Shifts in water supply and demand drive land cover change across Chile

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Abstract

Globally, droughts are becoming longer, more frequent, and more severe, and their impacts are multidimensional. These impacts typically extend beyond the water balance, as long-term, cumulative changes in the water balance can lead to regime shifts in land cover. Here, we assess the effects of temporal changes in water supply and demand over multiple time scales on vegetation productivity and land cover changes in continental Chile, which has experienced a severe drought since 2010. Over most of continental Chile, we have observed a persistent negative trend in water supply and a positive trend in atmospheric water demand since 2000. However, in water-limited zones, we have observed a negative trend in the vegetation's water demand. All the trends intensify over longer time scales. This long-term decrease in water availability has led to a decrease in vegetation productivity, especially for the Chilean matorral and the Valdivian temperate forest. Drought indices of soil moisture and actual evapotranspiration from short- to mid-term time scales primarily explain this decrease. Besides, our models indicate that the intensity of the drought explains up to 78% of the changes in shrubland land covers, decreasing to 40% for forests, but the change in cropland surface is explained by the surface burned. Long-term climate change may cause regime shifts in land cover, which context-specific adaptation strategies can mitigate.

Keywords: drought, land cover, water demand, water supply

Introduction

Across many regions of the world, droughts are becoming longer, more frequent, and more severe[1, 2], impacting ecosystems via tree mortality[3], reducing vegetation productivity[1] and inducing shifts in land use and cover [4]. However, identifying drought events is idiosyncratic due to the varying criteria used for classification. Droughts can be classified as 1) meteorological, i.e., when precipitation in a specific period falls below mean precipitation values observed over multiple years [5] (usually more than 30 years); 2) hydrological, i.e., when precipitation anomalies last for long periods (months to years) and affect the hydrological system [6, 7] (e.g., streamflows, reservoirs and groundwater); 3) agricultural, i.e. when precipitation deficits negatively impact plant health, leading to decreases in crop or pasture productivity [8]; or 4) ecological, i.e., when water availability negatively affect the provisioning of ecosystem services and trigger feedbacks in natural or human systems [4]. Such feedbacks include drought impacts on human decision making and activities, which can lead to land-cover change [9, 10], which may have cascading effects on biodiversity and ecosystem services [e.g., 11, 12]. Despite the high degree of confidence in the impacts of rising temperatures on the extent, frequency, and severity of agricultural and ecological droughts [2], which are likely to increase even if global warming stabilizes at 1.5°–2°C, the severity of meteorological droughts has been remarkably stable globally over the past century [13, 14]. A global study analyzing drought severity trends from 1980 to 2020 reveals that in a few regions (some mid-latitudinal and subtropical areas), rising temperatures during the warm season have increased atmospheric evaporative demand (AED), leading to an increase in agricultural land area [13]. Thus, rising atmospheric water demand may reflect parallel changes in land cover—primarily agriculture—that can exacerbate the effects of meteorological droughts on ecosystems.

Expanding analyses to include multiple dimensions of droughts can provide complementary insights into the Earth's water balance - and its impacts - over multiple time scales. Yet, the World Meteorological Organization recommends the use of a single drought index for monitoring droughts [15], i.e., the multi-scale Standardized Precipitation Index (SPI; [16]), which is limited in that it only considers water supply in the form of precipitation. The Standardized Precipitation Evapotranspiration Index (SPEI; [17]) builds upon SPI by incorporating the effects of temperature on drought, and is now used widely for drought monitoring [e.g., 18, 19]. Indices derived from soil moisture products [20, 21], such as the Standardized Soil Moisture Index [SSI, 22, 23] also monitor water supply and are thought to better capture water availability for crops, thus providing more relevant information for evaluating agricultural droughts. To disentangle the effects of precipitation from those of temperature [17], as well as to capture droughts in terms of water atmospheric demand, AED has been integrated into the Evaporative Demand Drought Index [EDDI, 24], which is particularly effective at detecting the rapid onset or intensification of droughts. To quantify vegetation water demand, we must use the actual evapotranspiration, or the amount of water removed from a surface by evaporation and transpiration; the Standardized Evapotranspiration Index (SETI; [25]) can be used for this purpose. In turn, ecological droughts, which capture the joint effects of precipitation and temperature in modifying natural and productive ecosystems [26–28], are complex to measure and can therefore be monitored using multiple drought indices that capture the multiple dimensions of drought, e.g., precipitation, temperature, evapotranspiration, and AED. Although such an approach accounts for the joint effects of changes in natural and productive ecosystems, its potential impacts on land cover change have been largely unexplored [29, 30].

