Statistical forecast of soil water storage in the rolling pampas, Argentina

M. E. Castañeda, M. H.González, M. E. Fernández, A. L. Rolla and L. B. Spescha

SUMMARY

Establishing a seasonal forecast for soil water storage (SWS) on a smaller spatial scale is of great interest for the agricultural sector since this could reduce uncertainty and facilitate decision making. On the other hand, we should consider that variations in soil moisture are due partly to small scale influences and to soil-specific features such as the capacity of the field. The purpose of this work is to propose a statistical forecasting methodology for different soil water availability scenarios in the Pampean region. For this purpose, monthly soil water storage values were calculated SWS for the INTA meteorological station, Pergamino (Buenos Aires, Argentina). Data was gathered using the Operating Hydrological Balance for Agro (OHBA) for October, November and December during 1979-2016. Relations between SWS and climate forcing on a monthly, bimonthly and quarterly scales were analyzed. Statistical forecasting models were developed for each month using the loop regression, a modern regression technique that uses cross-validation k fold. The efficiency analysis of different models takes into account the adjusted values of square correlation coefficient (R^2_{adj}) and cross-validation coefficient (CV). These models appropriately represent the SWS values, particularly the most extreme ones.

Key words: Hydrological balance, Statistical forecasting, Climate forcing

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RESUMEN

En el sector agrícola, disponer de un pronóstico estacional del almacenaje del agua del suelo (AAS) a una escala espacial más pequeña es de gran interés ya que ello podría reducir la incertidumbre y facilitar la toma de decisiones. El objetivo de este trabajo fue proponer una metodología de pronóstico estadístico para los diferentes escenarios de disponibilidad de agua del suelo en la región pampeana. Para este propósito, se calcularon los valores mensuales de almacenaje de agua del suelo AAS para la estación meteorológica INTA Pergamino (Buenos Aires, Argentina). Dicha información se estimó utilizando el

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Balance Hidrológico Operacional para Agro (BOHA) para los meses de octubre, noviembre y diciembre durante 1979-2016. Se analizaron las relaciones entre AAS y los forzantes climáticos en escalas mensual, bimestral y trimestral. Los modelos de pronóstico estadístico se desarrollaron para cada mes utilizando la regresión de Lasso, una técnica de regresión moderna que utiliza la validación cruzada para seleccionar los mejores predictores El análisis de la eficiencia de diferentes modelos tiene en cuenta los valores ajustados de coeficiente de correlación cuadrado (R^2_{adj}) y coeficiente de validación cruzada (CV). Estos modelos representan adecuadamente los valores de AAS, particularmente los más extremos.

Palabras clave: Balance hídrico; Predictores meteorológicos, forzantes climáticos

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INTRODUCTION

The role of climate forecasts in agricultural planning enables the mitigation of the risk of future adverse conditions or the benefit of taking advantage of them when they are favorable. However, despite a diverse and growing offer of this kind of information, its incorporation into decision-making is not yet widespread. Seasonal climate forecasts are provided by some institutions (Climate Prediction Centre, Inter-American Institute, ECMWF, CPTEC, UKMO, among others), and for Regional Climate Outlook Forums that are held in different regions of the world. They produce regional climate forecasts of monthly to quarterly precipitation and temperature. The availability of agro-climatic information, not only in real time but at the beginning of the agricultural campaign, in user-friendly formats which show the risk of occurrence of extreme events, is relevant, both for productive systems and for subsistence agriculture in large regions of the country.

The Pampas region (Hall *et al.*,1992) is located in central eastern Argentina and its economic resources are based highly on agriculture. Agricultural production depends on temperature and precipitation and the strategies adopted, which usually take into account a normal behavior of the climate variables. The physical basis of seasonal climate predictability lies in the fact that slow variations in the boundary conditions of the earth influence the atmospheric circulation. To address this issue, dynamical and statistical models are derived but there is still a great deal of uncertainty about the efficiency of dynamical models, especially in restricted areas and, in those cases, statistical forecasts seem to have the best performance. Many authors have pointed out the difficulties detected when forecasting seasonal climate (Barnston *et al.,* 2005; Leetmaa, 2003; Coelho *et al.,* 2005; Kumar, 2006) and an evaluation of seasonal climate forecast in South America has been done by some authors (Goddard, 2003; Nobre *et al.,* 2005; Barreiro, 2009).

