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RESEARCH ARTICLE

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SIE-Climate: A methodological and technological tool for predicting local climate variability in managing socio-ecological systems

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Abstract

Climate variability, as an element of uncertainty in water management, affects community, sectoral, and individual decision-making. Long-range prediction models are tools that offer the potential for integration and joint analysis with the hydrological, hydrodynamic, and management response of the socio-ecological systems to which they are linked. The main objective of this article is to present a seasonal climate prediction model, the open-source algorithm SIE-Climate, whose application consists of three phases (exploration, development, and evaluation), and to describe its application to the Lake Sochagota socio-ecological system (Paipa, Boyacá, Colombia). The K-nearest neighbours method is used when defining a target matrix that represents and integrates macro- and micro-climatic phenomena (Oceanic Niño Index, local temperature, and local rainfall) to identify periods of similar climatic behaviour. Considering a 1-year horizon and management purposes the tool is calibrated and validated in periods with and without climatic anomalies (2000–2018), giving reliable adjustment results (RSME:4.86; R^2: 0.95; PBIAS: −8.89%; EFF: 0.85). SIE-Climate can be adapted to various contexts, variables of interest, and temporal and spatial scales, with an appropriate technological and computational cost for regional water management.

KEYWORDS

climatic variability, K-nearest neighbours (KNN), SIE-climate software

1 | INTRODUCTION

The management of socio-ecological systems linked to water should always consider climate variability. The concept of the socio-ecological system is useful to understand the dynamic interrelation between environmental and social changes, as well as the interdependence of social and ecological subsystems (Fischer *et al.*, 2015). In water systems, human activities and climate variability can be key factors affecting the natural flow regime in river basins (Zolfagharpour *et al.*, 2020). Consequently, climate variability analysis and its prediction are a connection point between socio-ecological dynamics, the hydrological, and hydrodynamic responses of basins, and water management in local or regional systems (Park *et al.*, 2014; Lee *et al.*, 2018; Kim *et al.*, 2019).

General circulation models have become essential tools for climate studies, but computer codes are heterogeneous, and their optimisation is not simple (Mechoso and Arakawa, 2015). Short- and medium-term meteorological predictions (days or weeks) are used to estimate the climatic variables of interest based on numerical models of atmospheric circulation. In turn, seasonal prediction models are used to establish average weather conditions over time horizons of up to 1 year (Manzanas, 2016). This latter prediction scale of time series offers management advantages over short- and medium-term scenarios.

The effect of macroclimatic phenomena of the atmosphere–ocean system on local climatic and hydrological patterns can be assessed using interannual and interdecadal climate variability indices or statistical downscaling algorithms (Poveda *et al.*, 2011; Manzanas, 2016; Kim *et al.*, 2019; Kundzewicz *et al.*, 2019). Intra-seasonal oscillations should also be incorporated into climate variability analyses because their extreme phases affect the intensity of hydroclimatic events, such as torrential rains, droughts, and floods, which affect water and land management (Contreras-Juárez *et al.*, 2016).

Different models are available for predicting the behaviour of climatic variables. These models provide quantitative estimates of the probability of future events (Contreras-Juárez *et al.*, 2016). The Holt-Winters method is a parametric exponential smoothing procedure based on updating, for each period, three parameters of each variable: mean, trend, and seasonality (Molina *et al.*, 2006). The Bayesian model analyses change points in the properties of time series for climate prediction (Perreault *et al.*, 2000; Karger *et al.*, 2017). A new, analogous approach is the K-nearest neighbours (KNN) method, which offers an alternative to statistical downscaling when deriving climate data at a local scale (Gangopadhyay *et al.*, 2005).

When regional time series data are available, different methods must be used to incorporate the effect of macroclimatic phenomena into seasonal climate predictions for water management in socio-ecological systems. These methods must be flexible enough to add climatic variability elements to the analysis of the hydrological, hydrodynamic, and management response of the system, at a regionally affordable computational and technological cost, without sacrificing sensitivity or representativeness in the intra-seasonal, inter-annual, and interdecadal oscillations of the local climate.

