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ASSESSING RECENT TRENDS OF AGROCLIMATIC INDICES USING MODIS DATA IN CENTRAL CHILE

Tesis presentada como requisito para optar al grado de

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A mi familia.

Contenido

Assessing recent trends of agroclimatic indices using MODIS data in Central Chile

Stephanie Orellana; Francisco Meza.

Abstract

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Agriculture is one of the most susceptible activities to climate change. Increasing temperatures and changes in precipitation will affect crop growth and development reducing agricultural productivity. Recent observed trends in temperature may have already produced changes in the suitability of crops. Trend analysis is one of the most accepted methodologies to assess the effect of observed changes in temperature on the physiological crop response. Unfortunately, only few studies analyze the effect of climate trends on agroclimatic indices, specially performing a comprehensive spatial analysis.

This work presents an analysis of recent trends (2002-2016) in central Chile for temperature based agroclimatic indices derived from MODIS Land Surface Temperature product. To investigate the spatial structure of calculated trends, directional variograms were estimated. Indices associated with a heat category show marked trends towards an early start of growing season and an increase in length of growing season, as well as to appositive response of growing degree days in winter and summer. The indices associated to a cold category have less clear trends and a smaller number of significant trends. The analysis of NDVI for vegetation response shows an adaptive debt, defined as to the difference between the potential growing season length and the actual response of vegetation, because the beginning and the length of the growing season present opposite trends to the ones found in agroclimatic indices. The most significant results in trends were found in the humid and sub-humid Mediterranean areas which present a new productive potential to be less limited by low temperatures. The cold indexes suggest an increase of frost period with a greater number of extreme events.

Key words: Agroclimatic indices, recent trends, MODIS, Mann-Kendall, variogram.

1 INTRODUCTION

Increasing levels of carbon dioxide (CO_2), temperature, and changes in precipitation patterns are the most common impacts of climate change, which have a direct effect on agriculture (Hatfield et al., 2011). These variables determine agricultural production by modifying crop yields, increasing water requirements, and affecting the suitability of different varieties for specific geographical areas, among others. However, not all changes produce negative consequences, under some circumstances, it is also possible to identify beneficial effects of climate change such as an increase of agricultural productivity in areas where temperature has been a limiting factor (Roco et al., 2014).

Knowledge of future climate change conditions allow farmers to modify cropping systems. An example of such response is found in Meza et al. (2008), who evaluated double cropping as an emerging adaptation strategy to future climate conditions in a Mediterranean region. This response becomes more efficient because climate change accelerates the rate of development, allowing the crop to complete its growing cycle in shorter periods of time.

The correct characterization of the climate environment and the development of agroclimatic indices that allow us to assess the effect of climate conditions on crop adaptability and yield potential during growing season, represents a fundamental step for the identification of successful adaptation strategies.

The most widely accepted agroclimatic indices, defined as an indicator of an aspect of the climate that has specific agricultural significance, are based on temperature and precipitation and are used as simple and straightforward variables to support agronomic decisions. Although temperature and precipitation are relatively easy to access from traditional weather stations, and the dissemination of automatic weather stations has increased substantially over the last decade, these networks are not equally spread in the territory as they tend to be concentrated around highly population centers, or areas of high productive interest, generating large gaps in information that prevent from reliable data interpolation and correct identification of spatial patterns (Li and Heap, 2008).

In Chile around of 66% of meteorological stations with temperature registers were installed after 2000 (44% after 2010) considering sources available in “Red Agroclimática Nacional” (www.agromet.cl) and data of “Dirección General de Aguas” (DGA) and “Dirección Metorológica de Chile” (DMC) compiled by Center for Climate and Resilience Research (www.cr2.cl). This condition precludes an exhaustive trend analysis because despite having a denser network of stations, most of them still do not have more than 10 years of complete records.

In the case of Chile, due to the great heterogeneity of the landscape (especially the area devoted to agriculture), it is important to model the spatial variability of these indexes as well as to characterize their temporal variability within the recent period to monitor impact of recently observed climate changes on the main productive activities of the country. Recent studies show a mega drought in Central Chile in 2010-2015 period, with changes in potential evapotranspiration (PET) contributed by a rise in temperatures between 0.5 and 1°C. Two areas with considerable increase in PET were identified: the interior valleys of northern Chile (30-33 °S) and to the south of 36 °S, this suggest a substantial water stress for vegetation in these areas (Garreaud et al., 2017a). This condition can be an advantage for agriculture to the extent that better irrigation systems are used, being less susceptible than other vegetation types to the decrease in rainfall recorded in the last decade (Garreaud et al., 2017b).

Trend analysis is the most widely used technique to detect changes in time series. The majority of the literature focuses on raw climatic variables with only few studies evaluating the performance of agroclimatic indexes and, even to a lesser extent, analyzing the spatial coherence of observed trends. An extensive review of historical (1940-2007) and recent (1975-2007) trends based on information from meteorological stations in Argentina is presented by Fernández-Long et al. (2013). The authors found significant trends that show a delay on the first frost day in comparison to the historical period, in addition to detecting an earlier appearance of the last frost day. However, this trend was not spatially homogeneous, because there have been areas where frost risk has increased and remains as a major environmental threat to agricultural production. On the other hand, earlier start and a delaying in the end of growing season were found, this larger growing period could be an opportunity to incorporate more flexible agricultural practices that would result into an increase in yields.

A similar exercise was carried out in Poland where the authors incorporated a climate change model to generate future scenarios (Graczyk and Kundzewicz, 2016). Using a point-based analysis (i.e. analyzing specific stations) the authors found trends consistent with climate change projections that showed an increase of the growing season and an increase in growing degree days. Because stations did not show similar results, authors concluded that the stations were subject to a strong natural variability. Another example of such analysis was the assessment of long-term trends in agroclimatic indices for three main field crops grown in Canada (Qian et al., 2010). Here, the authors found an increasing trend in growing season and a longer frost-free period.

An alternative to the use of measurements from meteorological stations, is the use of satellite images that can cover larger areas and enable us to identify spatial patterns in these changes. Remote sensing data has been used to study the effect of climate on natural vegetation by evaluating indices such as the widespread used Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI). These variables have been commonly used to evaluate Gross Primary Productivity as a proxy of growing season length (Suzuki et al., 2006). NDVI uses the reflectance of the red and near-infrared channels and can be obtained for series that date back to 1970 using the Advanced Very High Resolution Radiometer (AVHRR) inside NOAA's meteorological satellites. Since 2000, the moderate resolution imaging spectroradiometer (MODIS) has allowed the calculation of a variety of new vegetation indices, such as EVI that require blue band information, enable us to monitor the index more frequently (with 1, 8 or 16 days products) and with a more detailed spatial resolution (250-1000 m.) (Zhou et al., 2014).

Even though the use of satellite data for the calculation of specific agroclimatic indices and detection of major trends and changes represents a promising alternative if a series of technical requisites are met. Records should have enough temporal resolution to perform daily calculations and are able to monitor nocturnal surface temperatures that can be used as proxies for minimum temperatures and have a considerable temporal extension to perform trend calculation. MODIS images are a good alternative, since their daily products satisfy all these requirements and are freely accessible. Their spatial resolution allows for studies at valley level that are of great interest for agricultural policy, while farm level specific studies require higher resolution images and/or the presence of a weather station nearby.

Given the advantages of MODIS images as tool to perform systematic spatiotemporal analysis of agroclimatic indices, we have designed a study to evaluate trends of agroclimatic indices that are relevant for agriculture with the greatest spatial coverage possible. This study focuses on temperature related indices as it represents the main variable for monitoring crop adaptability, and because reliable indirect measurements of this variable can be obtained from satellite images. Our hypothesis is that, in the recent period, changes in temperature have been verified in agricultural areas that turn out to be significant and may have an impact on crop growth and development.

2 METHODS

The assessment of trends in agroclimatic indices requires the integration of databases and the derivation of specific variables from remote sensing data. A diagram of the methodological framework adopted in this work, including a sequence of the processes followed and input data required to obtain the necessary database is presented in Figure 1.

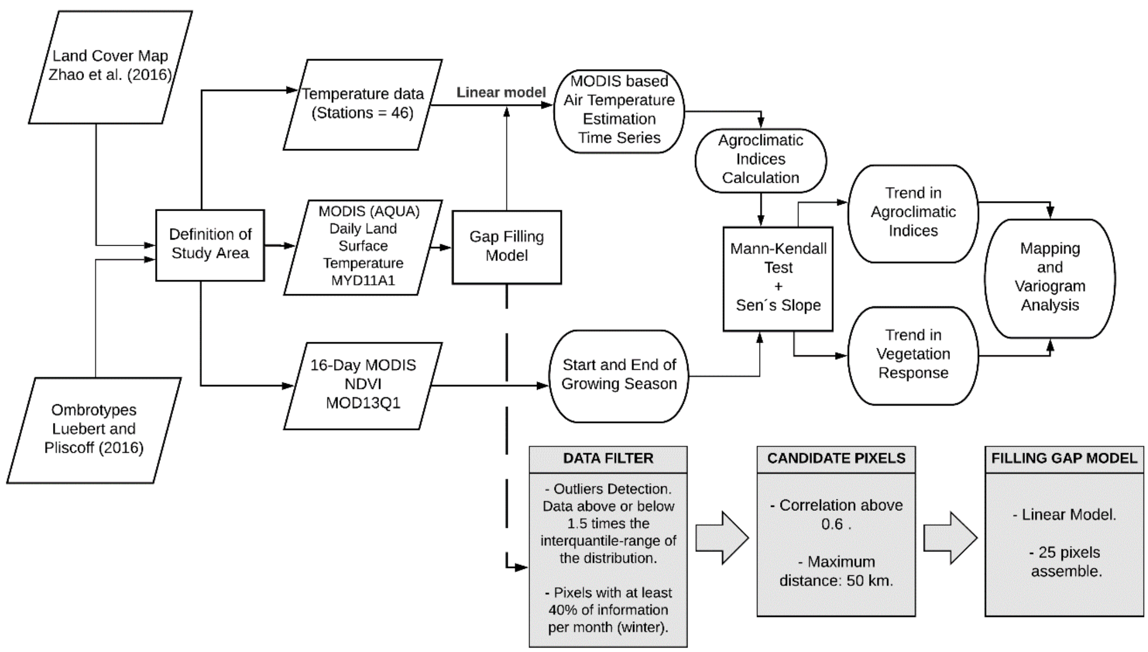

Figure 1: Methodological framework for the study of trends in temperature based agroclimatic indices using remote sensing data from MODIS images.

2.1 STUDY AREA

The study area corresponds to the main agricultural locations between Coquimbo and Biobio regions in Chile. This area is known to have a Mediterranean climate, with a range of subtypes that vary from a semi-arid condition in the northern part, with eight to ten dry months per year, to humid in the south, with two to four months without precipitation in the summer season (DiCastri and Hajek, 1976; Luebert and Pliscoff, 2008). While precipitation gradient is significant, there is a slight downward temperature gradient towards the south.

