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Abstract

Since 2010, a large area of Chile is in a period of severe drought, with impacts on the population and the water resource systems. Therefore, it is necessary to carry out research on drought behavior in Chile, its prediction and monitoring, should be addressed to find suitable measures to reduce its effects. A simple calculation model is presented for the SPI, PPN, DEC and EDI indexes. Based on the hypothesis that these indexes are an indicator of the drought condition in the central-southern area of Chile; the proposed model takes as the only input variable the cumulative number of raining days. The most efficient index for the model is identified, the study is regionalized and temporal and spatial analysis of the model is carried out. A modified index of drought is obtained, based on a simple rainfall day counter. The model represents an efficient method to show a drought event.

Keywords: drought; SPI; rainy days; drought in Chile

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Not applicable

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Abstract

Since 2010, a large area of Chile is in a period of severe drought, with impacts on the population and the water resource systems. Therefore, it is necessary to carry out research on drought behavior in Chile, its prediction and monitoring, should be addressed to find suitable measures to reduce its effects. A simple calculation model is presented for the SPI, PPN, DEC and EDI indexes. Based on the hypothesis that these indexes are an indicator of the drought condition in the central-southern area of Chile; the proposed model takes as the only input variable the cumulative number of raining days. The most efficient index for the model is identified, the study is regionalized and temporal and spatial analysis of the model is carried out. A modified index of drought is obtained, based on a simple rainfall day counter. The model represents an efficient method to show a drought event.

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1. Introduction

Any drought index is a quantitative measure that uses information such as climate variables, precipitation, evaporation or temperature to characterize a moisture condition over a specific region. This index, as a single value, is compared on a qualitative scale to understand a particular drought condition. This absolutely qualitative procedure can find from moderate, severe or extreme droughts; to normal or exceptionally humid conditions (Kim et al. 2012). Hydrologist and water resource engineers use these indices as an "ideal" representation of a specific condition, which in fact reflects a climatic anomaly (Mishra and Singh 2011).

The essences of these indices is mainly based on rainfall, as it is the most important input variable for many water-related activities (hydrological drought) and their direct impacts on agriculture (agricultural drought). Any proposed index would include loss of soil moisture, change in groundwater storage or decrease in reservoir levels (Zargar et al. 2011, Van Loon and Laaha 2015) as the main inputs. Because the occurrence of droughts cannot be predicted with certainty, it should be studied as a random variable (Sirdas and Sahin 2008).

For the monitoring and implementation of drought warning systems, meteorologists have added to these indices; the probabilistic component of rain behavior (Dhurmea et al. 2019). The analysis of rainfall patterns on different time scales has proven to be useful in detecting and monitoring droughts (Moreira et

al. 2008). The Standardized Precipitation Index (SPI) is one of the most widely used because it easily allows a comparison between different regions and climates. (Palmer 1965, McKee et al. 1993, Edwards and McKee 1997, Gutierrez-Lopez et al. 2016).

On the other hand, the Percentage of Normal Precipitation (PPN) index is a very simple index that can be easily calculated; this allows the diffusion of hydro-meteorological conditions to a general audience (Dogan et al. 2012). As well as the Deciles Precipitation Index, the Effective Drought Index (EDI), and the SPI, their values are standardized; which allows detailed comparison between regions with different climates (Byun and Wilhite 1999, Danandeh et al. 2019). Because the prediction of drought periods is of high importance for water planning around the world, forecasting models must become more robust and simple (Sirdas and Sahin 2008).

The effects of droughts are most directly affected by population growth and the increase in agriculture. Energy and industry also put pressure on water demand in several countries of the world. Other forces, such as climate change and pollution, are contributing to the extremes of water abundance and scarcity, which lead to more severe floods and droughts (Myronidis et al. 2018)

The understandings of the different variables that explain droughts, as well as the historical impact on a region, are useful tools for model development for right forecasting of the incidence of a drought period (Mishra and Singh 2010). The variables that are usually used to explain the duration of drought include the physiographic characteristics of the region as in addition to the climatological ones. Zargar et al. (2011) suggest that the main climate variables are: precipitation, runoff, snowpack depth, storage volume in reservoirs, temperature, evapotranspiration, soil moisture, evaporation and water retention in vegetation. It is clear that since there are several variables with different dimensions, it is necessary to carry out multivariate analyses to set up indices and any type of regional analysis.