The statistical forecasts are based on the detection of the relation between climate variables and circulation patterns previously observed. Many authors have advanced in the development of statistical models to predict seasonal climate variables in some regions of Argentina. For example, statistical forecasts were developed for the Standardized Precipitation Index for the rainy season in the Comahue region (González and Dominguez 2012, González 2015), for seasonal rainfall in the Argentine Chaco region (González *et al.,* 2012), for the Bermejo river basin (González and Murgida, 2012), for the Patagonian region (González and Herrera, 2014) and for snow in the Central Andes in Argentina (Bisero *et al.,* 2017; Barreiro and Díaz 2011) which showed that seasonal forecast in South America can be improved if the teleconnection processes and the regional earth-atmosphere interactions are adequately represented.

Mo and Berbery (2011) noted that local factors such as the seasonal cycle, soil moisture and moisture transport provide the initial conditions for extreme events to develop and persist, but do not trigger droughts or persistent waves. The persistent nature of drought and wet periods are linked by large-scale low frequency forcing, such as sea surface temperature anomalies. In particular, soil moisture is a key variable of the earth-atmosphere system that not only reflects the soil conditions of a given region (for example, as an indicator of agricultural drought), but also has the potential to influence the atmospheric variability in controlling surface water and energy balances, from synoptic to seasonal time scales (Kanamitsu *et al.,* 2003; Seneviratne *et al*., 2010).

The interannual variability of rainfall has a significant impact on agriculture. Reserve or storage of water in the soil is determined by the interaction between the supply of water, the infiltration and retention in the soil, and the evapotranspiration. Soil moisture is characterized by the field capacity, the permanent wilting point and the available water content. According to Allen *et al.* (1998), soil water availability concerns to the capacity of a soil to retain water available for plants. Soil water availability (SWA) is derived from two important physical-hydric properties of soils: moisture at field capacity (FC), the amount of water retained by a well-drained soil after rainfall or irrigation application and moisture at wilting point (WP), the water content at which plants will wilt. (SWA) is the difference between soil moisture at (FC) and soil moisture at (WP). Thus, actual soil water storage (SWS) can range between moisture content at WP and FC.

The aim of this paper is to develop a statistical forecast model for SWS in a location in the rolling Pampas in summer. In October and November, the soil water requirement by wheat reaches the highest values and frequently soil water content due to rainfall is not enough. Therefore, the SWS forecast may be a good tool for decision making.

DATA AND METHODOLOGY

Data

Monthly SWS data series was calculated for Pergamino meteorological station (33 ° 56 ‘ S, 60 ° 33 ‘ W, 56 m.a.s.l.), by the Operational Hydrological Balance Model for Agro (BOHA, 2012) for the period 1979-2016. Meteorological data from the National Institute of Agricultural Technology (INTA) was used. The station is located in the Regional Center Buenos Aires North (RCBAN), which has an area of just over 11 million ha, of which approximately 5.8 million ha are lands with agricultural capacity with 2.3 million ha for livestock-agricultural and the rest are cattle and forestry lands.

The model computes the amount of water contained in the soil profile which can be absorbed by the roots, allows the growth of the crops and allows the development of water available maps in the soil. The general water balance equation in the BOHA is:

$$PP - AE - \Delta SWS - EXC = 0 \qquad (1)$$

where PP is precipitation, AE is actual evapotranspiration, ΔSWS is soil water storage change and EXC is precipitated water that exceeds the maximum storage capacity of an agricultural land. Additional information on the methodology and characteristics can be found in Fernández Long *et al*. (2012).

Pergamino, representative site of the wheat area II north (Zarrilli, 1997), and the months October to December, have been considered for this study. Two relevant wheat yield components, the number of grains per spike and the 1000-grain weigh are set in October (heading/anthesis) and between October 15th and November 15th, respectively (Garcia *et al*., 2018). In December, wheat reaches its physiological maturity. It should be noted that the crop soil water requirements are different in each month. In October and November, the soil water requirement by the crop reaches the highest values and frequently soil water content due to rainfall is not enough. Thus, it is crucial to know the soil water storage SWS to predict the soil moisture availability for the crop in Pergamino.