From 1960 to 2019, land-use change has impacted approximately one-third of the Earth's surface, which is four times more than previously thought [31]. Despite the considerable interest in land-use change dynamics [e.g., 31, 32], the direction and magnitude of drought impacts on land cover change and vegetation productivity remain uncertain [33–35]. Meteorological droughts are responsible for approximately 37% of land cover change and variability in vegetation productivity globally [35]. However, the evidence supporting these results is derived from only one drought index, SPEI, which combines a proxy for water supply - precipitation - with a proxy for water demand - AED - at one time scale (12 months). The use of only one time scale may bias results of drought impacts towards ecosystems dominated by plant growth forms such as grasses and herbs that respond more rapidly to drought stress (< 12 months). This is because physiological differences among and within dominant plant growth forms may increase (or decrease) tolerance of drought stress [36, 37]. For example, trees growing in more arid ecosystems typically respond over longer time scales than those in more humid ecosystems [38]. Another source of uncertainty regarding drought impacts on land cover change and vegetation productivity are extrinsic factors, such as large-scale public policy (e.g., national and international reforestation initiatives), agricultural practices (e.g., clearing forest for soybean or oil palm), and rural and urban land use planning [39].

To deepen current knowledge on the multidimensional impacts of drought on the temporal dynamics of natural and productive ecosystems, we evaluate temporal changes in water supply and demand, net primary productivity, and land-cover change across terrestrial ecosystems in continental Chile for 2000-2023. Chile's diverse climate and ecosystems [40, 41] make it an ideal natural laboratory for assessing the dynamic interactions between climate and ecosystems, and potential impacts on land-cover change. Additionally, large parts of Chile have experienced severe drought conditions that have significantly affected vegetation and water storage in recent years; north-central Chile has faced a persistent precipitation deficit (or "mega-drought") since 2010 [42], which has broadly impacted native forests [e.g., 43–45] and agricultural productivity [e.g., 46–48]. However, the effects of this prolonged extreme drought may also extend to changes in land cover, altering the provision of key ecosystem services and agricultural production. Here, we aim to assess: short- to long-term time trends in multi-scalar drought indices that capture variation in the components of water balance, i.e., water supply (SPI, SPEI, SSI) and demand (EDDI, SETI) and their impacts on vegetation productivity and land-cover change across continental Chile. By doing so, we aim to deepen understanding of how water supply and demand affect vegetation productivity and influence changes in the surface of land cover in a severely drought-impacted region. This may enhance understanding of the alterations, due to drought, to ecosystems in various regions across the world.

Materials and Methods

Study area

Continental Chile has a diverse climate, with strong environmental gradients from north to south and east to west [49] (Fig. 1a), which, together with its complex topography (Fig. 1b), determine its ecosystem diversity [41, 50] (Fig. 1c). We therefore divided Chile into ecoregions [51], which are regions that share similar geography and ecology, and have comparable levels of precipitation and solar radiation. There are seven ecoregions: Atacama desert, Central Andean dry puna, Southern Andean steppe, Chilean Matorral, Valdivian temperate forests, Magellanic subpolar forests, and Patagonian steppe. The Atacama desert is predominantly arid with hot (Bwh in the Koppen-Geiger classification) and cold (Bwk) temperatures, as well as the northern part of the Chilean Matorral. Most of the land in these two northern regions is bare, except for a small area where shrublands and grasslands are present. With an annual rainfall of less than 400 mm, the Central Andean dry puna ecoregion has low, yet highly seasonal precipitation with an eight-month dry season, low temperatures (Bwk) and is dominated by grasslands, shrublands, and savanna. The climate of the Southern Andean steppe ecoregion is cold desert (BWk), with most precipitation occurring in the winter. There is little vegetation in this ecoregion because the plants have adapted to its windy, dry, and cold climate. In central Chile, the climate of the Chilean Matorral changes to that of an arid steppe with cold temperatures (Bsk). Then, towards the center-south of the country, the climate of the Chilean Matorral changes to a Mediterranean climate, with warm to hot summers (Csa and Csb). Land cover in this ecoregion consists of a significant amount of shrublands and savannas. The Valdivian temperate forests have a mostly oceanic climate (Cfb) and a large area of forests and grasslands. The Magellanic subpolar forests have a tundra climate. Lastly, the Patagonian steppe has high aridity, cold temperatures (Bsk), and primarily consists of grasslands.