In this sense, Principal Component Analysis (PCA) and Correspondence Factor Analysis (CFA) are two of the main techniques for the design and implementation of new drought monitoring indices (Ma et al. 2013, Azmi et al. 2016). Whether or not the drought modelling technique is used, always, access to data is critical and the most difficult to find. The number of rainy days in a certain period is a variable that is easy to collect and get; Gutierrez-Lopez et al. (2016) analyzed the relationship between this variable and the incidence of a drought event in Mexico, proposing a simplified model of the SPI index with favorable results.

In Chile, since 2010, there has been a long period of drought known as the "mega-drought", which is unprecedented. From latitude 35°S to the south (Garreaud et al. 2017), thus making necessary the development for studies of drought behavior in Chile; by indices focused on detecting the required actions to reduce the negative effects in the short, medium and long term. This work presents a simple method to calculate drought indices based on the number of rainy days to estimate the drought condition in Chile.

Under the hypothesis that the number of rainy days in specific periods and regions would decide the condition of drought in Chile, three specific goals are developed: (1) to find the most suitable index for the use of the model based on the rainy days score; (2) to set up the regions of the drought phenomena in the central-southern zone of Chile through a regionalization based on the index chosen; and (3) to analyze the temporal and spatial behavior of the proposed model. The results show that it is possible to apply this procedure in the forecast and monitoring of droughts.

2. Material and methods

2.1 Description of the study area

The area between the Regions of Valparaíso and Araucanía (32°S to 39.5°S), in the central zone of Chile, are studied (figure 1). The Köppen classification shows a predominance of semi-arid climates (Bsk) in the north, warm or Mediterranean temperate (Csb) in the center and rainy oceanic temperate (Cfb) in the south, as well as cold tundra (ET) in the Andes Mountains (Kottek et al. 2006). The study zone has a mountainous topography due to two important ridges (Cordillera de Los Andes and the Cordillera de la Costa), with elevations between 0 and 6100 meters above mean sea level (msnm).

On the other hand, annual precipitation is characterized by a rising trend to the south, from 200 to 500 mm per year in the Valparaíso and Metropolitan Regions (32°S); up to 3000 mm in the Andean areas of the Araucanía Region (39.5°S). The main source of rainfall is from the frontal systems, which report seasonal rainfall up to latitude 39°S, changing to a rainy regime all year-long, to the south.

2.2 Database available

Daily rainfall data from 145 weather stations operated by the General Water Authority (DGA) and the Chilean Meteorological Office (DMC) are used. They are located in the study area are distributed as follows: 37 stations in the Valparaíso Region, 17 in Metropolitana, 17 in O' Higgins, 29 in Maule, 25 in Biobío and 20 in Araucanía, as shows is Figure 2, For calculating drought indices, the World

Meteorological Organization (Svoboda et al. 2012) requires a minimum record size of 20 to 30 years of continuous data. Our database considers the last 32 years, from January 1985 to December 2016.

Figure 1. Study area

Figure 2. Topography area and rain gauge stations

2.3 SPI Index Description

The Standardized Precipitation Index was developed by McKee et al. (1993) to improve the detection of the onset of a drought event and to follow its evolution. The SPI represents the standard deviation of an accumulated precipitation value, with respect to the mean precipitation in a specific time (3, 6 or 9 months). It is obtained by adjusting a Gamma-type probability distribution to the series of precipitations and then it is transformed to a normal distribution with mean zero and standard deviation equal to one. The positive values of the index refer to rainfall that is greater than the median and the negative values refer to rainfall that is less than the median.

Figure 3 shows the procedure to get the SPI for a given month and time scale, based on cumulative rainfall data. For example, for 520 millimeters of rainfall (left), it corresponds to a probability of 0.82 according to the Gamma distribution. This same value 0.82 is read in the normal probability distribution (right); which matches an SPI value equal to 0.9.