Under normal production conditions, all extensive crops are exposed to soil water deficiencies. This drought conditions strongly affect yield components depending on the overlapping with critical periods, such as that determining the number of grains.

Therefore, knowing the dynamic of an agro meteorological variable such as SWS, it will be a double fold: a better crop management and the implementation of adaptation measures aimed at reducing the impacts of climate variability on agriculture activities

The ERA-Interim reanalysis of the ECMWF with a 1.25° horizontal resolution, available in a global coverage since 1979 (Dee *et al.*, 2011) was used in the present study. The linear correlations between SWS and one, two and three months lagged meteorological variables related to precipitation and temperature (González *et al.*, 2016), were calculated and the predictors were defined by taking into account the areas with significant correlation using 95% confidence level.

The variables considered were: geopotential heights of the 1000 hPa, 500 hPa and 200 hPa pressure levels (hgt1000, hgt500 and hgt200, respectively), zonal and meridional wind components at 850 hPa (u850 and v850), sea surface temperature (sst), volumetric soil moisture (vsl) available for two soil depth layers, the first from the surface to 0.07m (vsl1.1) and the second, 0.21m thick with the top in 0.07m and the bottom in 0.28m (vsl1.2) and the total column of water in the atmosphere (tcw).

Methodology

The monthly relationship is defined as the correlation between SWS for October- November-December and any selected variable from the previous month this is September-October-November, respectively); the bimonthly-correlation is defined as the correlation with any selected variable averaged for the two previous months (August-September/ September-October/October-November) and the quarterly correlation is defined as the correlation with the quarter average (July-August-September / August-September-October / September-October-November). The set of potential predictors, all physically consistent and independent from each other to avoid multi collinearity, were defined as the average value of the variables in the region where the correlation coefficients R were greater than 0.37 (significant with a confidence level of 95% using a normal test).

Statistical forecast models were developed using multiple linear regression which .is a regression with a single predicted value, *y*, and more than one predictor (*x*) variables:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \beta_p x_p \quad (2)$$

where *p* is the number of predictor variables.

The objective of the selection of potential predictors is to find a model that fits well with the data and, at the same time, it is simple, produces and provides robust efficiency coefficients.

A useful method in the selection of explanatory variables of the regression models is the penalized least squares. The regularized regression method used in this work is the regression called least absolute shrinkage and selection operator (LASSO). Proposed by Tibshirani (1996), LASSO minimizes the residual sum of squares to the sum of the absolute value of the coefficients if it's less than a constant value:

$$\left(\beta_0{}^{lasso}, \beta^{lasso}\right) = \min\left\{\sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_j \beta_j x_{i,j}\right)^2\right\}$$

$$subject\ to\ \sum_j \left|\beta_j\right| \le s$$

or, equivalent

$$\min\left\{\sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_j \beta_j x_{i,j}\right)^2\right\} + \lambda \sum_j \left|\beta_j\right| \quad (3)$$

where s and ≥ 0 are constant parameters. The LASSO enables estimation and variable selection simultaneously in one step.

When there are many possible predictors, several models are generated and therefore it is necessary to evaluate which is the best statistical model predicting SWS. Evaluation of our predictions was done by computing the adjusted R^2 (R^2_{adj}), the leave-one-out cross-validation statistic CV and the Akaike's Information Criterion (AIC).

Adjusted R^2 is explained as the proportion of total SWS variance that the model explains, given by:

$$R^2_{adj} = 1 - (1 - R^2)\frac{N - 1}{N - k - 1} \quad (4)$$

where N is the number of observations, k is the number of predictors and R^2 is the coefficient of determination. Using this improvement of R^2, the best model will be the one with the largest value of R^2_{adj}.