Data

Gridded meteorological and vegetation data

To derive a proxy for vegetation productivity, we used the Normalized Difference Vegetation Index (NDVI) from the MOD13A3 Collection 6.1 product derived from the MODIS (Moderate-Resolution Imaging Spectroradiometer) sensor onboard the Terra satellite. MOD13A3 provides vegetation indices with a 1 km spatial resolution and monthly frequency [52]. We also utilized the MOD16A2 collection 6.1 [53] product from MODIS to gauge the water consumption of vegetation. This product gives us monthly actual evapotranspiration (ET) and atmospheric evaporative demand (AED) with a ~500m spatial resolution. For soil moisture, water supply, and water demand variables, we used ERA5-Land (ERA5L; ECMWF Reanalysis version 5 over land) [54], a reanalysis dataset that provides atmospheric and land variables since 1950. It has a spatial resolution of 0.1° (9 km), hourly frequency, and global coverage. We selected total precipitation, maximum and minimum temperature at 2 meters, and volumetric soil water layers between 0 and 100 cm of depth (layer 1 to layer 3; Supplementary Materials and Methods, Supplementary Tables 2 and 4).

Gridded indicators for land use

To account for the impacts of human activity on land cover change, we obtained data on road density [55] and night lights for the period 2012–2023 [56]. These products are frequently used in the literature to quantify the human footprint (e.g., [57, 58]) or biodiversity threats (e.g., [59, 60]).To capture changes on land cover due to fires, we calculated the total burned area for 2002-2023 [61].

Short- to long-term drought trends

Atmospheric Evaporative Demand (AED)

To compute drought indices that use water demand, it is necessary to first calculate AED. To do this, we employed the Hargreaves method [62, 63] by applying the following equation:

$$AED = 0.0023 \cdot Ra \cdot (T + 17.8) \cdot (T_{max} - T_{min})^{0.5} \tag{1}$$

where Ra $(MJ\, m^2\, day^{-1})$ is extraterrestrial radiation; T, T_{max}, and T_{min} are mean, maximum, and minimum temperature ($°C$) at 2m. For calculating Ra we used the coordinate of the latitud of the centroid of each pixel as follow:

$$R_a = \frac{14,400}{\pi} \cdot G_{sc} \cdot d_r\, [\omega_s \cdot sin(\phi) \cdot sin(\delta) + cos(\phi) \cdot cos(\delta) \cdot sin(\omega_s)] \tag{2}$$

where:

Ra: extraterrestrial radiation $[MJ\, m^{-2} day - 1]$,
G_{sc}: solar constant = 0.0820 $[MJ\, m^{-2} min^{-1}]$,
d_r: inverse relative distance Earth-Sun,
ω_s sunset hour angle $[rad]$,
ϕ: latitude $[rad]$,
δ: solar declination $[rad]$.

We selected the method of Hargreaves to estimate AED because of its simplicity, as it only requires temperature and extraterrestrial radiation, and because access to the data needed for alternative methods (e.g., Penman-Montieth) is often limited [38].

Drought indices

To derive the drought indices of water supply and demand we used the ERA5L dataset, with a monthly frequency for 2000–2023. Drought indices capture historical anomalies of water supply and demand. To quantify each anomaly, the common practice is to derive it following a statistical parametric method in which it is assumed that the statistical distribution of the data is known [64]. The use of an erroneous statistical distribution that does not fit the data is usually the highest source of uncertainty [65]. In the case of Chile, due to its high degree of climatic variability, it is difficult to choose a statistical distribution that can be used across its entire extent. We therefore use a non-parametric method for the calculation of the drought indices, following [66].

For monitoring water supply, we used the Standardized Precipitation Index (SPI; [16]), which only uses precipitation data. To evaluate water demand, we chose the Evaporative Demand Drought Index (EDDI; [67] and [24]), which is based on AED, and the Standardized Evapotranspiration Index (SETI; [25]), which quantifies actual evapotranspiration, i.e. the amount of water removed from a surface due to evaporation and transpiration. To quantify the combined effect of water supply and demand, we estimated SPEI [68]. For SPEI, we calculated an auxiliary variable (D) with the following formula:

$$D = P - AED$$

where P is precipitation. Soil moisture is often considered to be the main driver of vegetation productivity, particularly in semi-arid regions [69]. Hence, we used the Standardized Soil Moisture Index (SSI) to estimate soil moisture (SM) [70]. For SSI, we used the average soil moisture from ERA5L at a depth of 1m. All calculated indices are multi-scalar and can be used for the analysis of short- to long-term droughts.