Considering the above, the Socio-ecological Indicators Evaluation (SIE) project developed a methodological and technological solution for seasonal climate prediction (SIE-Climate) that is applicable to hydrological, hydrodynamic, and water resource management models. These simulation tools are integrated through a platform and are a resource for strengthening the resilience of socio-ecological systems in climate variability scenarios. This management tool can help the sectors and actors involved in managing these systems by facilitating strategic decision-making in a timely manner.

The main objective of this article is to present the seasonal climate prediction method and open-source software developed within the framework of the SIE project. This study describes the usefulness of the tool for predicting essential climatological variables (rainfall and temperature) on daily and monthly scales over a 1-year horizon, as well as their categorisation based on the probability of climatic anomalies (El Niño, La Niña, and average-year phenomena) in the Lake Sochagota socio-ecological system (Paipa, Boyacá, Colombia). Lastly, the benefits, flexibility, and limitations of this climate prediction tool in different territorial contexts are presented in the context of water management challenges and needs considering climate variability.

2 | STUDY AREA AND LOCATE CLIMATE

Lake Sochagota in Paipa, Boyacá, Colombia, is part of a volcanic hydrothermal system located in the Andes mountain range. It is a reservoir built on an old natural wetland that forms a small endorheic basin in the lower course of the Salitre River (Figure 1), a tributary of the Chicamocha River (Cifuentes *et al.*, 2020). The Salitre basin has a drainage area of approximately 81.61 km^2 and is the main Sochagota Lake tributary. The elevation varies between 2,501 and 3,588 m. In the area, there are two orobiomes, the middle and the upper humid forest, with paramos, sub-paramos, high Andean forest and wetlands in the lower part of the basin (Corpoboyacá, 2019). These systems coexist with agricultural, agroforestry, subsistence crops and mining areas.

The local climate has a bimodal behaviour with high rainfall from March to May and from September to November and low rainfall from December to February and from June to August. This dynamic is associated with the double passage of the Intertropical Convergence Zone (ITCZ), atmospheric circulation patterns in the Pacific and the Caribbean, topographic gradients, and land-atmosphere interactions (Poveda *et al.*, 2011).

The El Niño Southern Oscillation (ENSO) is a significant forcing mechanism in local short- and long-term climate variability (Poveda *et al.*, 2011).

The variables of interest (rainfall and temperature) do not show a normal daily distribution on a daily scale. Historical records from the Tunguavita station (13.7°C) show that the monthly average temperature varies $\pm$0.8°C, and the daily average temperature ranges from 8.3 to 20.4°C, while the daily rainfall (977.1 mm annual average) ranges from 0 to 77 mm·day^{-1}.