The leave-one-out cross-validation statistic CV is calculated using one subset (of n-1 data) as testing data and the remaining value as the training data. The CV is computed as:

$$CV = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{e_i}{(1-h_i)}\right]^2 \quad (5)$$

where e_i is the residual obtained from fitting the model to all *N* observations and h_i are the diagonal values of the projection matrix of the predicted matrix. The lower the CV value is, the coefficients of the models differ slightly, and the stability is guaranteed.

Akaike's Information Criterion (AIC) offers an estimate of the relative information lost when a given model is used to represent the process that generated the data (Hyndman and Athanasopoulos, 2018). It is defined as:

$$AIC = N\log\left(\frac{SSE}{N}\right) + 2(k+2) \quad (6)$$

where *N* is the number of observations, *k* is the number of predictors and *SSE* is the sum of square errors. The model with the minimum value of the AIC is often the best model for forecasting.

These statistics are computed for the different models. The best models were defined as those with the lowest CV and AIC and the highest R^2_{adj}.

The skill of the best models is proved in a semi-quantitative way (Wilks, 2011). Two series were considered: the SWS derived from OHBA ("observed values") and the series resulting from the cross-validation method ("predicted values"). The observed and predicted SWS distributions were categorized in three equiprobable classes. The upper interval refers to values greater than the second tercile, labeled "above normal", the values lower than the first tercile are called "below normal", and "normal" refers to values greater than the first and lower than the second terciles. The first two categories refer to the driest and wettest soil conditions respectively.

Usually, verification data is displayed in a contingency table of absolute frequencies of the possible combinations of forecast and observation pairs (Wilks, 2011). The proposed categorization generated 3x3 contingency tables, which are converted into 2x2 tables considering the "event" and the "non-event" to evaluate the efficiency from the scalar attributes most widely used in the forecast literature. The Hit Rate (HR) index gives the proportion of events that were correctly forecasted. The probability of detection (POD) is defined as the fraction of those occasions when the forecast event occurred on the one which was also forecast. The best (POD) value is 100%. The false alarm relation (FAR) is the proportion of forecast events that fail to happen. The best (FAR) value is 0.

RESULT AND DISCUSSION

SWS average performance

The average distribution, maximum values, minimum values and the standard deviation of SWS for the period 1979-2016 are shown in Figure 1.

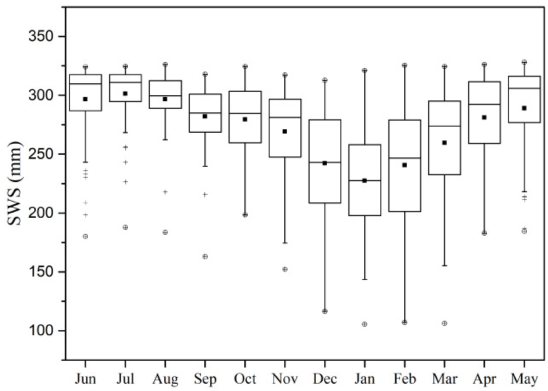

Figure 1. Seasonal soil water storage (SWS) in Pergamino. Boxplots indicate the central 50% interquartile range, the median, and the lower and upper bounds, the outliers (circles) and the mean (black square).

The average values show an annual cycle with a maximum in winter and a minimum in summer, and most of its variability takes place from November to May. The average maximum value is 322.8 mm and the average minimum value is 108.8 mm. High SWS values are detected in the 1990s and very low SWS are registered especially in two different periods: from June to September 2008 (Scarpati and Capriolo, 2013)

SWS trends are calculated using both the nonparametric Mann–Kendall test (Mann, 1945; Kendall, 1975) and the Sen method (Sen, 1968). Tests were performed for the 1979 -2016 period. Table 1 shows a positive trend

In February, trend is significant at 99% confidence level, according to the Mann-Kendall test. This significant SWS increase could be the result of a change in the management of production systems, leading farmers to replace early planted for late-planted maize. In the Pampean region, previous studies suggest that late sowing date determines a reduction in the potential corn crop yields (Otegui *et al.*, 1996; Maddonni, 2012). However, in recent years, the productivity of maize for late sowing dates has experienced a sustained growth in the region, largely sustained because of the greater availability of water in February. Also, the fact that the first frost day in the region has shown a delay

Table 1. Trends in SWS for the period 1979–2016. Trend analysis with non-parametric Mann-Kendall test (Sen's slope estimates and significance of Mann-Kendall test). *** for $p < 0.001$, ** for $p < 0.01$, * for $p < 0.05$, + for $p < 0.1$, NS for $p > 0.1$.