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

$$A_i^s = \sum_{i=n-s-i+2}^{n-i+1} V_i \; \forall \, i \geq n - s + 1 \tag{3}$$

The A_i^s corresponds to a moving window (convolution) that sums the variable for time scales s. This is summed over s months, starting from the most recent month (n) back in time until month $n - s + 1$. For example, using as a variable the precipitation, a period of twelve months (n), and a time scale of three months (s):

$$\begin{aligned} A_1^3 &= P_{oct} + P_{nov} + P_{dic} \\ \vdots\ &= \vdots + \ \vdots + \ \vdots \\ A_{10}^3 &= P_{jan} + P_{feb} + P_{mar} \end{aligned}$$

Then, we used the empirical Tukey plotting position [71] over A_i^s to derive the $P(A_i^s)$ probabilities across a period of interest:

$$P(A_i^s) = \frac{i - 0.33}{n + 0.33'} \tag{4}$$

An inverse normal approximation [72] obtains the empirically derived probabilities once the variable cumulates over time for the scale s. Thus, the drought indices SPI, $SPEI$, $EDDI$, and SSI are obtained following the equation:

$$DI(A_i^s) = W - \frac{C_0 + C_1 \cdot W + c_2 \cdot W^2}{1 + d_1 \cdot W + d_2 \cdot W^2 + d_3 \cdot W^3} \tag{5}$$

DI is referring to the drought index calculated for the variable V. The values for the constats are: $C_0 = 2.515517$, $C_1 = 0.802853$, $C_2 = 0.010328$, $d_1 = 1.432788$,

$d_2 = 0.189269$, and $d3 = 0.001308$. For $P(A_i^s) \leq 0.5$, W=$\sqrt{-2 \cdot ln(P(A_i^s))}$, and for $P(A_i^s) > 0.5$, replace $P(A_i^s)$ with $1 - P(A_i^s)$ and reverse the sign of $DI(A_i^s)$.

The drought indices were calculated for time scales of 1, 3, 6, 12, 24, and 36 months at a monthly frequency for 2000–2023.

Temporal trends of drought indices

To determine if there are statistically significant positive or negative temporal trends for the drought indices, we used the non-parametric modified Mann-Kendall test for serially correlated data [73]. To determine the magnitude of the trend, we used Sen's slope [74]. Sen's slope is less affected by outliers than parametric ordinary least squares (OLS) regression, and as a non-parametric method, it is not influenced by the distribution of the data. We applied both methods for SPI, EDDI, SPEI, SETI, and SSI and six time scales, resulting in a total of 30 trends. We then aggregated temporal trends for each ecoregion and land cover type.

Vegetation productivity

We also used the MODIS product (MOD13A3[52]) to calculate vegetation productivity, and calculated anomalies of cumulative NDVI using zcNDVI [47], which was derived from the monthly time series of NDVI, with Equations 2 and 4. For vegetation productivity, we selected the time scale that best correlates with annual net primary productivity (NPP) across continental Chile. For this purpose, we calculated zcNDVI for time scales of 1, 3, 6, and 12 months (from December) and compared it with the annual NPP. We obtained NPP from MOD17A3HGF90. We chose to use six months because the R^2 between zcNDVI and NPP reaches its highest value at six months, obtaining an R^2 of 0.31 for forest and 0.72 for shrubland (Supplementary Information Section S2). We subsequently used zcNDVI with a time scale of 6 months and calculated it at a monthly frequency for 2000–2023.

Drought impacts on vegetation productivity

For each land cover, we analyzed the trend of vegetation productivity. To this end, we identified areas within each land cover that are persistent over time to reduce the possibility that trends in vegetation productivity may be influenced by changes in land cover. We examined the correlation between drought indices and vegetation productivity across land cover types to determine to the extent to which soil moisture and water demand and supply affect vegetation productivity.

We estimated pixel-to-pixel Pearson's correlations between drought indices at time scales of 1, 3, 6, 12, 24, and 36 months with zcNDVI. We extracted the Pearson correlation coefficient corresponding to the time scale with the highest value. For each index, we then generated two maps: 1) a raster with values of the time scales and drought index that reached the maximum correlation, and 2) a raster with the magnitude of the correlation between the drought index and vegetation productivity.

Drought impacts on land cover change

Land cover change

To analyze land cover change, we used the classification scheme of the International Geosphere-Biosphere Programme (IGBP) from the product MCD12Q1 Collection 6.1 from MODIS. The MCD12Q1 product is produced for each year from 2001 to 2023 and defines 17 classes (see Table S1). Following the FAO classification [75], we classified native and planted forests as "forests", which represent natural and productive ecosystems dominated by large trees. To analyze the land cover change, we use the IGBP scheme from the MCD12Q1 product. We regrouped the 17 classes into ten macro-classes, as follows: 1-4 to forests (native forest and plantations), 5-7 to shrublands, 8-9 to savannas, 10 as grasslands, 11 as wetlands, 12 and 14 to croplands, 13 as urban, 15 as snow and ice, 16 as barren, and 17 as water (Table S3). This resulted in a time series of land cover with ten macro-classes for 2001-2023. We validated the land cover macro-classes using a high resolution (30 m) land cover map for 2013-2014 [76]. Our results showed a global accuracy of ~0.82 and a F1 score of ~0.66 (Supplementary Information, S2).