Figure 3. SPI procedure calculating

Source: Edwards and McKee 1997

2.4 PPN index description

The Percentage of Normal Precipitation Index (PPN) is one of the most popular indices used globally for monitoring meteorological droughts. It is considered a direct measure of the standard deviation of total rainfall from its average over time (Morid et al. 2006). It represents the ratio between the rainfall accumulated in the month or time considered (P_i) and the mean of the rainfall values in the same month (P_{med}) and is obtained using equation 1.

$$PPN = \frac{P_i}{P_{med}} * 100 \quad (1)$$

2.5 Deciles Index description

The Deciles Precipitation Index (DEC) was formulated by Gibbs and Maher (1967) as a method of improving the PPN approach. As its name suggests, the index categorizes the value of total monthly precipitation accumulated in a given decile, based on the total rainfall registered in the same month. To calculate DEC, the series of rainfall data is ordered in increasing order, which is divided into 10 equal shares or deciles, with the same number of data and the same occurrence probability. In this way, the index value is the decile where the precipitation value is located.

2.6 EDI Index description

The Effective Drought Index (EDI) was developed by Byun and Wilhite (1999). It introduces the concept of “effective rainfall” that includes the daily rainfall with a time reduction-function. However, while the EDI was first formulated for a daily scale, it was later adapted to a monthly scale, defining a fixed time scale of 12 months (Smakhtin and Hughes 2007).

The procedure to calculate the index is, first, to compute the effective precipitation for month j (EP_j) by means of equation (2), where N is the time scale of the index and P_i the precipitation of the previous month i . Accepting that i , m and N are equal to 12 (fixed time scale), EP_j is given as $P_1 + (P_1 + P_2)/2 + \dots + (P_1 + \dots + P_{12})/12$. Then, the parameter DEP_j is obtained by the deviation of the effective precipitation from equation 3, where $\overline{EP_j}$ is the mean of EP_j values. Then, precipitation is calculated for a normal condition (PRN_j parameter) according to equation 4. Finally, the EDI index is obtained by equation 5, where $\sigma(PRN_j)$ is the standard deviation of the PRN_j values.

$$EP_j = \sum_{m=1}^N \left(\frac{\sum_{i=1}^m P_i}{m} \right) \quad (2)$$

$$DEP_j = EP_j - \overline{EP_j} \quad (3)$$

$$PRN_j = \frac{DEP_j}{\sum_{i=1}^N \left(\frac{1}{i} \right)} \quad (4)$$

$$EDI_j = \frac{PRN_j}{\sigma(PRN_j)} \quad (5)$$

2.7 Drought classification based on indices

For the comparison of indexes and drought events, a categorization of the values is necessary to define the different intensities of an event, which is presented in table 1.

Table 1. Drought classification based on indices.

Source: Svoboda et al. (2012) and CRC-SAS (2016)

2.8 Rainy day method description.

This method was proposed by Gutierrez et al. (2016). It is a method for the simplified calculation of the SPI index, which is based on the hypothesis that a series of events occur in a random sequence over time. A Poisson process is used to explain the number of rainy days and an Exponential distribution is used to characterize the mean rainfall height. In search of a physical interpretation of the sense of their probability distribution parameters, they are directly correlated with the SPI index. In this process a modified index is obtained by simple counting of rainfall days over the period; hence a trustworthy drought condition is obtained. This index is created with the total rainfall in 12 months, from the daily rainfall data. To know when a rain event starts and ends, the concept of Minimum Intervent Time, known as MIT, is used (Hanel and Maca 2014).

2.9 Validation of the proposed model.

In order to compare the drought conditions obtained from the different indices used in this research, it is essential to define the numerical intervals and the drought conditions of each index, which are presented in table 1. To understand the behavior of each proposed drought model, it is proposed to compare the observed values and the estimated values of each index at each station (table 2). In order to remark the differences between each index it is proposed to make the following questions:

1. Did the proposed model get the exact drought condition for the month analyzed (table 1)?
2. Did the observed index present an extreme, severe or moderate drought condition?
3. Did the estimated index present an extreme, severe or moderate drought condition?
4. Did the proposed model match the exact drought condition for the whole period analyzed?
5. Did the model match the numerical value that defines the drought, as extreme, severe or moderate?

Table 2. Model analysis for station i.