Month	Sen's slope estimate	Significance
January	0.597	+
February	0.886	**
March	0.692	*
April	0.341	+
May	0.221	+
June	-0.009	NS
July	-0.068	NS
August	-0.062	NS
September	-0.152	NS
October	-0.120	NS
November	0.169	NS
December	0.420	NS

(Fernández Long, *et al.*, 2013) of early frosts, which is one of the most important restrictions for late maize (Maddonni, 2012).

Selection of predictors

Monthly, bi-monthly and quarterly linear correlation fields enabled the definition of a set of predictors over the area (180° W – 40° E and 20° N – 60° S). Figures 2a to 2c resume predictors that better estimated SWS for October, November and December.

In October (Figure 2.a), SWS is related to the hgt1000 in the Caribbean region. This result agrees with the one obtained by González and Barros (2002) when they explored the relation between the inter-annual variability of the South American monsoon and the inter-annual variability of spring precipitation in the subtropical Argentina. Vsl1.1 of the previous month in Buenos Aires province is also an important SWS predictor. Therefore, the initial state of the water contained in the first layer of the soil affects the subsequent value. The high bi-monthly correlations between SWS and tcw over the location and the neighboring ocean portion and hgt500 over the Indian Ocean and the south of Africa are used to define other predictors. Clearly, the water in the atmosphere affects the possibility of in situ precipitation and the western circulation also affects the displacement and development of the systems that move like Rossby waves.

Both hgt1000 over the Caribbean region and vsl1.1 over Buenos Aires province in the previous month are also SWS predictors in November (Figure 2.b). Besides, V850 on the Chilean coast has a positive correlation in a region associated with the South Pacific High. The bimonthly predictor included in the model is the hgt200 over the Pacific Ocean and the southern the Niño4 region, indicating the influence of the jet stream

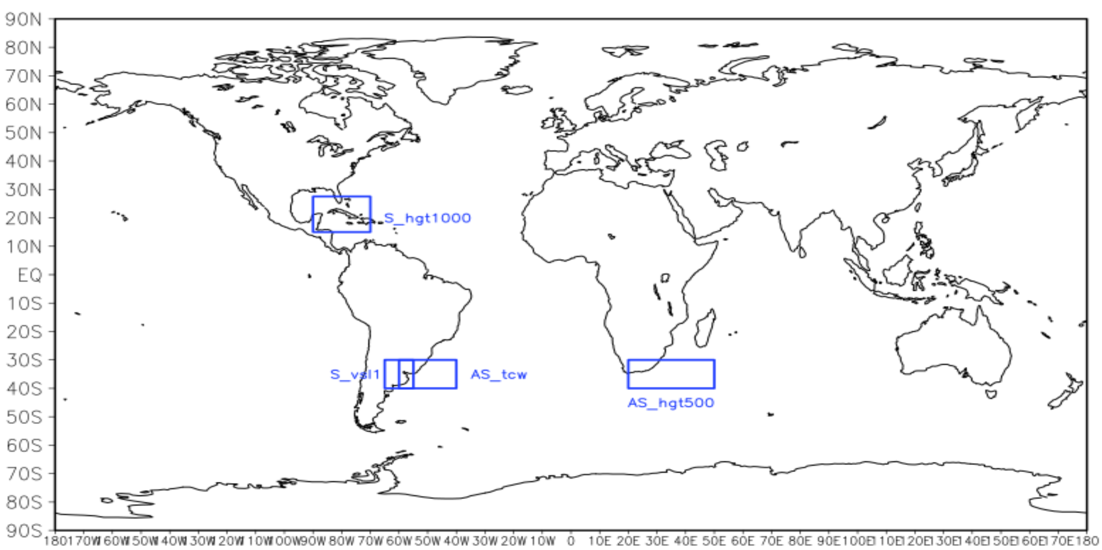

Figure 2.a. Geographic areas used to define the October predictors of Soil Water Storage. Prefix S_ indicates September, prefix AS_ denotes August and September average.