We calculated the area for each land cover class in the five study regions for 2001–2023. We then estimated the temporal change in area for each land cover type and macro-class, and determined the statistical significance (p-value < 0.05) and magnitude of the trend as described above.

To assess how water demand and supply, and soil moisture affect the variation in vegetation productivity across various land cover types, we avoid analyzing areas that experienced major land cover changes in the 2001–2023 period. To assess how zcNDVI varied irrespective of land cover change, we developed a persistence mask for land cover, which only retains pixels for which the macro-class remained the same for at least 80% of the 23 years (Fig. 1d).

Relationship between land cover and drought trends

To identify which drought indices and time scales have a major impact on changes in land cover type, we examined the relationships between the temporal trends in the surface of land cover classes, drought indices, road density, burned area, and night lights, and for each ecoregion. We performed the analysis at the sub-basin scale, using 485 river basins, which have a surface area between 0.906 and 24,408 km2 and a median area of 1,249 km2 (Supplementary Fig. S8/Table S5). For each basin, we calculated the trend per land cover, considering the proportion of the type relative to the total surface of the basin. For each basin we extracted the average trend of all drought indices and at time scales of 1, 3, 6, 12, 24, and 36 months. In the case of burned area, we used as variables the total and the trend of burned area for 2002-2023, and for night lights we used the average and the trend of nightlights for 2012-2023.

Prior to modelling relationships between trends in land cover and drought indices, we assessed multi-collinearity among explanatory variables, i.e., drought indices, road density, night lights, and burned area, with the variance inflation factor (VIF). We analyzed the VIF for all drought indices at time scales of 1, 3, 6, 12, 24, and 36 separately because each index has a strong correlation across time scales. As VIF values greater than five may affect the interpretation of model results [77], we therefore excluded SPI from all subsequent models.

To assess the relationship between land cover trends and drought indices, we modeled trends in the surface of land cover types. We made a regression analysis using the random forest method93, which employs multiple decision trees. Some advantages of random forest include the ability to find non-linear relationships, reduce overfitting, and derive variable importance. We incorporated the trends of the five drought indices (SPI, SPEI, EDDI, SETI, and SSI), the trends of night lights (2) and burned area (2), the road density, for a total of ten predictors. We then constructed random forest models for each time scale (1, 3, 6, 12, 24, and 36) and each land cover class (forest, grassland, shrubland, savanna, cropland, and barren land), resulting in a total of 36 RF models. We trained each model using 1000 trees, setting the minimum number of nodes per decision tree at five and the number of predictors per split (boosting) to the square root of the total number of predictors. To account for uncertainty, we trained all the models ten times using a resampling strategy (ten folds) in a cross-validation scheme. Finally, we evaluate model fit by calculating R^2, root mean square error (RMSE), and variable importance. Variable importance identifies which variables have a higher contribution to explaining model variation. We calculated variable importance by permuting out-of-bag (OOB) data per tree and calculating the mean standard error of the OOB data. After permuting each predictor variable, we repeated the process for the remaining variables. We repeated this process ten times per fold to assess model fit.

Finally, we visually explored the relationship between drought indexes and changes in land cover across sub basins within Chile. To achieve this, we compared the relative changes in land cover surface with the drought indices, burned area, nighlights, and road density and other variables for the time scale that were deemed more significant in the random forest model.

Software

For downloading, processing, and analysis of the spatio-temporal data, we used the open source software for statistical computing and graphics, R [78]. For downloading ERA5L, we used the {ecmwfr} package [79]. For processing raster data, we used {terra} [80] and {stars} [81]. For managing vectorial data, we used {sf} [82]. For the calculation of AED, we used {SPEI} [83]. For mapping, we used {tmap} [84]. For data analysis and visualization, the suite {tidyverse} [85] was used. For the random forest modeling, we used the {tidymodels} [86] and {ranger} [87] packages.

Results

The Chilean matorral and Patagonian steppe increase atmospheric water demand but decrease vegetation evapotranspiration