To analyze the results, we divided the study area into four main regions given by ombrotype indices in Mediterranean macrobioclimate as calculated by Luebert and

Pliscoff (2016). For simplification, we merged the humid ombrotypes subclasses (hyperhumid, ultrahiperhumid) under the name of “humid” because this class was predominant in agricultural pixels for the study area and its subclasses represents less than 1% of pixels. The ombrotermic index is calculated as the ratio between average precipitation and temperature accumulation in months whose average temperature is higher than 0°C, this index evaluates the annual water availability and is used as predictor of the relationship between the climate (temperature and precipitation) and the presence of vegetation (Rivas-Martínez et al., 2011).

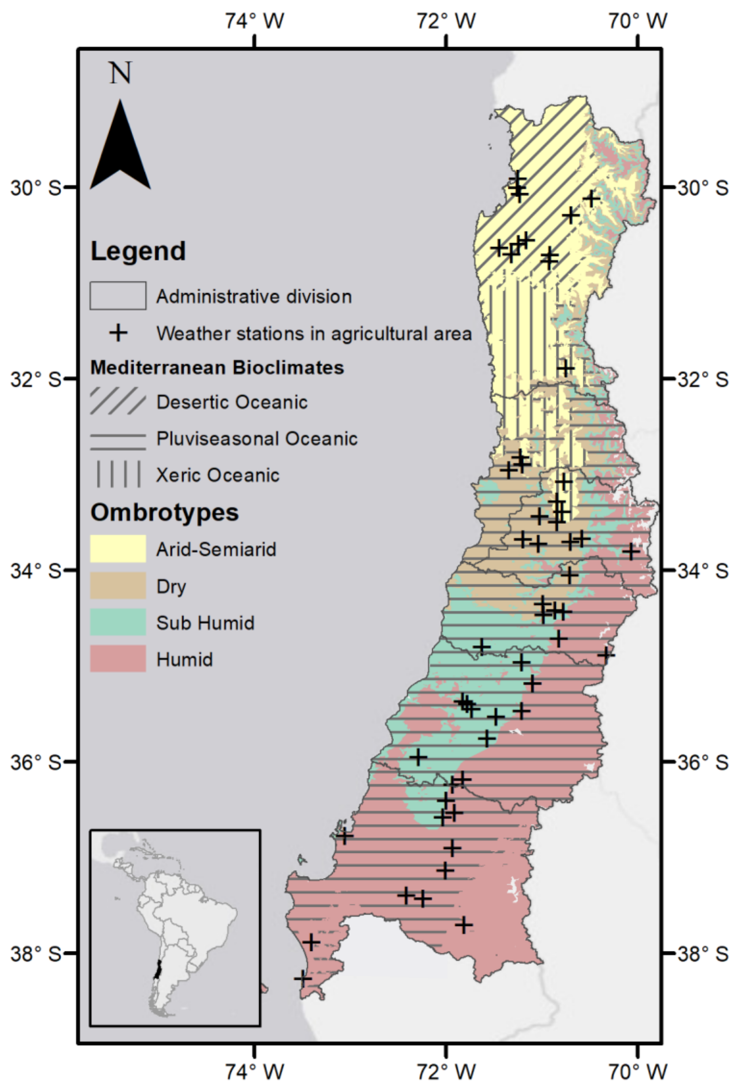

Figure 2: Mediterranean bioclimates and ombrotype division for the study area. Adapted from (Luebert and Pliscoff, 2016b)*. The crosses represent selected weather stations in cropland and grassland pixels.*

The geography is shaped by the Cordillera de Los Andes (3500 - 4500 m) in the east, the low coastal mountains in the west (Cordillera de la Costa), which has few important agricultural valleys. Between these two major features we can identify a central valley, where the main cities and economic activities, along with most important agricultural locations, are found. The study area concentrates around 47% of all farm land used for agriculture in the country, 93% of all agricultural area is concentrated in farms larger than 100 hectares (ODEPA, 2017).

Between 30 and 35° of latitude (administrative regions of Coquimbo, Valparaiso, Santiago and O´Higgins), most of the agricultural activities are found in the longitudinal valleys and Cordillera de la Costa with greater dependence on irrigation, whereas towards the south in Maule and Biobio regions (36 - 38°S), agriculture becomes more extensive and diversified. In this part of the country natural grasslands are sustained by greater amounts of precipitation.

The soil cover characterization for Chile (Zhao et al., 2016) was used to define agricultural areas. This classification uses images from the Landsat and MODIS satellites and control points throughout the national territory to conduct a supervised classification of soil cover at 30 m resolution. We carried out a downscaling to MODIS resolution of 1000 x 1000 meters using a majority algorithm within filter window of 33 neighbor pixels.

For this study, we selected those pixels represented with class 100 (agricultural crop). Towards the south (36°S) we also included pixels with class 300 (grassland) associated with livestock farming. One of the assumptions of the study is that there has not been a significant change in land use during the last 16 years, and therefore pixels with some type of agricultural or grassland type vegetation have not changed abruptly into other classes such as urban or forestry (Miranda et al., 2017; Schulz et al., 2010).

2.2 AGROCLIMATIC INDICES

Agroclimatic indices allow us to study the effect of changes in the climatic variables on the growing season conditions. Agroclimatic indices can be used in agricultural planning and crop management, for example, in the characterization of suitable land for a certain crop and the selection of varieties, as well as, to monitor changes in weather variables in real time (Qian et al., 2012, 2010).

Crops have different environmental requirements throughout their life cycles (Hatfield et al., 2011). With regards to temperature, these requirements are associated to a range defined by cardinal temperatures: the maximum temperature and the minimum temperature and the optimum temperature, allowing us to characterize the response of crops to the fluctuations of ambient temperature (Qian et al., 2010).

While in some cases low temperatures are beneficial for the development of certain crops inducing changes in their phenological stages, it is more common that cold temperatures, especially if they fall below zero, limit the growth and/or induce severe damages to crop. Warm temperatures, on the other hand, contribute to accelerate the rate of development, allowing crops to reach maturity earlier within the growing season.

Selected yearly agroclimatic indices were obtained for Fernández-Long et al. (2013) and Graczyk and Kundzewicz (2016). These indices have been classified into “heat” and “cold” category. Specific description of these indices is provided in the subsections below.

2.2.1 Indices for heat category

Here Tx is the maximum temperature, and *Tn* is the minimum temperature of day t. Sub indices i and n in the summation correspond to May 1st and December 31st in the case of winter crops, and October 1st to March 31st in the case of summer crops. Although crops have specific base temperatures for the calculation of growing degree days, in this case we have used a single value of 7 ºC to facilitate the calculation. One would expect only minor changes in the trend analysis results when using a different set of base temperatures for winter and summer crops.

shows those indices associated to a “heat” category. The selected indices are: the start of growing season (SGS), which is calculated as the first occurrence of seven consecutive days with mean temperature above a threshold of 7°C; the end of growing season (EGS) that is calculated as the last occurrence of the previously described condition; and the length of growing season that corresponds to the number of days between SGS and EGS. A fourth index in this category corresponds to Growing Degrees Days, that are calculated separately for winter crops (considering a growing period between May 1st –December 31st) and summer crops (covering the period between October 1st –March 31st).

Table 1: Description of indices associated with "heat" category.

Indices	Abbr.	Description
Start of growing season	SGS	Seven consecutive days with mean temperature above 7°C.
End of growing season	EGS	Last seven consecutive days with mean temperature above 7°C.
Length of growing season	LGS	Number of days between SGS y EGS.
Growing degree days	GDD	Cumulated degree days between October 1st –March 31st for summer crops and May 1st –December 31st for winter crops. (**Equation 1**)

The calculation of growing degree days is done using a single base temperature and according to the following equation:

Equation 1

$$GDD = \sum_{t=i}^{n} \varphi_t$$

$$\varphi_t = \begin{matrix} \dfrac{Tx_t + Tn_t}{2} - 7 & if \ \dfrac{Tx_t + Tn_t}{2} > 7 \\ 0 & otherwise \end{matrix}$$

Here *Tx* is the maximum temperature, and *Tn* is the minimum temperature of day t. Sub indices i and n in the summation correspond to May 1st and December 31st in the case of winter crops, and October 1st to March 31st in the case of summer crops. Although crops have specific base temperatures for the calculation of growing degree days, in this case we have used a single value of 7 ºC to facilitate the calculation. One would expect only minor changes in the trend analysis results when using a different set of base temperatures for winter and summer crops.

2.2.2 Indices for cold category

Table 2 shows the indices used to describe the "cold" category. In this category, the first and last day with frost (FFD, LFD), the period of frost (FP) and the number of days with frost (NFD) are included. We assume that frost occur whenever minimum temperature falls below 0 °C. In addition to those indices, we recorded the lowest minimum temperature (LMT) and chilling hours (CH) (i.e. hours with temperature less than or equal to 7°C).

Table 2: Description of agroclimatic indices asociated with "cold" category.

Indices	Abbr.	Description
First frost day	FFD	First day before 15th July with minimum temperature under 0°C
Last frost day	LFD	Last day after 16th July with minimum temperature under 0°C
Frost period	FP	Number of days between FFD y LFD.
Number of frost days	NFD	Number of days with minimum temperature under 0°C
Lowest minimum temperature	LMT	Lowest minimum temperature (°C)
Chilling hours	CH	Hours with temperature under less or equal to 7°C. (**Equation 2)**

The calculation of chilling hours was done using the following equation:

Equation 2

$$CH = \sum_{t=j}^{m} \omega_t$$

$$\omega_t = 24 \times \frac{(7 - Tn_t)}{(Tx_t - Tn_t)}$$

This method assumes that the fraction of the number of hours that can be counted as chilling hours depends linearly with the minimum temperature. If maximum temperature in day t is lower than 7 °C the value of the function should be set to the maximum number of chilling hours in a day (24).

2.3 MODIS DATA

To determine changes in agroclimatic indices based on satellite data, we collected images from MODIS sensor for the Daily Land Surface Temperature (MYD11A1) (Wan et al., 2015) and 16-Day NDVI (MOD13Q1) (Didan, 2015) products. Land Surface Temperature and NDVI data was downloaded and processed in the software R with "rts" library (Naimi, 2015) and MODIS Reprojection Tool from NASA to carry out mosaics from tiles and projected to WGS1984 coordinate system. Additionally, a resampling of NDVI information of a resolution of 250 m. to 1000 m. was made using MODIS Reprojection Tool using bilinear method.

Quality filter of the products was done using QC bands, keeping only the pixels classified as good quality (value = 0) in order to ensure reliable information of land surface temperature (daytime and nighttime) and NDVI.

2.3.1 Daily Land Surface Temperature

For the calculation of agroclimatic indices associated with “cold” and “heat” categories it is necessary to have data of minimum temperature and maximum temperature. For this purpose, the use of satellite images that have nighttime temperature is crucial. In the case of the spatial calculation of agroclimatic indices, the surface temperature data from MODIS sensor turns out to be a good alternative as a proxy for extreme temperatures (Bustos and Meza, 2015; Gregory et al., 2009; Zhu et al., 2013). These images, besides being free, can be obtained at a daily level, four times a day and with a spatial resolution of 1000 meters, which allows to rescue general patterns in variables associated with agriculture.