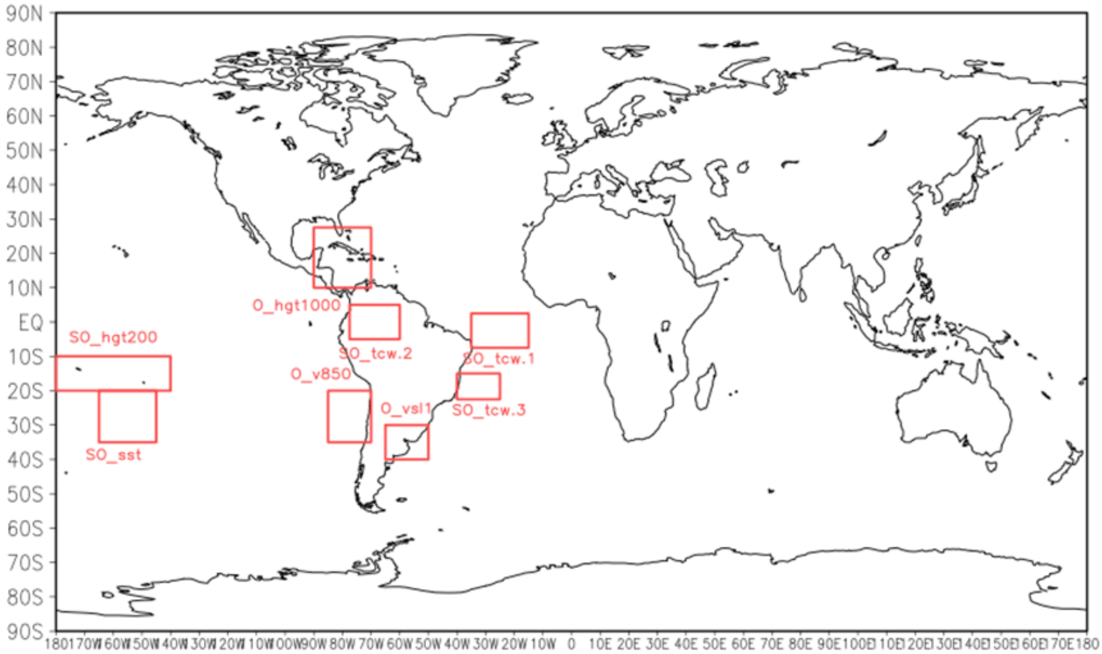

Figure 2.b The same as for (a) for November. Prefix O_ indicates October and prefix SO_ indicates September and October average.