2.10 Homogeneous regions

In hydrology, a challenge is to know the magnitude of extreme hydrological events in sites with scarce or no data (ungauged sites). The use of regional methods that allow the spatial data transfer of some

hydrological variable is one possibility to face this problem (Requena et al. 2018). In this way, hydrological regionalization is defined as a set of equations within a mathematical model that allows the transfer of hydrological information from one site to another (Yang et al. 2019).

In Latin America, where weather stations are generally more abundant than hydrometric stations, the concept of “regionalization of rainfall” is particularly important in a study of hydraulic developments (Li et al. 2018). There are many benefits in using a regional procedure over a group of hydrological homogeneous catchments, compared such as, to a single site frequency analysis (Evin et al. 2016). The heterogeneity of regions represents a problem when it is required to study the spatial-temporal distribution of some hydrological phenomena. Usually, an approach is made to reduce the uncertainty involved to transfer hydrological information from one site to another, reducing a region into hydrological homogeneous sub-regions (Berton et al. 2017).

At present the techniques to define homogeneous regions have many applications. The main concept of this procedure is based on the idea that the quantitative variables of a data matrix can be represented in p-dimensional space. A Principal Component Analysis, such as, allows for visually grouping homogeneous groups of hydrological variables or stations with similar climate behavior (Lebecherel et al. 2016).

In order to divide an area into homogeneous sub-regions, it is necessary to consider that all elements within the homogeneous sub-region will have similar behavior. In the same way, the behavior between sub-regions will be different (Yang and Burn 2019, Zambreski et al. 2018). The sub-regions must be divided with methods that take into account the hydrological similarities or the physiographic characteristics of a watershed, which do not always have a geographical sense (Valdes-Pineda et al. 2018).

Several techniques have been used to find homogeneous regions, including residual analysis, analysis of statistics of historical series, Andrews-curves, Langbein homogeneity tests, proximity indices, and others (Guo et al. 2018). Multivariate techniques such as the Principal Component Analysis are also widely used (Zhou et al. 2019). However, any procedure used to delimit homogeneous regions always requires prior identification of the significant variables or characteristics of the region to be studied (Gutierrez-Lopez et al. 2019). In this context, each author suggests, usually, the physiographic, climatological and geographic characteristics that will be used in the regionalization process.

With the aim to analyze the spatial behavior of the proposed drought indexes, a multivariate analysis technique is proposed (Principal Component Analysis) since it is widely used in several processes of the

hydrological cycle (Gutierrez-Lopez et al. 2014). Furthermore, this technique has been proven to be very effective in detecting similar behavior patterns of climate variables at different latitudes (Tallaksen and Hisdal 1999).

3. Results

3.1 SPI vs SPI*

All the described procedures were applied and the correlations were obtained for every season, for every month and for the four indices in a time scale equal to 12 months. The correlations are logarithmic and follow equation 6, where A, and B are constant and L means the number of total rainy days over 12 months. It is important to consider that as well as applying the method by months, a correlation was obtained with all the annual data for each station (annual fit).

As an example, we present the fit for the month of October and the annual fit for the Villa Alhue station (34°S) (figures 4 and 5), which explains the use of only one fit for this station. As a consequence, only the annual adjustments for the other stations are shown.

$$SPI^* = A \ln(L) + B \quad (6)$$

Figure 4. SPI Octubre Villa Alhue fit.

Figure 5. General SPI Villa Alhue fit.

The results of the proposed SPI* model, for all stations, is represented in table 3. The proposed SPI* index found an average of 63.2% for the exact drought condition in each month (column 1). The exact drought condition for every year was 31.7% (column 4). A total of 49.8% was able to define some of the extreme, severe or moderate drought conditions (column 5).

The SPI* model fails on average by 6% when a drought condition is compared (the difference between columns 2 and 3). Nevertheless, of total registered drought events, the value of SPI* is able to test the drought condition by 50%. Thus, there is certainly a direct relationship between rainy days and the drought condition.

Table 3. Results of SPI model.

3.2 PPN vs PPN*

The correlation between PPN and PPN* has a lineal form according to equation 7, where A and B are the model parameters and L is the number of total rainfall days over 12 months. The results of the proposed PPN* model, for all stations, is represented in table 4.