In this study, data from the AQUA platform registered at 13:30 p.m. and 1:30 a.m. local time were used, as they were close to the time when maximum and minimum daily temperatures are usually observed. Unfortunately, this information presents several gaps due to cloud cover. For this reason, it was necessary to fill out missing values before performing the calculation of agroclimatic indexes that require a consecutive recording of days under a specific condition (e.g. beginning and end growing season).

2.3.1.1 Gap filling model

Gap filling procedure allowed us to easily calculate indices, especially those that require consecutive days in a particular condition (e.g. beginning and end growing season).

We selected a simple regression model where candidate pixels (independent variables) are used to fill the objective pixel (dependent variable). Independent variables must fulfill two conditions. First, each candidate pixel must be located within 50 kilometers of the pixel where temperature values are going to be estimated (filled), the main assumption is that the closest pixels are under the same cloudiness condition. Second, candidate pixels must have a linear Pearson correlation greater than 0.5 to ensure a reasonable fit. To simplify the calculation, we considered a set of no more than 25 candidate pixels, whose contribution in the model was determined by distance and correlation.

The resulting filled pixels were subjected to an outlier detection process, excluding data above and below 1.5 times the inter-quartile range of the distribution (Hodge and Austin, 2004). In addition, we excluded pixels whose proportion of available data per month was less than 40% for not having enough information for the calculation of agroclimatic indexes. We selected 40% considering that the monthly distribution proportion of all pixels has the inflection value between the pixels with less and more information in value of 0.4.

2.3.1.2 MODIS based air temperature estimation

Oftentimes surface temperature obtained by satellite images is not equivalent to air temperature measured under standard conditions in meteorological stations. The relationship between the two variables has been studied in Chile by (Bustos and Meza, 2015), finding high correlation between both variables, especially in pixels that correspond to agricultural areas.

To validate the use of the satellite information we composed a dataset containing 46 meteorological stations for the period 2002 to 2016 located at cropland and grassland pixels (Figure 2). These data were obtained in “Red Agroclimática Nacional” (www.agromet.cl) and Center for Climate and Resilience Research (www.cr2.cl) who compiled information of “Dirección General de Aguas” (DGA) and “Dirección Metorológica de Chile” (DMC). The selected stations must have at least 24 days of records for each month in minimum and maximum temperatures, which is 80% of the complete monthly information, and no missing years.

Furthermore, we extracted data of time series of surface temperature for each pixel where a meteorological station is located. The relationship between both series was studied by adjusting a linear model, recording the values of the determination coefficient and Root Mean Square Error.

The coefficients b_0 (intercept) and b_1 (slope) of the obtained linear model are used to create a continuous surface using interpolation by weighted inverse distance (IDW). The results of this interpolation were used, applying the corresponding linear equation for time series obtained in each pixel of satellite surface temperature, to convert satellite data into a more reliable estimate of air temperature.

2.3.2 NDVI

To study the response of vegetation to observed trends in temperature, we used NDVI MODIS (MOD13Q1) 16 days product for the period 2002 to 2016 at a spatial resolution of 1 km. This product used an algorithm that chooses the best available pixel value from all the images in the 16 days period using the criteria of low clouds, low view angle and the highest NDVI value (Didan et al., 2015).

For each pixel, the beginning and end of growing season was assessed considering an agricultural year as the period between May 1st (mid-autumn) and April 31st (late summer early autumn) of the following year. The start of the growing season was considered as the date after of minimum NDVI value, above this date the values start an ascending curve to the maximum NDVI. After the maximum NDVI the curve start a decreasing slope value which marks the end of growing season (Verbesselt et al., 2010).

2.4 TREND ANALYSIS

Mann-Kendall test was performed to assess the statistical significance of observed trends in the time series of agroclimatic indices calculated both with station and satellite data. Mann-Kendall is a nonparametric test, where the null hypothesis states that data are independent and ordered randomly, implying that there is no trend or structure of serial correlation between observations (Hamed and Ramachandra Rao, 1998). The value of the linear trend is computed with Sens´s slope estimator (Sen, 1968) where the trend is the median of all possible trend estimates from a pair of estimations in two distinguished times. Mann-Kendall and Sen´s slope are not reliable in series with autocorrelated data (Zhang and Zwiers, 2004). For this study we consider that the annual step series of agroclimatic indices are statistically independent as proposed by (Fernández-Long et al., 2013), as no previous autocorrelation whitening process was conducted. Both tests were performed using the "wq" library (Jassby and Cloern, 2016) in the software R (R Core Team, 2014).

2.5 DIRECTIONAL VARIOGRAM ANALYSIS

To evaluate spatial patterns of trends found via Mann-Kendall and Sen´s slope analysis, we conducted a directional variogram analysis using latitude, longitude and trend value for pixels with significant trend. This method allows us to understand the spatial structure of the data. In this case, we were interested in identifying if trends are grouped at lower distances and what is the predominant direction of variability.

The variogram method allows us to know the variability between two separated points at determined intervals and their evolution at increasing distances. There are different techniques to identify (fit) the best model that describes the spatial variability, which is later used in interpolation by means of Kriging (Li and Heap, 2014, 2011). In this case we used an auto fitted model available in the geoR library (Jr and Diggle, 2016) in the R software. As variability can occur asymmetrically (anisotropy) or symmetrically (isotropy) in space, we studied the variability in nearby points in cardinal directions, using the azimuth angles 0, 45, 90 and 135° that represent vertical (north/south), horizontal (east/west) and diagonal directions.

3 RESULTS

3.1 GAP FILLING MODEL

Figure 3 shows the proportion of complete data by month using diurnal MODIS data before and after gap filling process. The amount of information varies depending on the degree of cloudiness of each month, whereby in summer months the complete data reaches an average proportion of 0.8, while in winter months this proportion drops to 0.3. There is no noticeable effect of the cloud cover comparing daytime and nighttime information. Note that, at the moment of accessing the data (year 2017) complete information never reaches above 80% due to missing MODIS data during the period April and June of 2015.

The gap filling model used in this study provides similar results for all months regardless of the land cover classifications. In pixels with classification 300 (grasslands) the proportion of complete data increased in average by 12%, whereas for pixels with classification 100 (agricultural), the proportion of complete data increased by 8 %. In all cases the differences in means are statistically significant.

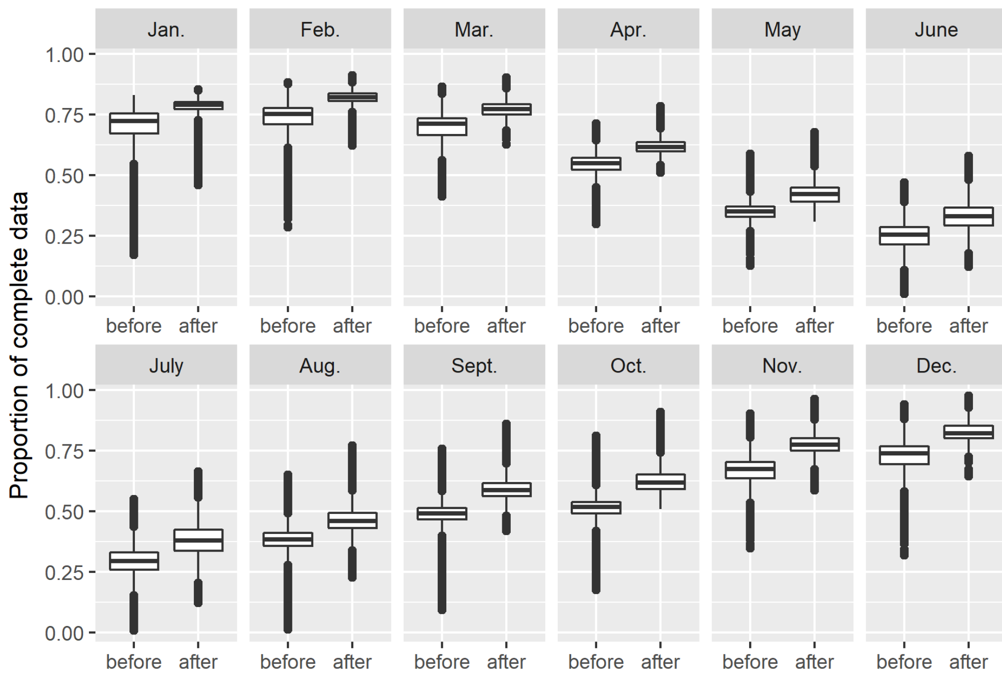

Figure 3: Proportion of complete data before and after gap filling process for daytime observations.

The gap filling procedure reduces the number of outliers in the lower part of the distribution and reduces the interquartile range for all months. Nevertheless, in May, June, July and August, the final proportion of monthly data reaches maximum 0.5 due to cloudiness.

3.2 MODIS BASED AIR TEMPERATURE

Results from the linear regression used to correct MODIS data using surface station data show that 90% of the stations have linear models with r-square above 0.65 (Figure 4), though only 5 stations have regression coefficients between 0.4 and 0.6.

For both cardinal temperatures, the major part of the stations has an R^2 value greater than 0.6, indicating a strong relationship between station registers of maximum and minimum temperatures with MODIS daytime and nighttime land surface temperature.