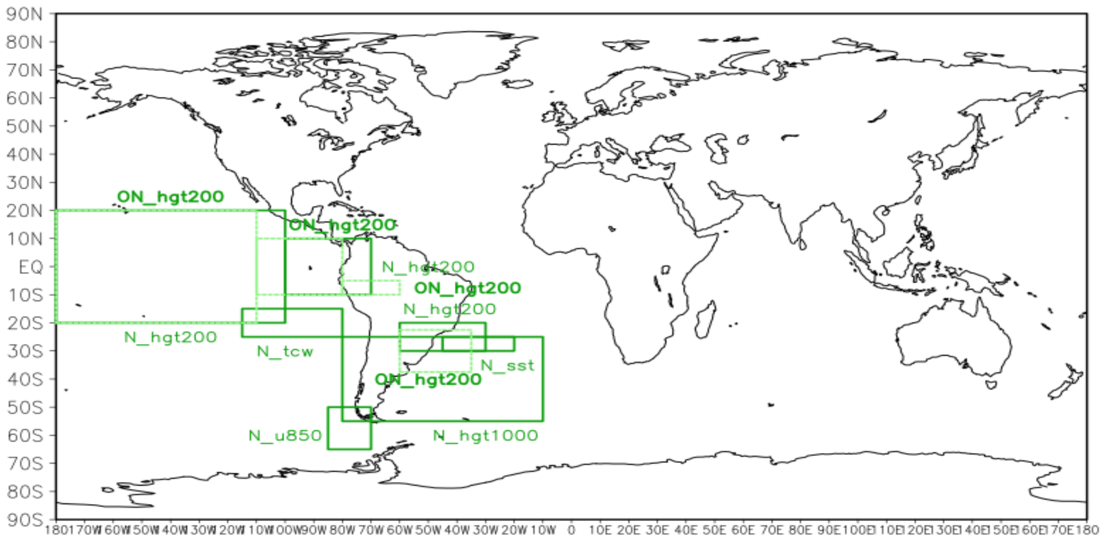

Figure 2.c The same as for (a) for December. Prefix N_ denotes November and prefix NO_ denotes October and November average.

and the ENSO teleconnection over the SWS, over precipitation and, therefore, over SWS in the northern portion of the province.

SWS predictors in December spread over large areas (Figure 2.c). It is important to notice that hgt200 averaged the two previous months over the tropical Pacific Ocean influences SWS. Hgt1000 over Argentina, the subtropical SST off the Brazilian coast, tcw over the tropical zone and the u850 over the Antarctic ocean are predictors defined the previous month. Statistical forecast models were developed using multiple linear regression.

The statistical forecasting models and their efficiency

Table 2 Best model for October (SWR_Oct), November (SWR_Nov) and December (SWR_Dec) and the efficiency coefficients cross-validation (CV), the Akaike's Information Criterion (AIC), and the adjusted R-squared correlation coefficient (**R^2**)

Best Model	CV	AIC	R^2
SWR_Oct = 0.0885 * S_hgt1000 + 299.480 * S_vsl1 + 0.0579 * AS_hgt500 + 3.843 * AS_tcw - 3193.70	469.08	235.60	0.523
SWR_Nov = 0.266 * O_hgt1000 -10.171 * O_v850 + 688.748 * O_vsl1 + 0.106 * SO_hgt200 + 5.605 * SO_tcw.1 + 31.961 * SO_sst - 8.756 * SO_tcw.2 + 8.175 * SO_tcw.3 -22986.7	519.98	232.30	0.726
SWR_Dec = -0.263* N_hgt200 - 0.065 * N_hgt1000 + 39.978 * N_sst + 8.533 * N_tcw - 3.477 * N_v850 + 0.3466* ON_hgt200 - 21870.42	816.52	255.49	0.597

Table 2 shows the best forecasting models resulting from the cross-validation method for each month and their efficiency coefficients are also specified. The observed and forecast SWS time series are shown in Figure 3.

All the models show R^2_{adj} higher than 0.5 (explaining more than 50% of the SWS variance). The models explain 60% of the SWS variance in December, 73% in November and 52% in October. However, the model in October is the most stable, as CV is lower than in November and December. The AIC values are similar in the three months.

Figure 4 shows the percentage of observed and predicted values according to the categories defined. The forecasted and the observed values agree in more than 60% of the cases and the highest value (73.7%) is registered in November, the only month when cases which differ in two categories (2.6%) were registered.

The scalar attributes are summarized in Table 3. The values for the October model show the best values of POD (0.69), TS (0.60) and FAR (0.08) for below normal events. The model also exhibits good values of POD (0.69) and FAR (0.16) for the above normal category, although TS is not as high as expected. The model complies with the POD but has a very high FAR for the normal category. Emphasizing on the below/above categories, this model has the best performance on forecast extreme (driest / wettest) events.