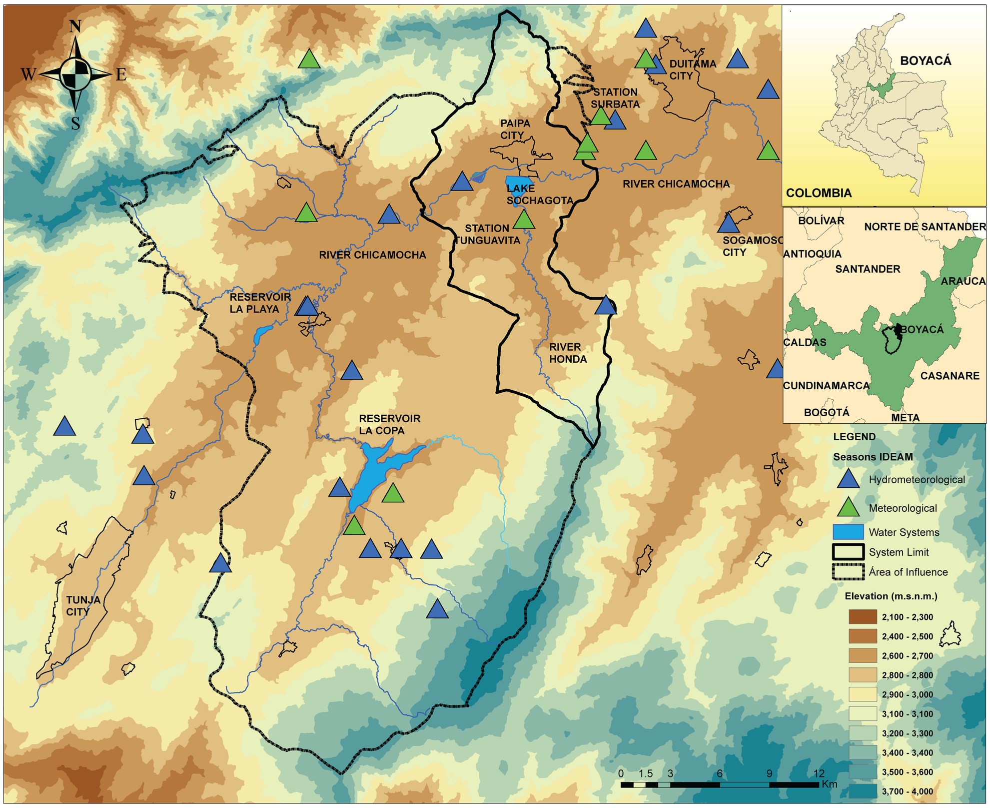


FIGURE 1 Geographical location, topographic map, and main hydrographic and weather stations used in the study [Colour figure can be viewed at wileyonlinelibrary.com]

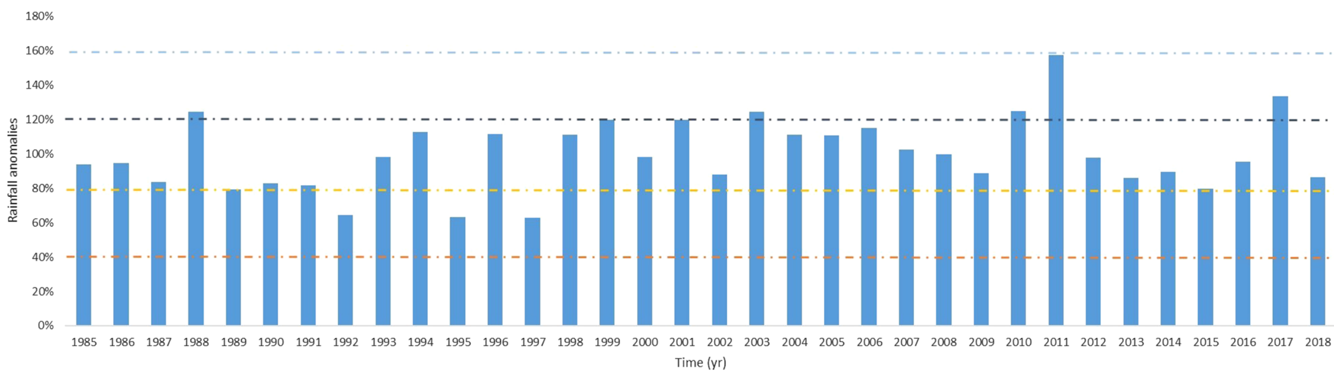


FIGURE 2 Historical rainfall anomalies at the reference station for the Lake Sochagota system [Colour figure can be viewed at wileyonlinelibrary.com]

Rainfall is considered a critical variable because it shows the greatest variability. Figure 2 displays rainfall anomalies according to the following classification (Montealegre, 2009): high deficit (<40%); deficit (40–80%); normal (80–120%); excessive (120–160%); and very excessive (>160%).