The proposed PPN* index found an average of 63.1% for the exact drought condition in each month (column 1). The exact drought condition for every year was 40% (column 4). A total of 53.8% was able to define some of the extreme, severe or moderate drought conditions (column 5).

The PPN* model fails on average by 7% when a drought condition is compared (the difference between columns 2 and 3). Nevertheless, of total registered drought events, the value of PPN* is able to test the drought condition by 54%.

A negative point is that there were cases where the PPN* did not detect drought situations, which did happen as seen in the PPN values. This reduces the confidence the PPN* can detect of the drought condition.

$$PPN^* = A (L) + B \quad (7)$$

Table 4. Results of PPN model.

3.3 DEC vs DEC* (Deciles)

The correlation between DEC and DEC* was calculated according to equation 8, where A and B are the model parameters and L is the number of total rainfall days over 12 months. The results of the DEC* model are represented in table 5.

The proposed SPI* index found an average of 47.3% for the exact drought condition in each month (column 1). The exact drought condition for every year was 19.3% (column 4). A total of 48.8% was able to define some of the extreme, severe or moderate drought conditions (column 5).

$$DEC^* = A (L) + B \quad (8)$$

Table 5. Results of DECILES model.

3.4 EDI vs EDI*

The correlation between DEC and DEC* was calculated according to equation 9, where A and B are the model parameters and L is the number of total rainfall days over 12 months. The results of the DEC* model are represented in table 6.

The proposed SPI* index found an average of 63.2% for the exact drought condition in each month (column 1). The exact drought condition for every year was 22.8% (column 4). A total of 30.9% was able to define some of the extreme, severe or moderate drought conditions (column 5).

$$EDI^* = A(L) + B \quad (9)$$

Table 6. Results of EDI model.

4. Regionalization

The results when the Principal Component Analysis (EOF) is applied, using the indices proposed as variables to do a hydrological regionalization; show three homogeneous regions (figure 6). The spatial representation of these results is shown in figure 7. The homogeneous regions resulting from this approach match with the different types of main climates in the study area. The homogeneous regions that were obtained are:

Region 1: It is located between 32° and 33.5°S, it has a semi-arid climate, with a mean annual rainfall of 200 to 600 mm, and 15 to 31 rainy days per year.

Region 2: It is located between 33.5° and 36°S, it has a moderate temperate or Mediterranean climate, with a mean annual rainfall of 340 to 2000 mm, and 22 to 68 rainy days per year.

Region 3: It is located between 36° and 39.5°S, and it has a tropical climate with a transition from warm temperate to wet oceanic, with a mean annual rainfall of 840 to 3400 mm, and 57 to 150 rainy days per year.

From the hydrological regionalization, the spatial distribution of the four proposed indices was analyzed; the results are shown in table 7. All the indices have a good success rate in the drought condition in region 1, and a few success rates in region 3.

Figure 6. Results of the EOF with the three homogeneous regions.

Figure 7. Homogeneous regions according to regionalization.

Table 7. Review of model results for the three homogeneous regions.

5. Discussion

While the numerical values of the measured index (SPI) and the proposed model (SPI*) are not expected to be the same, the important factor is to be precise when comparing the drought condition and the presence of the drought event (Wong et al. 2013, Paparrizos et al. 2016). For example, for the Armerillo station at a latitude of 35.5° S (with a 50% success in the drought condition with the SPI*), the results obtained are acceptable if the historical evolution of the drought condition is observed in figure 8.

Figure 8. SPI and SPI* historical series, Armerillo station

One unanticipated finding was that parameters A and B of the SPI model* are correlated with the geographical latitude of the stations, as shown in figures 9 and 10. This finding has important implications for developing a potential test for the delimitation of homogeneous regions. Also, the A and B values correlated with latitude made it possible to verify the delimitation of regions already done. It is possible therefore that the parameters A and B have some physical meaning, for example with the C parameter of the IDF curves. However, this is an important issue for future research.

