, Marco Maneta, and Marina Peña-Gallardo. 2018. “Global Assessment of the Standardized Evapotranspiration Deficit Index (SEDI) for Drought Analysis and Monitoring.” *Journal of Climate* 31 (14): 5371–93. <https://doi.org/10.1175/JCLI-D-17-0775.1>.

Vicente-Serrano, Sergio M., Dhais Peña-Angulo, Santiago Beguería, Fernando Domínguez-Castro, Miquel Tomás-Burguera, Iván Noguera, Luis Gimeno-Sotelo, and Ahmed El Kenawy. 2022. “Global Drought Trends and Future Projections.” *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 380 (2238): 20210285. <https://doi.org/10.1098/rsta.2021.0285>.

Wang, Menghao, Lucas Menzel, Shanhu Jiang, Liliang Ren, Chong-Yu Xu, and Hao Cui. 2023. “Evaluation of Flash Drought Under the Impact of Heat Wave Events in Southwestern Germany.” *Science of The Total Environment* 904 (December): 166815. <https://doi.org/10.1016/j.scitotenv.2023.166815>.

West, Harry, Nevil Quinn, and Michael Horswell. 2019. “Remote Sensing for Drought Monitoring \& Impact Assessment: Progress, Past Challenges and Future Opportunities.” *Remote Sensing of Environment* 232 (October). <https://doi.org/10.1016/j.rse.2019.111291>.

Wilhite, Donald A., and Michael H. Glantz. 1985. “Understanding: The Drought Phenomenon: The Role of Definitions.” *Water International* 10 (3): 111–20. <https://doi.org/10.1080/02508068508686328>.

Wilks, D. S. 2011. “Empirical Distributions and Exploratory Data Analysis.” Edited by 3rd. *Statistical Methods in the Atmospheric Sciences* 100.

WMO, Mark Svoboda, Michael Hayes, and Deborah A. Wood. 2012. *Standardized Precipitation Index User Guide*. Geneva: WMO. <http://library.wmo.int/opac/index.php?lvl=notice_display&id=13682>.

Zambrano, Francisco. 2023. “Four Decades of Satellite Data for Agricultural Drought Monitoring Throughout the Growing Season in Central Chile.” In *Integrated Drought Management, Two Volume Set*, edited by Rasoul Mirabbasi Vijay P. Singh Deepak Jhajharia and Rohitashw Kumar, 28. CRC Press.

Zambrano, Francisco, Mario Lillo-Saavedra, Koen Verbist, and Octavio Lagos. 2016. “Sixteen Years of Agricultural Drought Assessment of the Biobío Region in Chile Using a 250 m Resolution Vegetation Condition Index (VCI).” *Remote Sensing* 8 (6): 1–20. <https://doi.org/10.3390/rs8060530>.

Zambrano, Francisco, Anton Vrieling, Andy Nelson, Michele Meroni, and Tsegaye Tadesse. 2018. “Prediction of Drought-Induced Reduction of Agricultural Productivity in Chile from MODIS, Rainfall Estimates, and Climate Oscillation Indices.” *Remote Sensing of Environment* 219 (December): 15–30. <https://doi.org/10.1016/j.rse.2018.10.006>.

Zhao, Yuanyuan, Duole Feng, Le Yu, Xiaoyi Wang, Yanlei Chen, Yuqi Bai, H. Jaime Hernández, et al. 2016. “Detailed Dynamic Land Cover Mapping of Chile: Accuracy Improvement by Integrating Multi-Temporal Data.” *Remote Sensing of Environment* 183 (September): 170–85. <https://doi.org/10.1016/j.rse.2016.05.016>.