For the Atacama desert and the Central Andean Puna, we found a positive temporal trend for drought indices of water supply (i.e., SPI, SSI), atmospheric water demand (i.e., EDDI), and vegetation water demand (i.e., SETI). For the Chilean matorral and Patagonian steppe, EDDI presents the higher positive trend and lower negative trends in SPI, SPEI, SSI, and SETI. This reflects a critical scenario of drought, where a rise in temperature increases atmospheric water demand, but vegetation cannot increase evapotranspiration due to a lack of water availability. In the Southern Andean steppe, there is a positive trend in AED (i.e., EDDI), but a negative in water supply (i.e., SPI, SPEI, SSI). The vegetation water demand (i.e., SETI) has negative trends, but it is increasing at higher time scales. The Valdivian temperate forests show a negative trend in water supply (i.e., SPI, SPEI, and SSI) and a positive trend in both AED and ET, as shown by the EDDI and SETI, respectively. Here, an increase in AED implies an increase in ET, likely due to a greater availability of water, unlike in the Chilean Matorral and Patagonian steppe. The vegetation water demand (SETI) in the Magellanic subpolar forests does not exhibit a significant trend over any given time scale. The AED and water supply present a positive trend. The trends of drought indices in the Patagonian steppe exhibit a similar behavior to the Chilean matorral, albeit to a lesser extent. Generally, the majority of the indices indicate that the trend (positive or negative) intensifies over longer time periods. (Fig. 2)

Vegetation productivity has strongly decreased in the Chilean matorral and the Patagonian steppe.

We found contrasting temporal trends in vegetation productivity for 2000-2023 (Fig. 3). The Atacama desert does not exhibit significant trends over time. The Chilean Matorral, Patagonian steppe, and the Southern Andean steppe exhibit negative trends of -0.023, -0.016, and -0.006 (z-score/per decade), respectively. In contrast, the Central Andean dry puna, Valdivian temperate forests, and Central Andean dry puna show positive trends ranging from 0.01 to 0.03 (z-score/per decade). The Chilean matorral was at its lowest point from 2019 to 2022, while the Patagonian steppe has experienced an increasingly negative trend since 2022.

Forest, savanna, and shrubland exhibit the highest change in surface area across ecoregions We also observed significant changes in land cover surfaces across continental Chile (Fig. 4). The forest surface has increased in the Chilean matorral and in the Valdivian temperate forest at rates of 78 and 316 km^2 yr ^{1}, respectively. Grassland surface has diminished in the Southern Andean steppe (-19 km^2 yr ^{1}) and has increased in the Patagonian steppe (90 km^2 yr ^{1}). Savanna exhibits a decrease in the Chilean matorral of -271 km^2 yr ^{1} and the Valdivian temperate forest of -276 km^2 yr ^{1}, but an increase at a rate of 133 km^2 yr ^{1} in the Magellanic subpolar forest. Shrubland has the highest increase in the Chilean matorral (160 km^2 yr ^{1}). Barren land has increased in the Central Andean dry puna (36 km^2 yr ^{1}) and the Southern Andean steppe (50 km^2 yr ^{1}), but has diminished in the Magellanic subpolar forest (-81 km^2 yr ^{1}). ## Drought impact on vegetation productivity are strongest in the Chilean matorral and Valdivian temperate forest

Our results indicate that drought impacts on vegetation productivity are highest in the Chilean Matorral and Valdivian temperate forests across all land cover types, except forest (Fig. 5, Fig. S5 and Table 1). For time scales of 6 and 12 months, SETI and SSI have the strongest positive correlation with vegetation productivity among the land cover types. Next, we found that grassland and savanna in the Patagonian steppe had higher correlations with SPI and SSI over 12 months. Further, there is a positive relationship between the vegetation in the Atacama desert and drought indices of 12 months of water supply and vegetation water demand. However, there is a negative relationship between the vegetation and atmospheric water demand over 12 months. All drought indices show a positive correlation with the vegetation in the Central Andean dry puna, particularly the drought indices of water supply (SPI, SPEI, and SSI) at time scales of 24 and vegetation water demand (SETI) at time scales of 36 months. For the Southern Andean steppe the SETI of 24 months showed the highest correlation with savannas, followed by the EDDI of 24 months. Our analysis also revealed that water demand and supply differentially affected the time scales at which vegetation productivity of land cover types within each region was most impacted by drought (Fig. 5, Fig. S5 and Table 1). While the spatial variation in the relationship between drought intensity and vegetation productivity was consistent across drought indices, the drought indices that captures water supply via soil moisture (Standardized Soil Moisture Index; SSI), and via vegetation water demand (Standardized Evapotranspiration Index, SETI) tended to show a stronger correlation with vegetation productivity over larger areas than the other drought indices (Fig. 5).

Drought strongly impacts land cover distribution for shrubland

Our random forest models show that drought indices explain between 32-79% of the variation in land cover change across continental Chile (Fig. 6). Moreover, these results highlight the importance of considering water supply and demand, as drought indices associated with both aspects of the water balance had high importance values across most ecoregions and land cover types. The variation in the time scale of drought indices that provide the strongest correlation with vegetation productivity also suggests that different types of vegetation are not equally sensitive to droughts of similar intensities (Table 1). The RF models show that the drought indices are explaining 71-78% of the variability in land cover surface change for shrublands. Second, the RF models explain approximately 58-78% of the variability in change on croplands. In the case of other land cover types, the RF models account for approximately 33-59% of the variability, with drought indices explaining less for the forest type (Fig. 6).