Figure 9. Relationship between station latitude and SPI model A coefficient

Figure 10. Relationship between station latitude and SPI model B coefficient

Therefore, the model for monitoring meteorological droughts with the SPI* index is proposed. The SPI*, also, shows the best results in success rates with the studied drought conditions and shows a possible physical meaning of its adjustment parameters. The benefit of having a simple model to define a reliable drought condition is that it is very easy to count the rainy days in a calendar, as opposed to fit a Gamma-probability distribution. Especially regarding the fact that in Latin America the climate records are not very extensive and a frequency analysis could seriously affect the validity of the drought indices (Bayissa et al. 2015).

This SPI* index can be used by the public and the productive sectors to take mitigation actions in case of a potential drought scenario (van Oel et al. 2018). Likewise, the systematic processing, through a hydro-

computing tool, of the database is easy to be implemented since it is only based on the number of rainy days.

Table 8. A and B coefficients for Region 1.

Table 9. A and B coefficients for Region 2.

Table 10. A and B coefficients for Region 3.

Figure 11. Isolines map of rainy days for moderate drought

Figure 12. Isolines map of rainy days for severe drought

Figure 13. Isolines map of rainy days for extreme drought

For the application of the model, it is only necessary to have the number of rainy days in the last 12 months, to find the coefficients A and B according to the region (tables 8, 9 and 10), to replace L (rainy days) in the equation $SPI^* = A \ln(L) + B$ and to classify the drought condition according to table 1 for SPI. In this way the conditions of moderate drought (figure 11), severe drought (figure 12) and extreme drought (figure 13) were obtained; from the accumulated rainy days in 12 months. These findings of the current study are consistent with those of Sarricolea et al. (2016) who found the same spatial distribution of drought conditions as shown in figures 11 to 13.

It is important to remark that, the percentage of drought success shown in column (5) of table 3 is the most relevant criteria when the performance of the indexes is evaluated; since it is the index that is sent to the decision-makers. This criteria includes any drought, whether moderate, severe or extreme ($SPI < -0.84$) and is the criteria used by the Chilean General Water Directorate (DGA) to decide a drought event under the DGA Resolution N°1674 of the year 2012 (DGA 2012).

6. Conclusions

Four drought indices were used to test the hypothesis that rainy days can explain a drought scenario. In that sense, the correlation between the SPI, PPN, DEC, and EDI with the total rainy days in 12 months was proved; the SPI* model was the best evaluated. Therefore, the total rainy days in 12 months are an important variable to explain the drought behavior in the central and southern zone of Chile, supporting

the study's hypothesis. In addition, there is a spatial correlation between the SPI* index and latitude, which is consistent with the fact that from north to south precipitation increases and the stationary-period of precipitation decreases.

A regionalization based on homogeneous regions was obtained, using a drought index as a variable, which is consistent with the climatic classification from semi-arid to semi-humid, thus reinforcing the validity of this regionalization. Furthermore, better performance of the model was obtained in the regions with the semi-arid climate, which could be interesting to apply to other regions of the world with the same climate.

Finally, a model is presented in which it is only necessary to introduce the total rainy days in 12 months to get a drought condition in the Chilean territory. The regionalization allows an estimation of drought conditions at ungauged sites, first locating the zone on the map and has the number of rainy days and then the SPI*.

It is important to note, that to date, only one study has explicitly included the number of rainy days (indirectly included in monthly rainfall) to estimate a drought index. Gutierrez-Lopez et al. in (2016), used a similar approach based on the expected total number of rainy days in the desert areas of Mexico at the same latitudes as the Chilean deserts, but in the northern hemisphere. This shows that a simple count of rainy days could be a valid estimate of the understanding of meteorological droughts both in Chile and in other regions of the world with similar climates.

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Figures

Figure 1

Study area

Figure 2

Topography area and rain gauge stations

Figure 3

SPI procedure calculating Source: Edwards and McKee 1997

Figure 4

SPI Octubre Villa Alhue fit.

Figure 5

General SPI Villa Alhue fit.

Figure 6

Results of the EOF with the three homogeneous regions.

Figure 7

Homogeneous regions according to regionalization.

Figure 8

SPI and SPI* historical series, Armerillo station

Figure 9

Relationship between station latitude and SPI model A coefficient

Figure 10

Relationship between station latitude and SPI model B coefficient

Figure 11

Isolines map of rainy days for moderate drought

Figure 12

Isolines map of rainy days for severe drought

Figure 13

Isolines map of rainy days for extreme drought