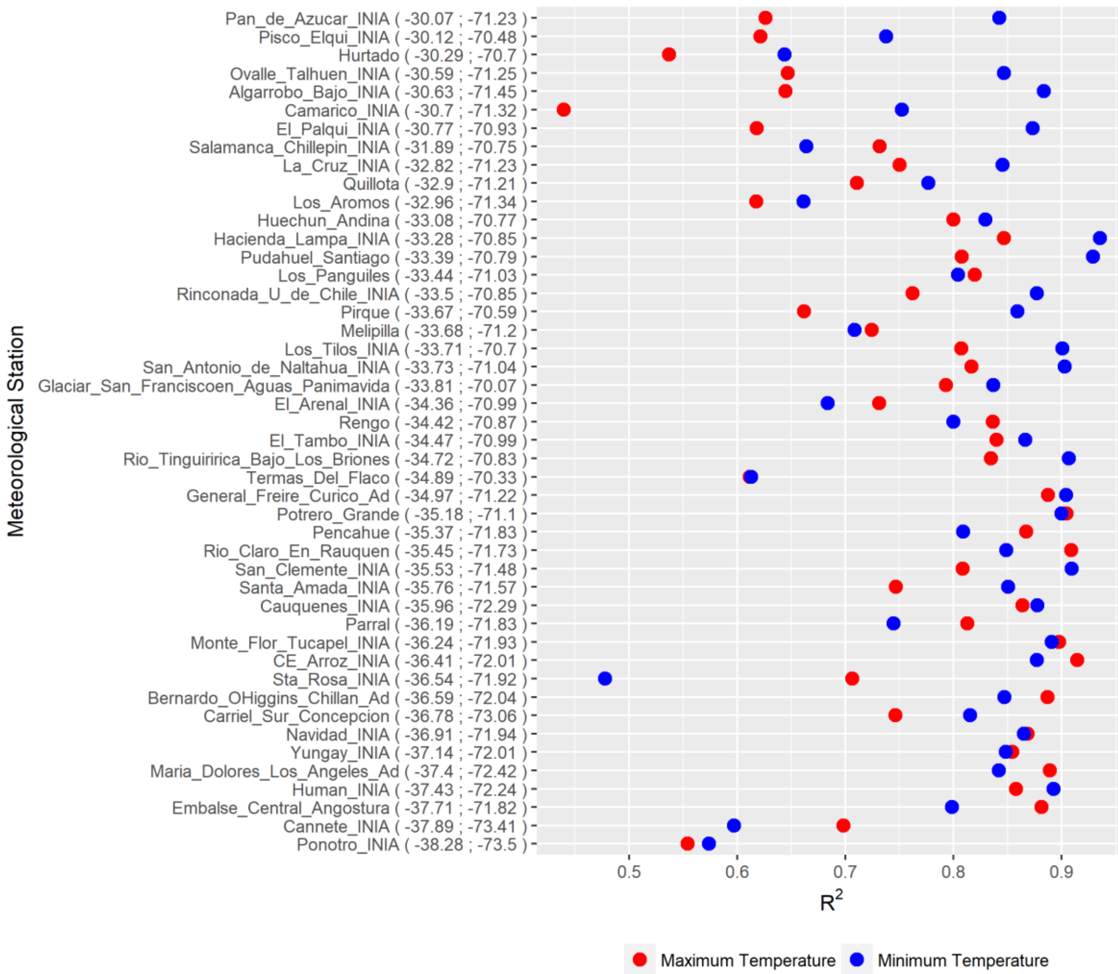

Figure 4: Coefficient of determination (R^2) for linear regression between registers of meteorological stations and MODIS data.

The root mean square error is higher for maximum temperatures than minimum temperatures when errors are, in general, bellow 2°C (Figure 5). For maximum temperatures mostly of the stations have errors above 2°C but no higher tan 4°C. For minimum temperatures the average of RMSE is 1.65 degree Celsius, the maximum error value corresponds to 2.8 °C in “Santa Rosa INIA” station (-36.5 S, -71.9 O). There is no latitudinal pattern in these values.

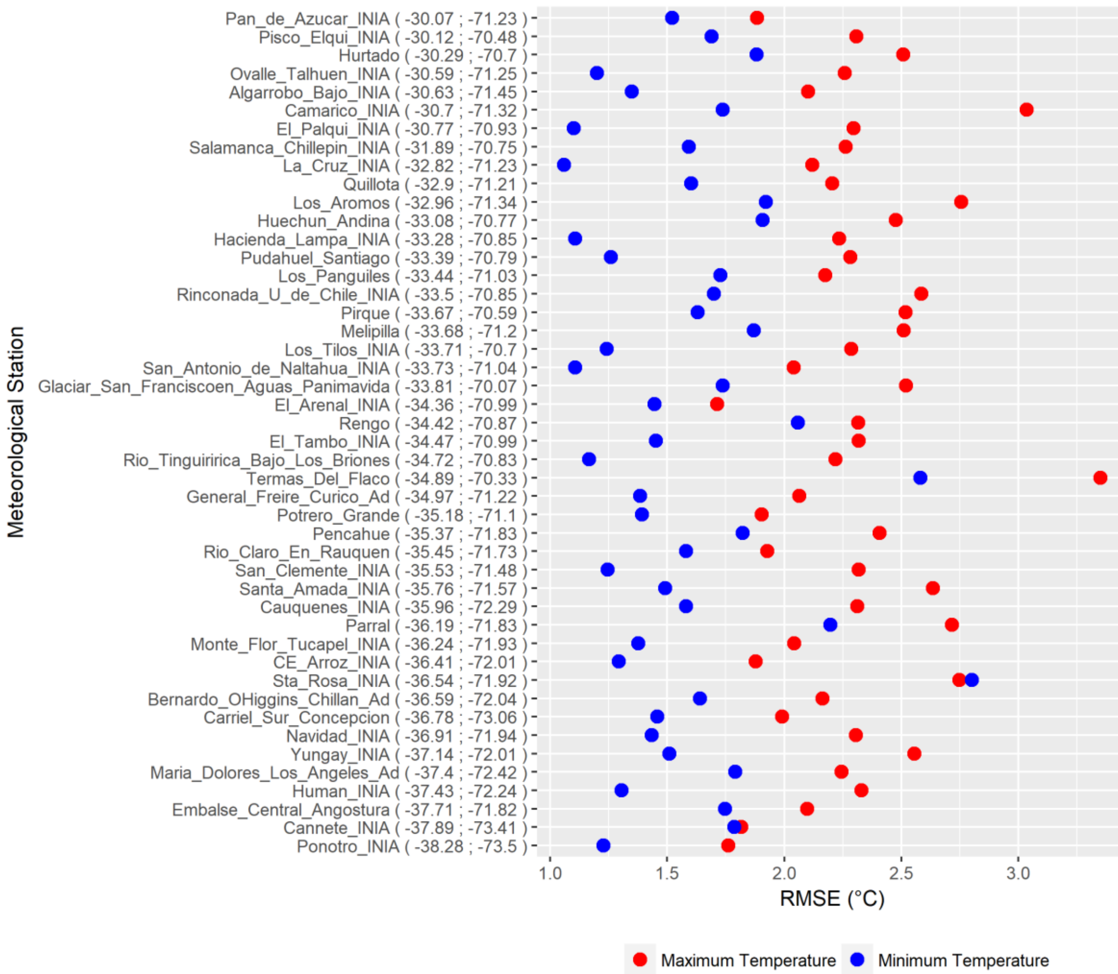

Figure 5: Root mean square errors in linear regression between registers of meteorological stations and MODIS data.

3.2.1 Maximum temperature

Maximum temperature derived from MODIS data was obtained using the interpolation of coefficients of linear models between maximum air temperature and daytime land surface temperature. The interpolation parameters are shown in Figure 6.

Between latitude -30 to -34 the intercept (bo) is above five, that means that daytime surface temperature is 5 - 15 ºC higher than maximum air temperature. Whereas in the southern part of study area, this difference is less than 5 °Celsius (Figure 6). The slope (b1 coefficient) indicates the average change in the response variable by increasing the predictor variable by one unit. For our study, this variation of maximum air temperature and daytime land surface temperature is below 1° Celsius, and lesser in the northern part of study area.

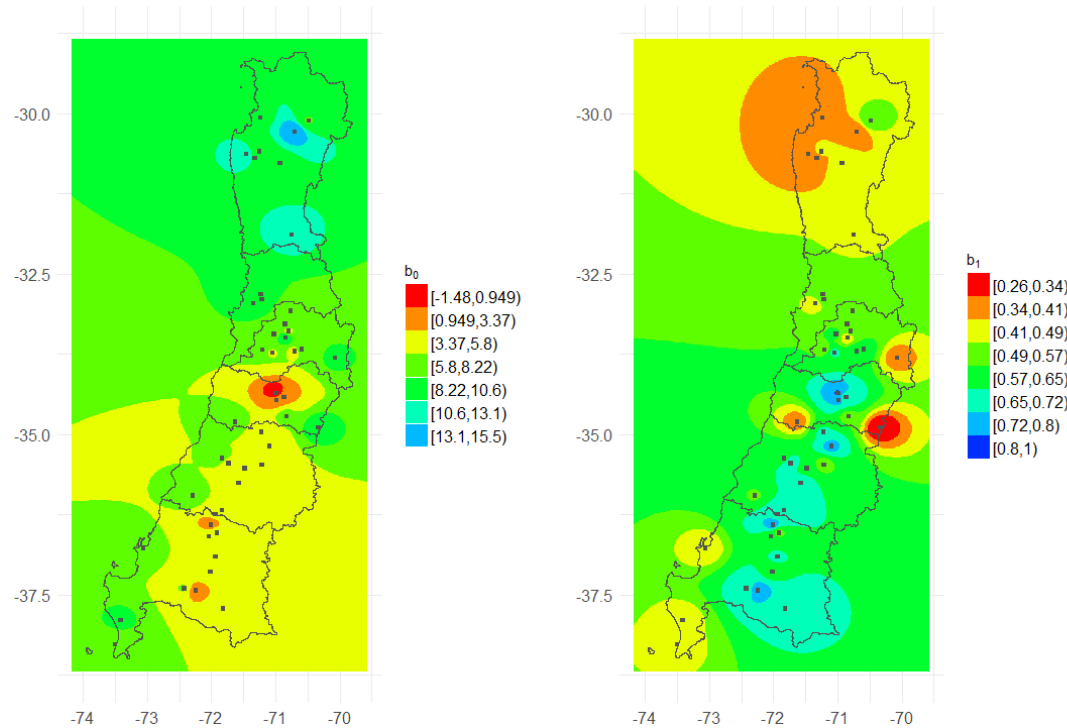

Figure 6: Spatial distribution of interpolated by IDW coefficients of a linear regression between MODIS data and surface station data, intercept (b_o, left) and slope (b_1, right). These coefficients are used for rescaling daytime land surface temperature to maximum air temperature.

3.2.2 Minimum temperature

For the case of minimum air temperature, the interpolation of regression coefficients is shown in Figure 7. The intercept has an average of 0.38°C showing that nighttime land surface temperature differs in less than 0.5 degree Celsius from the minimum temperature recorded in meteorological stations.

The slope coefficient (b_1) varies between 0.42 and 0.97 °C, similar to the coefficient found for maximum temperature.

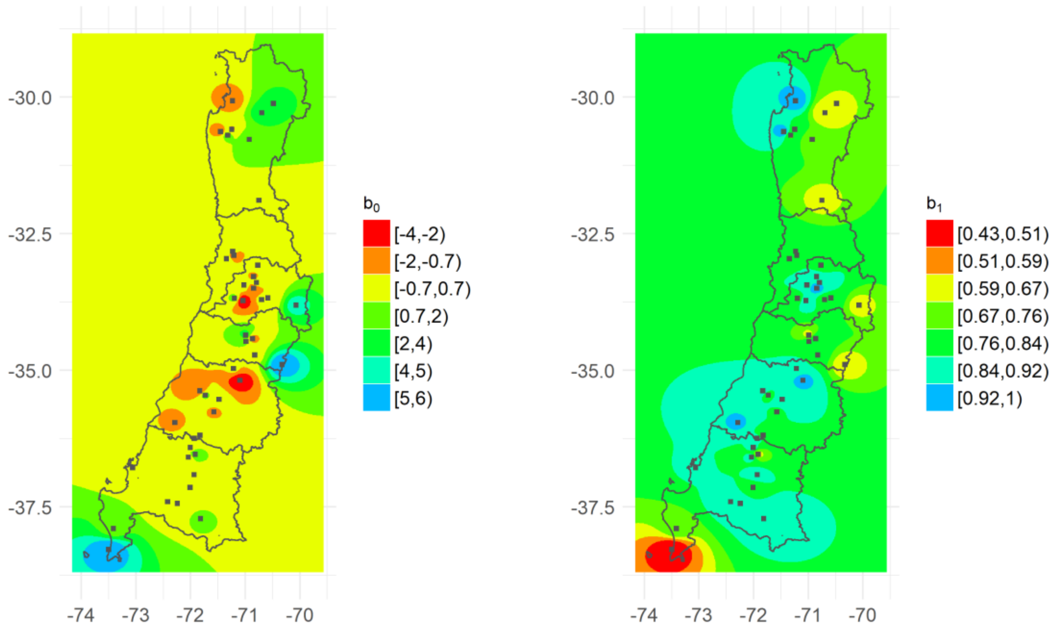

Figure 7: Spatial distribution of interpolated by IDW coefficients of a linear regression between MODIS data and surface station data, intercept (b_0, left) and slope (b_1, right). These coefficients are used for rescaling nighttime land surface temperature to minimum air temperature.