Our model has the highest r-squared for shrublands, followed by croplands, and barren land (Fig. 6). Ecoregions most frequently observed the variables SETI and SSI, which significantly influenced surface changes for each land cover (Fig. 7). In cropland, the primary factor is not the drought indices, but rather the total surface or trend of the burned area. The nightlight variable, which reflects urban areas, primarily explains the change in the surface of barren land, followed by the drought indices SPEI at time scales of 3 and 6 months (Fig. 7).

Our results also show that drought intensity was associated with the magnitude and direction of land cover change (Fig. 8). We observe that shrublands are sensitive to both increases and decreases in SETI and SSI, reaching a point of equilibrium around a normal climatic situation (drought index = 0). This could potentially stem from the fact that favorable water supply conditions alter the type and quantity of vegetation. Conversely, a reduction in water supply results in the shrublands losing their vegetation and transforming into bare soil. Thereby, both situations alter the land cover type. Changes in the burned surface impact the cropland surface; an increase in the burned area leads to an increase in the agricultural surface. Agricultural areas likely replace the burned area, explaining this phenomenon. In the case of bare soil, values that indicate low urban development (nightlights) are associated with a larger surface of bare soil. However, when the variable's range extends beyond the normal urban situation (zero value), an increase in bare soil correlates with a fluctuating increase in urban development. The relationship between SETI and SPEI in grasslands is opposite; an increase in SPEI leads to an increase in grassland area, while an increase in water demand by grasslands, as reflected by SETI, results in a decrease in grassland area.

Discussion

Temporal trends in water supply and demand

We discovered that the Atacama desert, Central Andean dry puna, and the Magellanic subpolar forests experience an increase in water supply (SPI, SSI), as well as an increase in atmospheric and vegetation water demand (EDDI, SETI). However, in the Magellanic subpolar forests, we found no evidence of either a significant increase or decrease in SETI across time scales. Also, we found a significant decreasing trend in water supply (SPI, SPEI, and SSI) across the Southern Andean steppe, Chilean Matorral[88, 89], Valdivian temperate forests, and Patagonian steppe, accompanied by an increase in atmospheric water demand (EDDI). Our results indicate that temporal trends of water supply and atmospheric demand tend to decrease or increase more strongly over longer time scales,a trend that is consistent with the progressive intensification of drought severity across much of Chile, and that has been observed in other regions facing long-term droughts[90, 91]. Simultaneously, we observed a divergent trend between EDDI and SETI. In the majority of ecoregions, a rise in atmospheric water demand (EDDI) typically leads to a rise in vegetation water demand (SETI). However, in the ecoregions most affected by drought (Fig. 3 and Fig. 5), i.e., the Chilean matorral, and the Patagonian steppe , we found that an increase in atmospheric water demand results in a decrease in the water demand of vegetation. Together, our findings demonstrate a persistent drying trend in the Chilean Matorral, the Patagonian steppe, and the Southern Andean steppe. We attribute this trend to a simultaneous decrease in precipitation and an increase in atmospheric evaporative demand, leading to a decrease in the water demand by vegetation in water-limited areas[92].

Temporal trends in vegetation productivity

The consequences of the persistent drying trend for ecosystems throughout continental Chile are manifold. First, the prolonged hydrological drought, i.e., precipitation deficit, has reduced groundwater storage (SSI; ref. [93]), leading to a steady decline in vegetation productivity (zcNDVI) since 2000 across the Patagonian steppe, the Southern Andean steppe, and the Chilean Matorral, which reached its lowest level between 2020 and 2022 and could be due to either a decrease in vegetation area, a loss of biomass, or browning in forest ecosystems. Recent studies examining natural and productive ecosystems[94–96] have attributed the decline in vegetation productivity with declines in soil moisture and increases in evapotranspiration. Second, the sharp decline in vegetation productivity in the Chilean Matorral and Valdivian temperate forest ecoregions showed that grasslands and shrublands respond to shifts in water supply over longer time scales (12 months) than savannas and croplands (6 months). Also, in the Valdivian temperate forest ecoregion, which has a large forested area, vegetation productivity responded to soil moisture (SSI) and vegetation water demand (SETI) most strongly at 12 and 36 months, respectively. This result is consistent with recent studies showing that progressive, long-term water deficits in central Chile have triggered forest browning and declines in native forest productivity [1, 43, 97]. While our analysis do not distinguish between native and planted forests, the latter of which are considered to be more drought tolerant in central and southern Chile[98], we show that forest area declines more sharply in response to increasing water demand due to rising temperatures (EDDI) than decreasing water supply (e.g., SPI, SSI; refs. [99, 100]), which may have cascading impacts on multiple facets of forest diversity[101, 102].