The percentage anomalies (PA_{iT}) calculation was made using as base period (m) the (i) years between 1985 and 2018 taking the moving average 3 ($mm3_T$) of each annual trimester (T) divided by the average multiannual summation of each mm3 during a same trimester (adapted from (Montealegre, 2009), see Equation (1).

$$PA_{iT} = \left[\frac{mm3_{T(i)}}{\frac{\sum_{i=1}^{i=m} mm3_{T(i)}}{m}} \right] * \tag{1}$$

3 | METHODS

3.1 | General description

The SIE-Climate model is a methodological and technological tool for predicting, on a daily or monthly scale, the annual behaviour of two climatic variables in a reference station or area. Climatic series are forecast from local historical data and from the characterization of the climatic variability on a global scale using an atmospheric index. This method requires identifying meteorological events from before the forecast period. From these events, three time series are estimated for each target climatic variable in the period of interest and at the reference station. The methodological path (Figure 3) includes the following phases: exploration, development, and evaluation of the climate prediction model.

The *exploratory phase* guides the process of selecting the target climate variables and the reference meteorological stations in the region of interest. This phase includes meetings with local institutional actors to identify reference stations; setting up the technological infrastructure for gathering, storing, and processing the available climate data; characterizing the developments and current scope of the existing prediction models and their prediction periods; and identifying the macro- and meso-scale phenomena with the greatest impact in the region.

In studies on water management, the reference station(s) is (are) selected by defining the limits of the basin or micro-basin that contains the socio-ecological system under study, which also makes it possible to select the index or variable representative of the macro-climatic phenomenon that has the strongest impact on a local scale, based on previous studies, graphical analysis, and spatiotemporal correlations between target variables and variables that represent the dynamics on a global scale.

The exploratory phase requires setting up the historical database (DB) that contains the target climatic variables on a daily scale. This DB must be validated to construct time series without data gaps and must be representative of the climatic behaviour of the study area. Similarly, the DB is transformed into quarterly anomalies (DB′) to analyse the data together with the representative index of the quarterly macro-climatic phenomenon.

Cross-correlation analysis makes it possible to determine the response time (m) of the local climate as a function of the phenomenon of macro-climatic variability and to establish possible causal relationships or repercussions

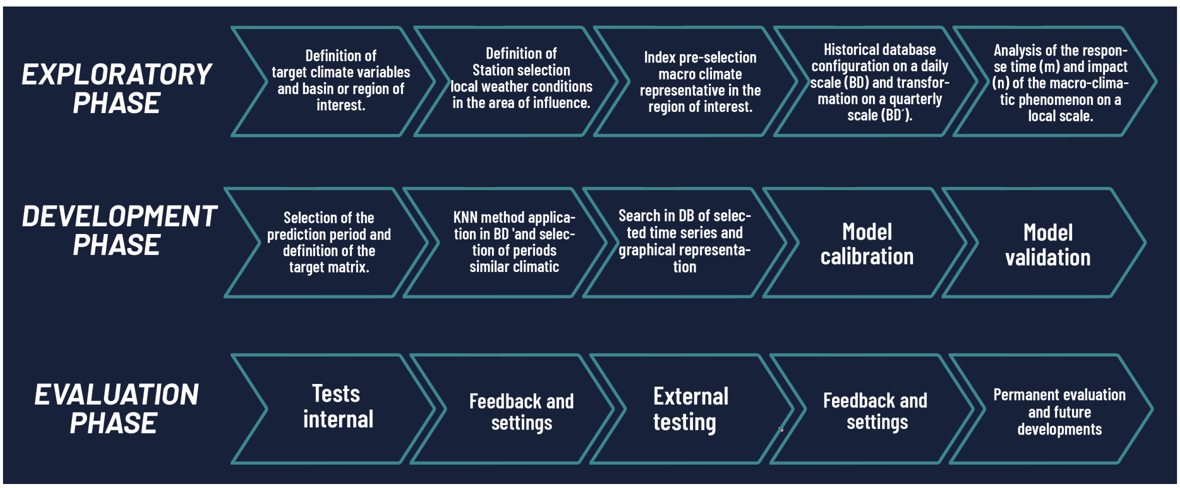


FIGURE 3 Methodological path for the development of the SIE-climate prediction model [Colour figure can be viewed at wileyonlinelibrary.com]