3.3 TREND ANALYSIS IN AGROCLIMATIC INDICES

Trend analysis is performed in each pixel of the land use class with sufficient information. Arithmetically, it is very likely that results show positive or negative trends but only a few of them can be regarded as statistically significant as the sample size is still very low (only 16 years)

Table 3 synthesizes the results of trend analysis by different Mediterranean zones. In order to establish spatial patterns in trend values we include directional variograms which are shown in Figure 8, directions with average maximum and minimum semi variance are highlighted with thick line.

Table 3: Summary of the spatial coverage of detected trends in agroclimatic indices expressed as a percentage of pixels in a specific type by main Mediterranean zones.

Mediterranean Zone	Index Name	**Number of pixels** Agricultural	No data	**Pixels with trend (%)** Positive	Negative	**Pixels with significant trend (%)** Positive	Negative
Arid - Semiarid	Start of growing season	1975	335	0.2	12.4	0	6.4
Arid - Semiarid	End of growing season	1975	305	50.7	48.2	0.2	2.5
Arid - Semiarid	Length of growing season	1975	382	56.6	41.4	4.6	1
Arid - Semiarid	Growing degree days (Winter crops)	1975	828	89.5	10.5	43.7	0
Arid - Semiarid	Growing degree days (Summer crops)	1975	540	84.5	15.5	1.5	0
Arid - Semiarid	First frost day	1975	1092	28.3	70.2	0.1	7.6
Arid - Semiarid	Last frost day	1975	1069	74.8	23.3	6.3	0.3
Arid - Semiarid	Frost period	1975	1071	75.8	15.3	8	0.2
Arid - Semiarid	Lowest minimum temperature	1975	447	19.1	80.4	0.1	10.5
Arid - Semiarid	Number of frost days	1975	343	44	0.4	1.7	0
Arid - Semiarid	Chilling hours	1975	302	99.8	0.2	7	0
Arid - Semiarid	NDVI Start of growing season	1975	131	33.8	35.3	4.3	4.5
Arid - Semiarid	NDVI End of growing season	1975	83	17.3	41.1	1.7	8.5
Arid - Semiarid	NDVI Length of growing season	1975	74	37.8	42.5	3.4	6.4
Dry	Start of growing season	4542	180	0.3	27.4	0	7.3
Dry	End of growing season	4542	280	40.7	56.6	0.9	0.2
Dry	Length of growing season	4542	284	67.2	31.7	5.3	0
Dry	Growing degree days (Winter crops)	4542	355	95.8	4.2	16.4	0
Dry	Growing degree days (Summer crops)	4542	234	92.7	7.3	2.1	0
Dry	First frost day	4542	2154	22.2	76.5	0.3	10.4
Dry	Last frost day	4542	2165	72	25.4	7.5	0.5
Dry	Frost period	4542	2119	77.5	13	7.9	0.1
Dry	Lowest minimum temperature	4542	203	14.2	85.6	0	12.1
Dry	Number of frost days	4542	174	46.7	0.3	1.5	0
Dry	Chilling hours	4542	144	99.9	0.1	1.7	0
Dry	NDVI Start of growing season	4542	171	30.3	29.7	3.8	3.2
Dry	NDVI End of growing season	4542	124	19.9	34	2.8	8.9

Dry	NDVI Length of growing season	4542	152	33.5	46.9	2.4	7
Sub Humid	Start of growing season	7185	213	0.4	61.5	0	21.6
Sub Humid	End of growing season	7185	574	39.8	59.1	0.2	1.3
Sub Humid	Length of growing season	7185	478	85.8	13.6	10	0
Sub Humid	Growing degree days (Winter crops)	7185	247	99.5	0.5	58.6	0
Sub Humid	Growing degree days (Summer crops)	7185	248	93.8	6.2	8.9	0
Sub Humid	First frost day	7185	1960	38.9	58.7	0.8	4.8
Sub Humid	Last frost day	7185	2030	76.4	18.7	11.6	0.1
Sub Humid	Frost period	7185	2032	73.6	19	4.7	0
Sub Humid	Lowest minimum temperature	7185	307	19.2	80.7	0.1	9.4
Sub Humid	Number of frost days	7185	236	63	0.3	1.4	0
Sub Humid	Chilling hours	7185	535	98.7	1.3	0.3	0
Sub Humid	NDVI Start of growing season	7185	136	27.9	35.4	2	2.8
Sub Humid	NDVI End of growing season	7185	207	13.2	44.7	1.6	11.8
Sub Humid	NDVI Length of growing season	7185	190	27.7	54.1	1.2	6.6
Humid	Start of growing season	8874	1012	0.8	71.2	0	40.2
Humid	End of growing season	8874	779	19	79.8	0.2	6.8
Humid	Length of growing season	8874	808	75.7	23.4	9.1	0.4
Humid	Growing degree days (Winter crops)	8874	593	100	0	83.7	0
Humid	Growing degree days (Summer crops)	8874	983	73.9	26.1	2.4	0
Humid	First frost day	8874	1295	38.9	59.4	1.1	6
Humid	Last frost day	8874	1279	52.2	33.7	4.3	1.8
Humid	Frost period	8874	1319	63.9	30.2	5.7	0.2
Humid	Lowest minimum temperature	8874	908	24.6	75.2	0.4	7.6
Humid	Number of frost days	8874	1048	79.7	0.7	3	0
Humid	Chilling hours	8874	921	99.9	0.1	2.8	0
Humid	NDVI Start of growing season	8874	266	31.2	35.7	2	3.7
Humid	NDVI End of growing season	8874	354	17.2	39.8	2.9	10.8
Humid	NDVI Length of growing season	8874	339	31	50.8	1.8	4.2

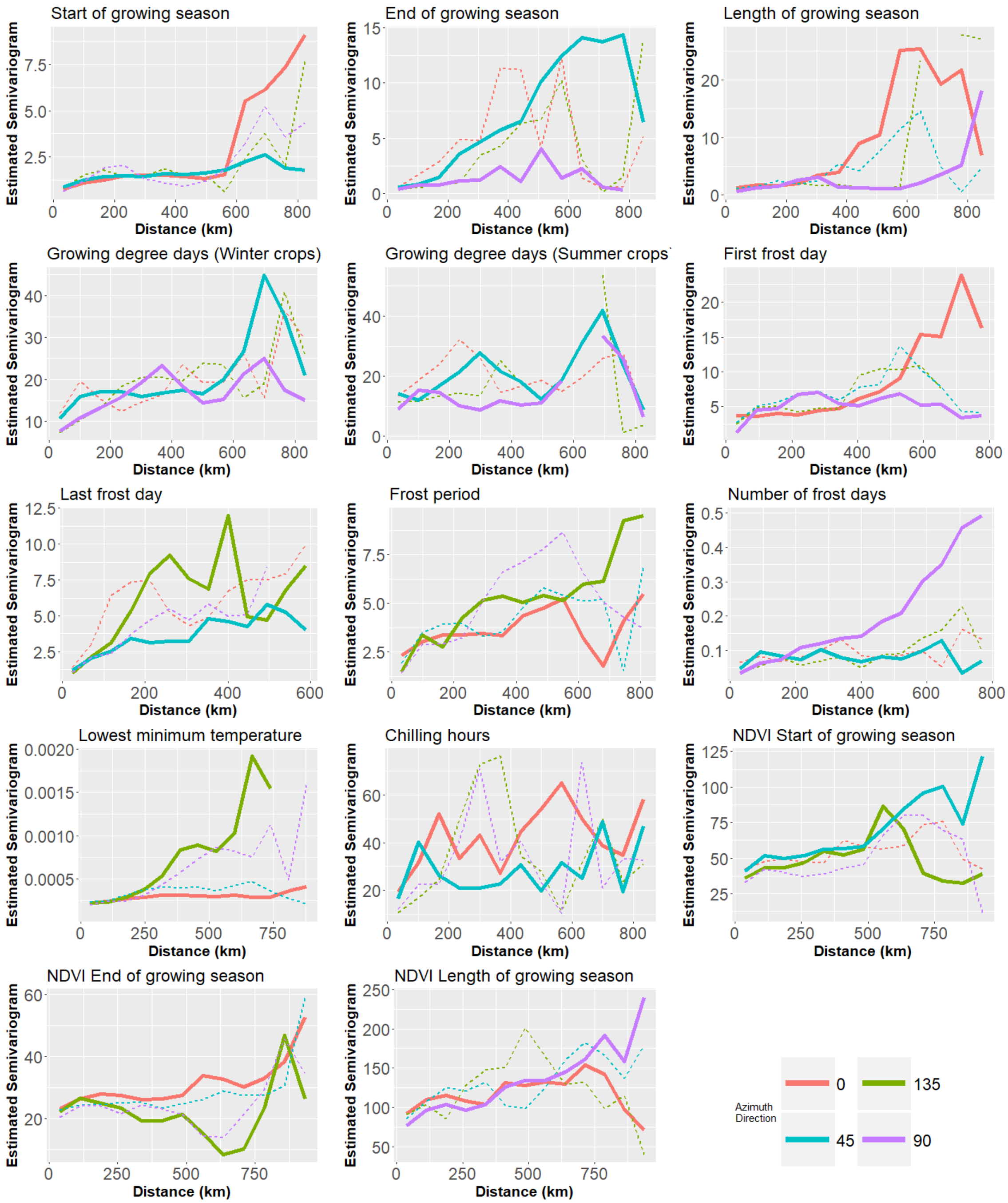

Figure 8: Directional variograms for the evaluated indices. Maximum and minimum semivariance curves are highlight in thick lines. Azimuth directions 0, 45, 135 and 90° corresponds with north, northeast, east and southeast coordinate

3.3.1 Heat category

3.3.1.1 Growing Season

Results of trend analysis for indices of start, end and length of growing season are shown in Figure 9. The start of growing season has a noticeable spatial pattern indicating a strong trend towards earlier occurrence of (4-5 days) in valleys near to the Andes mountain (east) and a slight trend in central valleys and valleys near to coastal mountains (west). Directional variograms in Figure 8 shows a low spatial variability in trend values in pixels located at 0 to 600 kilometers of proximity, up to this distance, there is a latitudinal pattern variation (0° direction). Significant negative trends were found in all zones. In humid and sub-humid Mediterranean types, the percentage of pixels with significative negative trends reaches 21.6 and 40.2% respectively, while in arid and dry zones this value falls below 10% (see

Table 3). This suggests a greater effect of high temperatures in the area between 35 and 38 ° S, which has more temperate climate and greater annual precipitation.