Moreover, the strengthening of the correlation between vegetation productivity and water supply (SPI, SPEI, SSI) or demand (EDDI, SETI) over multiple time scales (up to 36 months) and across land cover types (Fig. 5) demonstrates the impacts of climate change on the water balance in Chile. These impacts may extend beyond vegetation productivity, as reduced soil moisture in central Chile and the western United States has increased wildfire activity[103, 104], which is a growing concern in Chile and may be further exacerbated by extensive plantations of highly flammable tree species, e.g., Eucalyptus spp. and Pinus spp.[105]. Lastly, we found that the decline in the vegetation productivity of croplands is largely due to a decrease in the water supply and vegetation water demand to a greater extent than to an increase in atmospheric water demand[106], causing a decline in water availability. This is consistent with evidence that more water-intensive crops have replaced less water-intensive crops in central Chile, leading to an increase in water extraction from rivers or groundwater [107, 108].

Drought impacts on land cover

We found evidence that temporal decreases in water supply (SPEI, SSI) and decreases in vegetation water demand (SETI) are driving shifts not only in vegetation productivity but also in temporal trends of land cover change across most of continental Chile. Despite differences in drought tolerance (e.g., shrublands, grasslands, and savannas), our results provide evidence that the area of most land cover types dominated by vegetation has been affected by water deficits, albeit to varying degrees (Fig. 8). Additionally, our results suggest that water deficits, to a greater extent than factors associated with human activity, have affected temporal trends in land cover change for most land cover types. Further, we found that temporal changes in cropland cover may not be a direct consequence of drought (Fig. 7), but rather an indirect one, likely associated with forest fires and possibly the decisions of resource-poor farmers to migrate to regions with more abundant water resources or to change economic activity[10, 109]. The reason for the non-linear increases in forest area in response to burned area across most ecoregions (Fig. 8) is unclear, as it could be due to forest recovery[44] or the establishment of forest plantations [110].

Study limitations

Our analysis of the impacts of water supply and demand on vegetation productivity and land cover change has some important limitations that need to be highlighted.. One of the principal limitations of this study is the use of secondary information. For instance, we used estimates of water supply and demand, such as ERA5L and MODIS, which, despite their improved estimation capacity, suffer from biases and uncertainties[111, 112] in different areas or climatic conditions. In this study, we compared the ERA5L data with climatic stations (see Table S2) to verify bias and uncertainty, but future studies that aim for more focalized analysis will need to improve the precision of these products. We used zcNDVI[47] (MODIS) as a proxy for vegetation productivity, which has proven to be a good estimate of NPP (see Fig. S1 and S2), but its quality varies between different types of vegetation.

A second limitation is that we used products that estimate land cover types using classification models, which are subject to quality errors that must be taken into account[113, 114]. In addition, in our case we used macro classes of land cover, where, for example, the different types of forests (e.g., monoculture, native forest) were pooled into the same land cover type. This approach may hinder our ability to understand the effects of drought on the various subclasses within each land cover class. In terms of croplands, we could not distinguish between rainfed and irrigated areas using macro classes. However, in this study, we aimed to provide a broad overview at a large spatial scale, but acknowledge that using sub-classes of land cover types at finer spatial resolutions may help to better understand underlying mechanisms.

In our analysis of the impacts of drought intensity on temporal trends of land cover change, we integrated proxies for human activity that also may affect land cover change. However, attributing land cover change to human activity and decisions is complex when using earth observation tools. While earth observation tools can analyze land cover change, whether a land cover type changes likely depends on a multitude of social and economic factors that are challenging to quantify[115, 116] and necessitate the integration of social, natural, and geographic information sciences.

Conclusion

Overall, our results show that long-term declines in water supply and demand have consistently induced widespread, multi-dimensional impacts on the vegetation productivity and on the temporal trends of changes in land cover types across a broad range of ecoregions. While prolonged droughts may directly cause shifts to more drought-tolerant land cover types, such as shrublands, we also found that areas affected by fires were associated with increases in the area of forests and croplands, highlighting the importance of socio-economic factors in shaping land use change dynamics. Our study extends current understanding of drought impacts by demonstrating how their multidimensionality emerges over multiple time scales and across land cover types, which can contribute to developing context-specific adaptation strategies for agriculture, biodiversity conservation, and natural resource management.

Data availability

The codes generated during the current study are available in the GitHub repository, https://github.com/FSEQ210022/drought_vegetation. The datasets generated and/or analyzed during the current study are available in the Zenodo repository, https://doi.org/10.5281/zenodo.10359547.

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