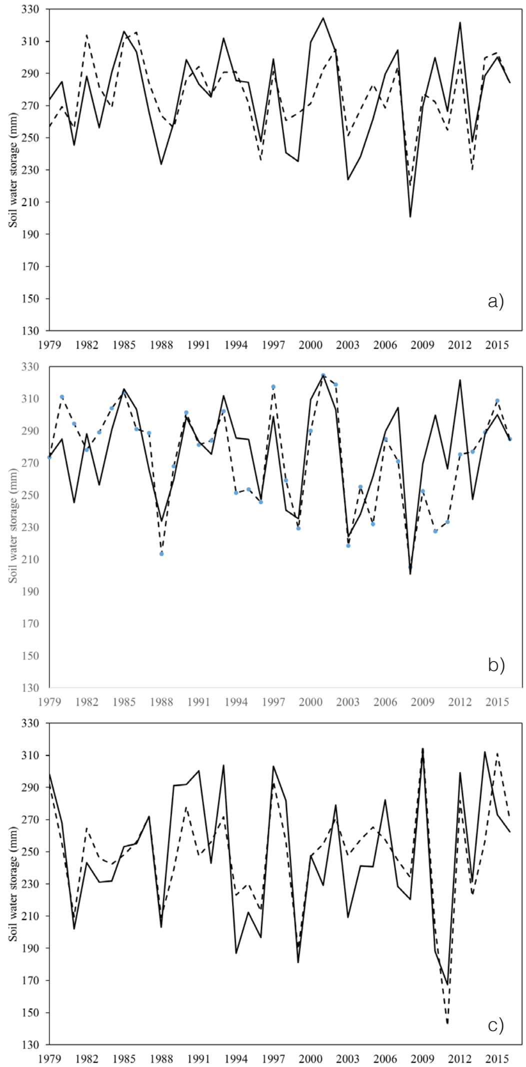

Figure 3. Observed (solid line) and forecasted (dashed line) SWS time series (a) for October, (b) for November and (c) for December.

The SWS forecasting model in November shows the highest R_{adj}^{2} (0.726) anthem lowest CV (519.98) and AIC (232.30), which suggests a great performance. For the below-normal category, the model has good POD (0.85) and FAR (0.08) attributes. For the above normal category, the model has better FAR (0.11) and worse POD than in the below normal case. In both categories the TS exceeds 0.5. No attribute is fulfilled for the normal category.

The SWS forecasting model in December shows the best R_{adj}^{2} (0.5970) and AIC (255.489), with low values of CV (859.3). The values of POD (0.62) and

Table 3. Statistical attributes resulting from the application of the verification contingency table (HR, POD and FAR), for events Below, Normal and Above.

Scalar Attributes		HR Hit rate	POD Probability of detection	FAR False Alarm Rate
	Below normal	0.84	0.69	0.08
October	Normal	0.63	0.50	0.31
	Above normal	0.79	0.69	0.16
	Below normal	0.89	0.85	0.08
November	Normal	0.76	0.75	0.23
	Above normal	0.82	0.62	0.08
	Below normal	0.84	0.62	0.04
December	Normal	0.66	0.92	0.46
	Above normal	0.82	0.46	0.00

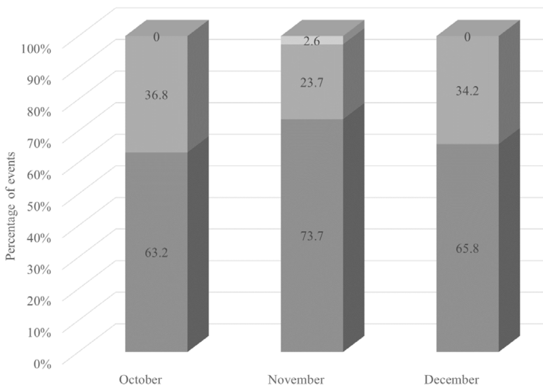

Figure 4 Shows the percentage of observed and predicted values according to the categories defined. The forecasted and observed values agree in more than 60% of the cases and the highest value (73.7%) is registered in November, the only month where cases which differ in two categories (2.6%) were registered.

FAR (0.11) for the below normal category and POD (0.42) and FAR (0) for the above normal category are good. The efficiency of the model decreases for the normal category.

CONCLUSIONS

A SWS statistical forecasting model for a location, representative of an important agriculture region, was developed for each month (October-November-December) in a typical location, using atmospheric and oceanic predictors that are usually correlated with precipitation and air temperature. Statistical forecasting models were developed for each month. Evaluation of our models was done by computing the efficiency statistics. The skill of the forecast was verified by computing some statistics like the thread score, the probability of detection and the false alarm ratio, which showed valuable results.

Development of statistical forecasting models implies an interdisciplinary approach and the opportunity to contribute to national institutes and agencies with relevant tools for decision-making related to the improvement of agricultural practices in the region.

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