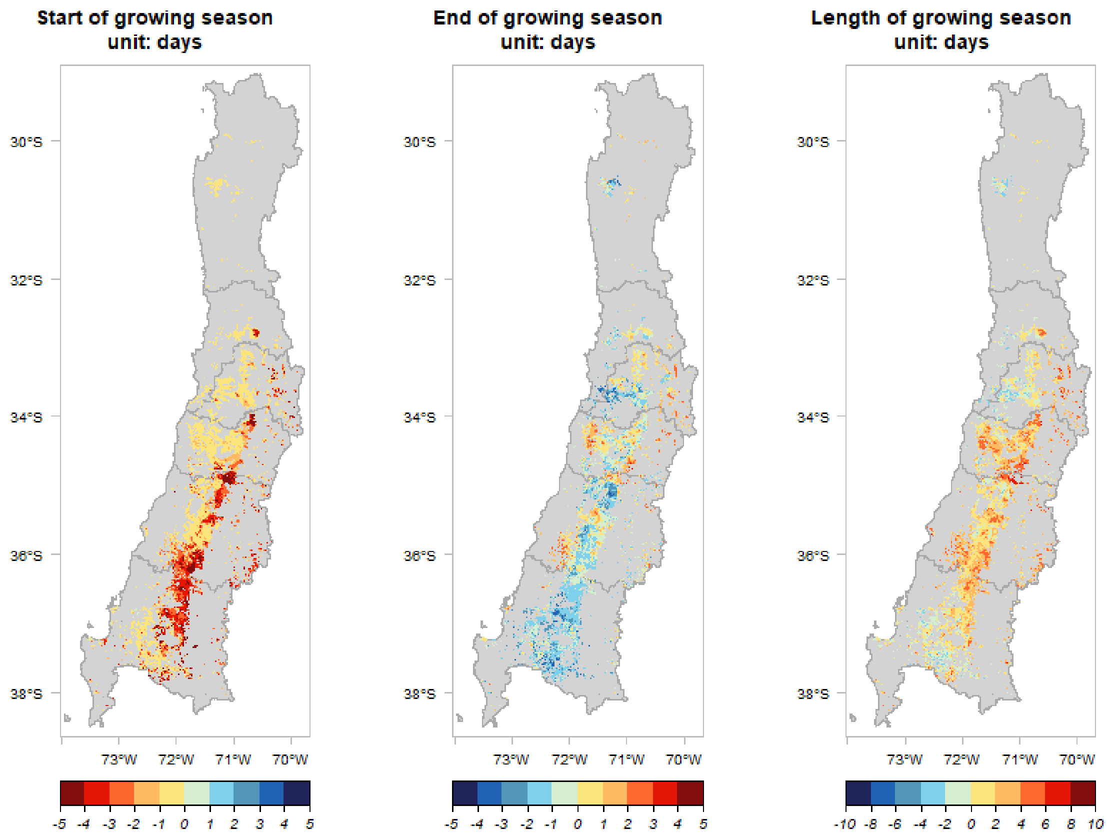

Figure 9: Trend values (number of days per year) for indices associated with growing season length.

The end of the growing season shows a negative trend below 36°S and above 32°S in northern areas, whereas central locations do not show trend except for some coastal valleys at 33.5 °S. For this variable, the number of significative trends is low, in humid type only 6.8 % of pixels exhibit negative significant trend, these values are concentrated in the southern region between 36 and 38°S, while in the arid zone, only 2.5% of pixels show a significative trend being concentrated in the agricultural valleys of the Coquimbo Region (30.5°S). The spatial variability occurs in shorter distances than SGS. Pixels with less than 100 km of proximity show a strong variability in the latitudinal component, while the maximum variability is found at distances between 400-800 km in the north east component. There is not longitudinal pattern (Figure 8). These trends must be monitored in the future, for a prompt detection and correct attributed of climate change or to evaluate the effect of natural variability associated with geography.

The length of the growing season varies from 4 days/year in eastern valleys near to mountainous regions (71.5°W) to 0-2 days/year in central valleys between 72 and 73°W. The spatial variability has a latitudinal trend at distances greater than 350 km. and there is no detectable longitudinal pattern, because the variability is similar for all the distances (Figure 8). Some western spots with negative trends around -2 to -4 days/year have agronomic importance for the cultivation of varieties requiring cold, these places correspond to valleys of San Antonio and Casablanca (around 33.5°S) and Biobio (around 37°S) which has recognized importance in viticulture. The number of significant trends is low, in zones with arid and dry Mediterranean type, positive trends only reach 5% of pixels, while in sub humid and humid zones, this value is around 10%.

3.3.1.2 Growing Degree Days

Growing degree days in Figure 10 show important upward trends for winter crops, between an average of 15-30 additional degree days per year. For the arid-semiarid zone, around 43.7% of the evaluated pixels have a significative positive trend in the case of winter crops (May to December), this value increases to 58.6% in the sub humid regions and up to 83.7% in the humid region. Only in the case of dry zone, there is a lesser percentage of significative pixels (16.4%) that are in agreement with a greater number of pixels with small or even zero trend (yellow colors).

The latitudinal pattern in number of pixels with significative trends suggest a higher incidence of increasing temperatures in the southern regions (sub humid and humid) characterized by moderate temperatures and higher amounts of rainfall than the ones located to the north in the study area. For all indices evaluated, growing degree days for winter crops have the greater number of significative pixels. Directional variogram analysis show similar patterns of variability in all directions and distances, except for points at distances greater than 700 km, this result sustains the homogeneous trend depicted in Figure 10.

For summer crops, the percentage of significative pixels is lower than the one reported for winter crops, only in sub humid zone there is a percentage of significative pixels above 5%. Maps show non-significative negative trends in coastal valleys in the below latitude 36°S, which may be attributable to natural variability because trends are near to -5 growing degree days and that is a reasonable difference in values between years. Variogram analysis shows results similar to those described for winter.

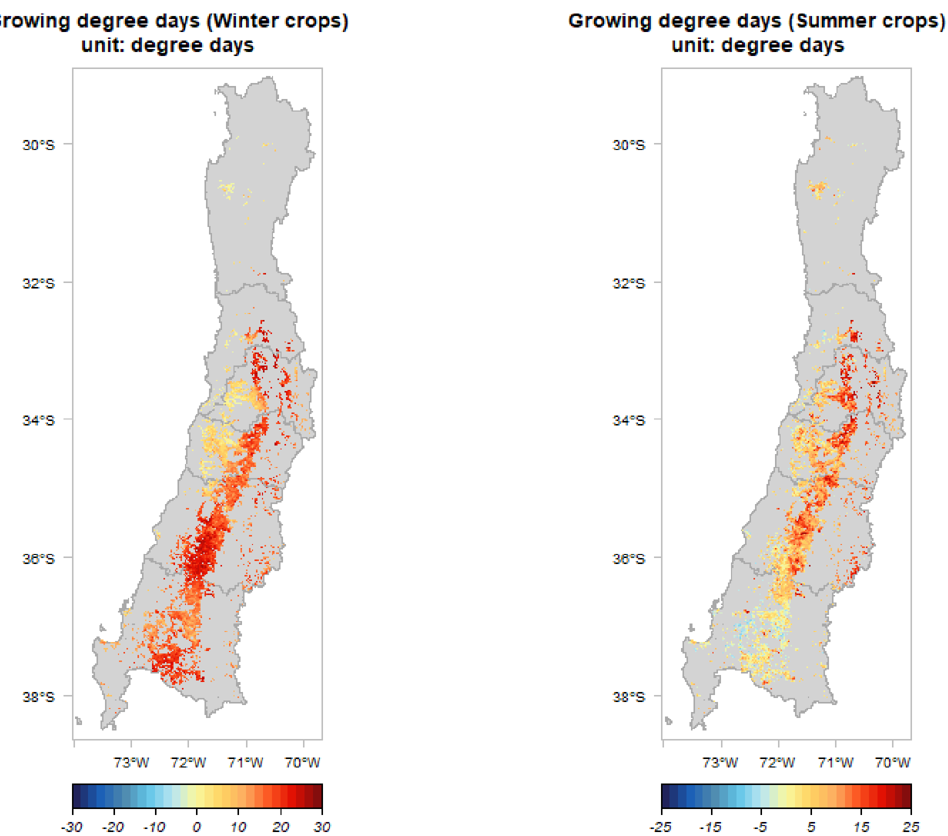

Figure 10: Trend values for growing degree days (degree days per year). In left panel, trends for growing degree days for winter crops (May to December) and in right panel trends in growing degree days for summer crops (October- May).

3.3.2 Cold Category

3.3.2.1 Frost season

Frost season indices are shown in Figure 11, note that the area covered by the maps is slightly smaller than the area covered by indices in Heat category, because of the lesser amount of minimum temperatures than can be estimated due to nocturnal cloudiness.

Negative trends are found for the first frost day, which implies an earlier appearance in the majority of the evaluated pixels. However, the percentage of pixels with significant values is below 10%. In the humid type zone, there are some pixels with significative positive trends (1.1%), this delay of first frost day is found in pixels located in the mountain areas. Variogram analysis shows a latitudinal pattern that is stronger in pixels distant from each other above 400 km. At the same time, no longitudinal variation can be identified.

For the case of the last frost day, we found a positive trend, with a delay between two and eight days per year in the last day with temperatures below 0°C. Nevertheless, some negative trends around 4-2 days/year are found in 1.3% of pixels at the east of humid region (72°W) in Biobio region (36 and 38°S), this zone shows a higher percentage of negative trends compared to the others. Directional variograms show similar variability in all directions, with the most important variability in latitudinal range for pixels that are more than 100 km. away.

Frost period has a positive trend, that means an increment of days when the risk of frost is present. However only a few pixels show significant results, with a percentage that varies between 5 and 10% among zones. The spatial variability is most important in the diagonal component, variability can be found in all directions but for the latitude range, its value is minimal.

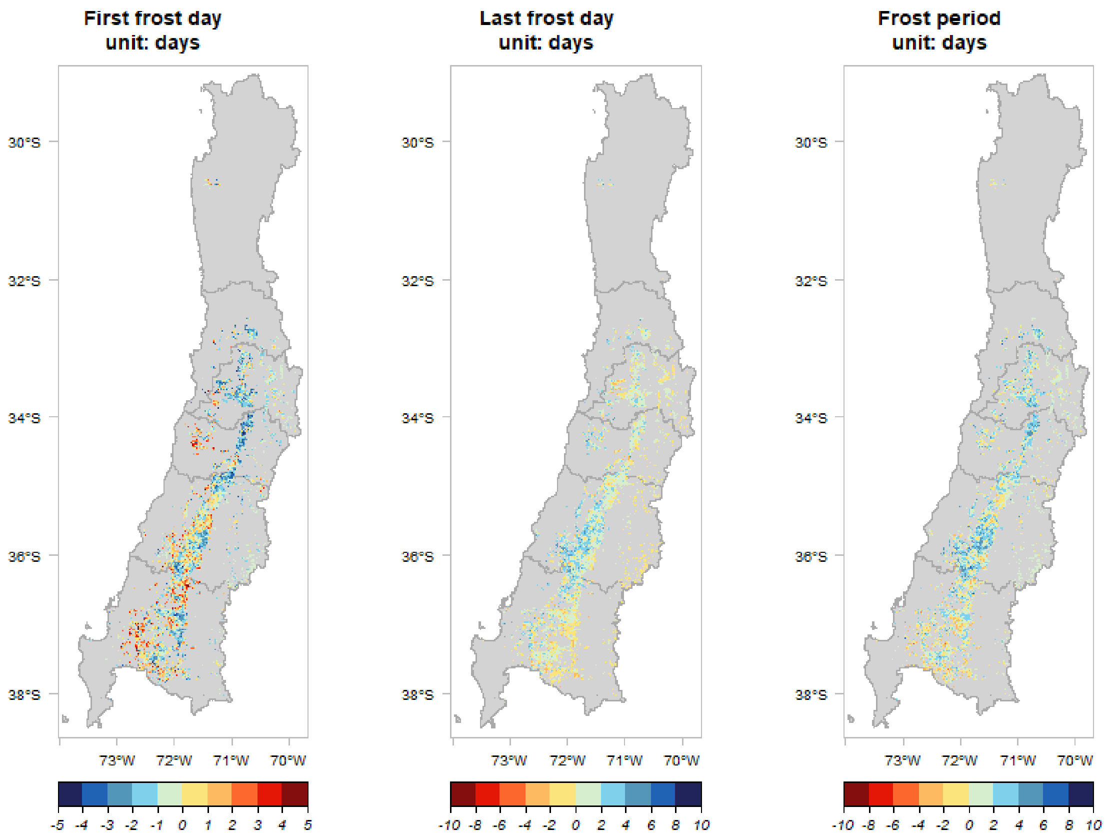

Figure 11: Trend values in days per year of indices associated to frost risk: First frost day (left), Last frost date (center) and Frost period (right).

3.3.2.2 Other cold indices

Figure 12 shows a map of the response of additional cold indices: number of frost events, minimum temperatures and chilling hours.

The number of frost events (days) has no trend or a slight positive trend for all zones, with its value being usually around +-1 days per year. This feature can be attributable to natural variability as only a limited number of pixels (around 1%) show significative results. There is a strong spatial variability that depends on longitude (90° direction) but its value of variability is smaller than 1 day.

The lowest minimum temperature (LMT) shows a fairly large number of pixels with a significative negative trend, being around 10% of total pixels in all zones, this negative trend suggests an increment in extreme minimum temperatures associated with frost risk. The spatial pattern responds to the south west direction, but the variability is very low.

Chilling hours has a consistent positive trend around all zones, but results indicate only a limited number of pixels with significant trends. An exception to this pattern is observed in the arid-semiarid zone which has 7% of pixels with significative positive trend. Although is not a zone that suitable for temperate fruit trees, this region has seen an increase in relative terms of the number of Chilling hours that could potentially host varieties with low chill requirements. There are not important differences in spatial variability pattern for all directions evaluated in variograms.

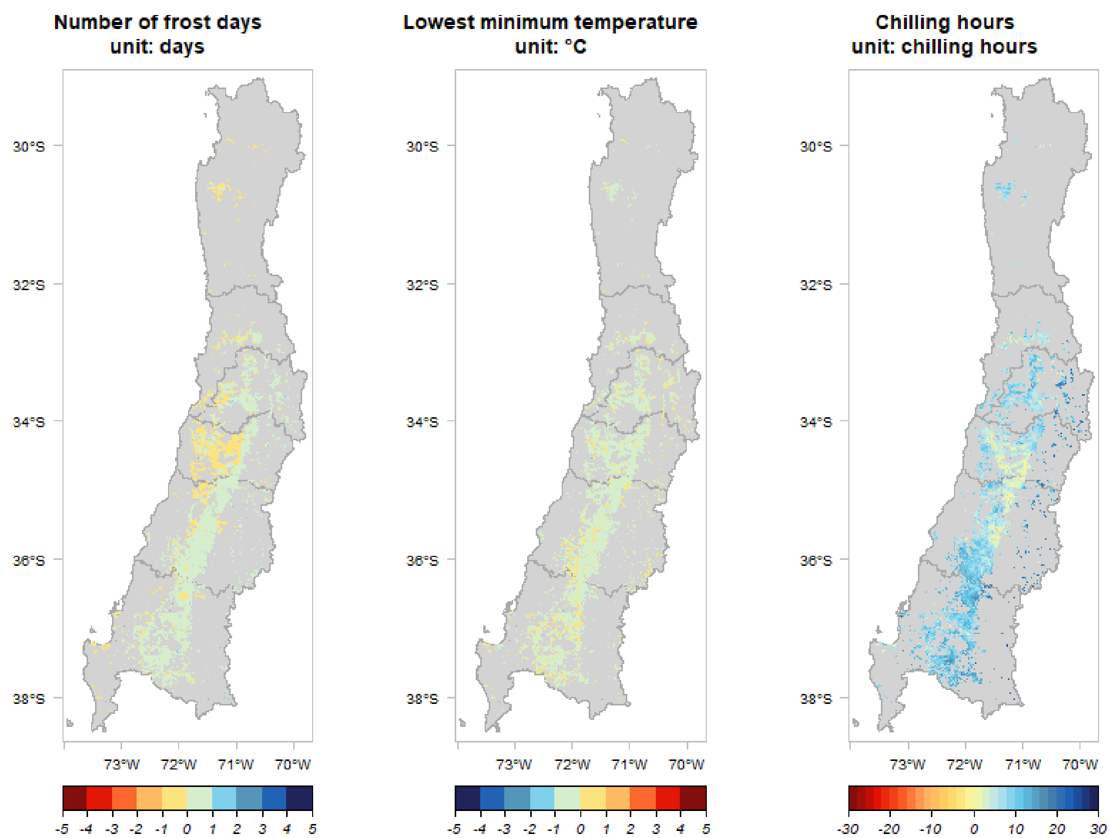

Figure 12: Results for indices that are associated to cold category: Number of frost days (days per year; left); Lower minimum temperature (°C per year, center); Chilling hours (chilling hours per year; right).

3.3.3 Start and end of growing season derived from NDVI data

The growing season indices based in 16 days NDVI are shown in Figure 13. A greater variability in trends can be noticed (Figure 8**¡Error! No se encuentra el origen de la referencia.**). For all NDVI indicators the variability is high in small distances, with a strong nugget effect (intercept with y axis) that represents errors in model and strong irregularity at small scale, this can be explained by different states of the crop (Garrigues et al., 2006). This difference between NDVI and temperature based growing season indices can be explained because NDVI rescues the variation of vegetation, unlike temperature-based indices represents the potential condition given by climate.

For the start of growing season there is a similar proportion of pixels with positive and negative trends, with bellow 5% of pixels with significate trend for all zones (

Table 3). The concentration of pixels with negative trends is similar to the one found in SGS, being grouped in eastern zones between 71 and 72°W while positive and neutral trends occur in the coastal zones with longitudes up to 72°W.

The EGS index presents trends in most of the pixels towards an earlier end of the growing season (negative value) with differences between 5-10 days per year, these differences are significative in around 10% of pixels in all Mediterranean zones evaluated.

Length of growing season presents both positive and negative trends equally distributed in the territory. In this variable, the percentage of significative trends is below 10%. Contrary to what was found in indices based on temperature for sub humid type, when positive trends were up to 85% of all pixels analyzed, and in humid zones where this value reached 75.7%, in the NDVI based calculation, these percentages are below 30% with predominant negative trends.

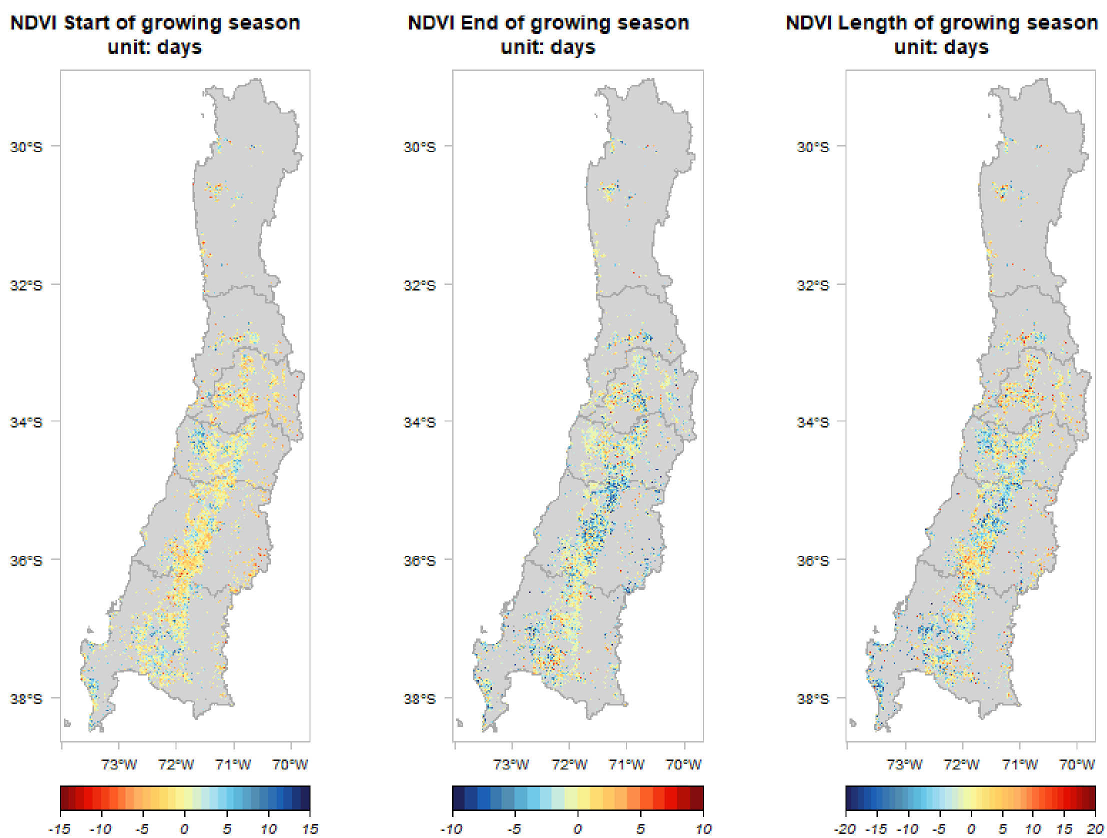

Figure 13: Trends in growing season indices (days per year) calculated using 16 days NDVI data: Start of the growing Season (left); End of the growing season (center) and Length of the growing season (right).

4 DISCUSSION

We applied a method to identify trends in agroclimatic indices based on satellite information that allow us to better describe the spatial structure and the main sources of variability. In our case calculated agroclimatic indices had mostly non significative trends as a result of Mann-Kendall test application. Similar results were found in trend analysis of recent decades temperature-related agroclimatic indices based on meteorological station data (Fernández-Long et al., 2013; Graczyk and Kundzewicz, 2016). One of the main limitation in our study is the relatively small time series derived from MODIS data, with only 14 years (2002 to 2016) of study. This imply that, as many of the agroclimatic indices corresponds to yearly accumulated values and/or the timing of individual events, at most we can only have 14 data points for trend assessment in agroclimatic indices. This situation is not the optimum given that Mann-Kendall test, although can be used with reduced time series, is most robust with longer registers (Yue et al., 2002).

Despite this situation, we found consistent spatial trends in indices of the heat and cold categories that provide valuable information about climatic variation in valleys located at Mediterranean regions of central Chile which have a wide topographic variability. The use of MODIS daily surface temperature data provides crucial information for the assessment of spatial variations in zones when meteorological stations do not cover homogenously the territory (Tomlinson et al., 2011) and in our study, demonstrates a good performance in the calculation of air temperature derived agroclimatic indices.

In this study, we used two very simple models for gap filling and air temperature conversion by virtue of optimizing the computational time in its application for the series of daily images between 2002 and 2016. For guarantee robust results, we compromise the number of agricultural pixels evaluated because we select only pixels with more than 70% of information in months which agroclimatic indices needs calculation. An alternative for spatially distributed air temperature estimation can be seen in Lerouxel et al. (2014) when the use of covariates and meteorological stations was used to test a methodology for worldwide estimation of air temperature for year 2011.

For four types of Mediterranean regions evaluated, the effect of temperature variations was most significant in sub humid and humid types when heat indices showed an early start of growing season and an increase in growing degree days in 10-15 units per year in average. This can be explained because these zones have, in general, lower mean temperatures than arid-semiarid and dry zones located in the northern part of the study area when mean temperature are all the time above threshold value of 7ºC. In this sense, for the calculation of growing season indices, warming temperatures have more incidence in sub humid and humid types by changing base conditions for the establishment of crops, this supposes the option of using crops that were previously limited by cold.

Also, in sub humid and humid zones, there are differences between climate based growing season indices and vegetation growing season by NDVI analysis. In these areas, the water availability is greater so that agriculture is mainly rainfed unlike in dry and semi-arid types where agriculture is carried out with greater irrigation technologies and considering adaptation measures to improve yields in conditions of water scarcity.

Our study demonstrates that in agricultural pixels, vegetation does not respond to the changes in climatic condition especially at the start and length of the growing season. Vegetation in agricultural related pixels does not respond to climatic trends in growing season, possibly due to agronomic decisions regarding crops choice, varietal selection and sowing/planting dates. This result suggests an “adaptive debt” in the study area that represents more than the 47% of agricultural land in Chile (ODEPA, 2017). Specifically, in zones with humid and semi-humid Mediterranean types which have rainfed agriculture this difference between temperature and NDVI based growing season is more important. This adaptive debt has been documented in Chile by Meza et al. (2008) with double cropping as an alternative for take advantage of the potential conditions provided by the current climate and Garreaud et al. (2017) when changes in EVI in 2010-2015 period shows a minimal variation with regard of 2001-2009 in conditions of deficit of precipitation, this study attributes such behavior to the combined effect of irrigation and warmer air temperatures.

Hodge and Austin (2004) assessing phenological changes mediated by climate change in wild vegetation, fruit-trees and crops in Germany. One of their main conclusion is that agricultural vegetation does not follow climate warming in the same extent that wild vegetation, being lesser affected by changes in temperature. The possible reasons for this behavior have to do with the access to technologies and machinery, the establishment of calendars of field work to meet the dates of suppliers, buyers or cooperatives, use of new varieties, application of fertilizers and pesticides, and delaying maturity practices. In our study, the difference between temperature based and NDVI growing season in Humid and Sub-humid zones may be due to a less access to this type of practices and technologies, as well as to the fact that the farmers have not perceived the changes in the climatic conditions and have not adapted their practices to take advantage of them, situation that can be improved with a better access for farmers to climatic and meteorological information (Roco et al., 2015).

Also, the NDVI results can be affected by annual rotation of crops, interannual variations or field practices which are impossible to detect without punctual field information, for these reason, these results must be interpreted in an aggregate way and not in particular for specific pixels. Badeck et al. (2004) discuss the importance of conducting a phenology monitoring that includes ground observations and satellite data as a complementary view. In this way, the trends found by means of satellite indexes such as NDVI or EVI can be endorsed by ground observations because, in general, satellite indices trends are not statistically significant depending of the quality of input data.

For indices of the cold category, there are mostly trends towards a lengthening of the frost period, with and early apparition of first frost day and a delay of last frost day. These trends are spatially reasonable but not consistent with the climate change studies that projected changes in cold indices associated with warmer condition (Alexander et al., 2006), our study suggests not only an increase in maximum temperature associated indices, but also, an increase in indices associated with lower minimum temperatures. We found a small number of significative trends associated with cold, which can be explained by the difficulty to estimate minimum temperatures due to cloudiness in nocturnal data and days with lower temperatures.

The detection of spatial patterns is an evolving knowledge that is fundamental when we analyze trends in phenomena using satellite data. In this work we carry out a simple study of directional variograms which can be improved by anisotropy tests which confirm the existence of patterns detected by visual inspection, a practical example can be found in (Weller, 2018). For the evaluated agroclimatic indices we found a differentiate behavior for trend variability in cardinal directions, in general, for nearby pixels, variability is low and not present anisotropy, while for pixels distant of more than 100 km variability present spatial pattern in latitudinal range.

The use of satellite information should be extended in the calculation of indexes commonly used in agriculture to recognize the valleys and their characteristics using the technology currently available. The use of large time series of images as in this study requires knowledge in satellite data processing, computational capacity and storage for base images. An alternative to facilitate the use of the proposed methodology is the use of the Google Earth Engine cloud-based platform that provides an extensive update library of satellite images and the capacity of web server processing by programing code routines (Gorelick et al., 2017).

5 CONCLUSION

The study of recent trends in agroclimatic indices based on satellite images of land surface temperature developed in this work allows us to analyze recent and current changes in the basic climatic conditions associated with agriculture. This type of spatial analysis provides the possibility of studying areas where the coverage of meteorological stations is nonexistent or heterogeneous and their limitations due to temporal coverage will be replaced in the future when the registration period increases.

Agroclimatic indices evaluated for the heat category showed consistent trends that suggest an increase in the growing season determined by the increase in temperatures affecting the Start of Growing Season, but the End of Growing Season presents variable trends according to geographical location. For Growing Degree Days exist a remarkable positive trend for winter crops calculation that suggest a higher heat accumulation in months with lesser temperature. For cold category indices, a lesser number of pixels with significative trends were found but a consistent trend towards an increase of extremes events was found.

In NDVI analysis of growing season parameters, we found an adaptive debt because agricultural vegetation does not respond to the changes in growing season propitiated by the increase in temperatures. This situation should be considered as an opportunity to improve field techniques, such as the choice of crop varieties and irrigation systems.

The use of satellite information allows a systematic study both in time and space of variables that allow to better understand the phenology and the early detection of climate change impacts on agriculture. It is essential to make greater use of satellite information and available technologies to communicate accurately the changes in the normal conditions that represent risks and development opportunities for farmers in the context of climate change.

The analysis of temporal trends is a method that becomes more robust as soon as a great number of data is evaluated, for the case of the agroclimatic indices that are yearly calculated, a joint analysis with registers of meteorological stations can be useful to know the variation regarding to the historical period not covered by satellite information. The analysis of spatial trends presents potential research by including covariates that can explain the values of differentiated trends in valleys and zones of agricultural development in the future; regionalization tools such as spatially restricted conglomerates can be used for agricultural territory planning.

In this sense, to take advantage of the information available in different temporal and spatial scales, other types of temperature-based indices related with agriculture, forestry and vegetation can be included at different time intervals from the annual level used in this study. This methodology also can be used for spatiotemporal analysis for variables such as precipitation, radiation, evapotranspiration, etcetera.

6 ACKNOWLEDGMENTS

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7 RESUMEN

Stephanie Orellana y Francisco Meza. Assessing recent trends of agroclimatic indices using MODIS data in Central Chile. Tesis, *Magister* en Recursos Naturales, Facultad de Agronomía e Ingeniería Forestal, Pontificia Universidad Católica de Chile. Santiago, Chile. 42 pp.

La agricultura es una de las actividades más susceptibles al cambio climático. El aumento de las temperaturas y los cambios en las precipitaciones afectarán el crecimiento y el desarrollo de los cultivos, reduciendo la productividad agrícola. Las tendencias recientes observadas en la temperatura pueden haber producido ya cambios en la idoneidad de los cultivos. El análisis de tendencias temporales es una de las metodologías más aceptadas para evaluar el efecto de los cambios observados en la temperatura sobre la respuesta fisiológica de los cultivos. Desafortunadamente, solo unos pocos estudios analizan el efecto de estas tendencias sobre los índices agroclimáticos, especialmente realizando un análisis espacial exhaustivo.
Este trabajo presenta un análisis de las tendencias temporales recientes en Chile central para índices agroclimáticos basados en temperatura derivados de imágenes satelitales de temperatura superficial MODIS. Para investigar la estructura espacial de las tendencias calculadas, se estimaron variogramas direccionales. Los índices asociados a la categoría de calor muestran tendencias marcadas hacia un inicio temprano y un aumento en la duración de la temporada de crecimiento, así como una tendencia positiva grados día acumulados en invierno y verano. Los índices asociados a la categoría de frío tienen tendencias menos claras y un número menor de tendencias significativas. El análisis de NDVI para la respuesta de la vegetación muestra una deuda adaptativa, definida como la diferencia entre la duración potencial de la temporada de crecimiento y la respuesta real de la vegetación, debido a que el inicio y la duración de la temporada de crecimiento presentan tendencias opuestas a las encontradas en los índices agroclimáticos. Los resultados más significativos en las tendencias se encontraron en las áreas mediterráneas húmedas y subhúmedas que presentan un nuevo potencial productivo menos limitado por las bajas temperaturas. Los índices de frío sugieren un aumento del período de heladas con un mayor número de eventos extremos.

Palabras Clave: Índices agroclimáticos, tendencias recientes, MODIS, Mann-Kendall, variograma.

8 REFERENCES

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