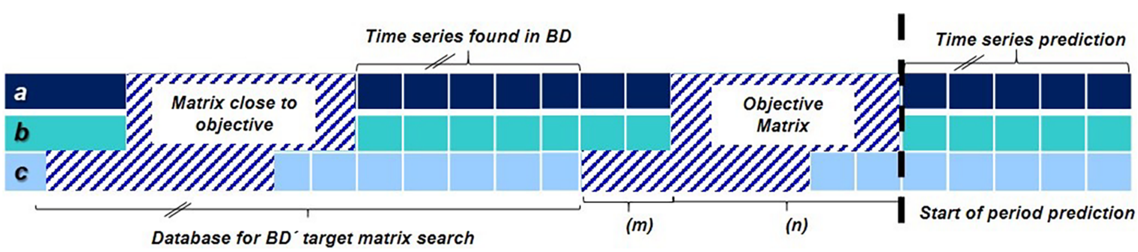


FIGURE 4 Graphical representation of the KNN method in the SIE-climate model [Colour figure can be viewed at wileyonlinelibrary.com]

(n) between variables. Using (synchronous and lagged) cross-correlation is key to determining the response time with which the explained (climatic) variables react to fluctuations in explanatory variables (meso- and large-scale indices). The response can be immediate (synchronous) or delayed (lagged) by one or several periods (Poveda *et al.*, 2011).

The *development phase* starts with the selection of the forecast period so as to defining the target matrix. The target matrix corresponds to the dataset of the time series of the climatic variables a and b and of the macro-climate index c, which are found within consecutive ($m + n$) periods before the forecast start date (Figure 4).

The KNN method is based on calculating the similarity (neighbourhood) between the real value and the predicted value (X_r) for each historical observation (X_t), which is expressed through the Euclidean distance function (D_{rt}) given in Equation (2).

$$D_{rt}=\sqrt{\sum_{t=1}^{m} w_i (X_{ir}-X_{it})^2}, t=1,2,\dots,n \tag{2}$$

wherein w_i (i = 1, 2,:::, m) is the weight of the predictor, all of which sum to 1; $X_r=\{X_{1n},, X_{2n,} X_{3n,} :::, X_{mr}\}$; and $X_t=\{X_{1b,}, X_{2b,} X_{3b,} :::, X_{mr}\}$.

The KNN method is highly sensitive to Euclidean distances between data (Wu *et al.*, 2008). However, the distance-based weighting schemes for the KNN classifier (Geler *et al.*, 2016) make it possible to weight the results by classifying the nearest neighbour with the number 1 and the farthest with the number N, which will depend on the number of records in the DB. In contrast to most linear regression models, which assume a Gaussian distribution of errors, KNN regression is a non-parametric technique that estimates the prediction value locally, making it possible to assess both linear and non-linear relationships between predictor and predicted variables (Grantz *et al.*, 2005).

The SIE-Climate prediction model uses weighting schemes to analyse the conditional probability that the target variables will show alterations or anomalies if a macro-climatic phenomenon occurs, characterized by the corresponding index. The KNN method is used to find the target matrix in the historical DB′ in order to identify the three most similar matrices (classifications 1, 2, and 3 of the KNN). After finding the analogous matrices (matrices close to the target), the time series of the variables a and b (365 days in each case) are extracted from the validated DB. These time series correspond to the climatic data in the period immediately after the time period of the selected matrices. The data of the time series can be represented on a daily or monthly scale, as required. For this purpose, modules have been developed to display and update the DB to move forwards in the seasonal forecast period.

The reliability of the model is verified through calibration and validation using past climatic events, in both typical (years with normal conditions) and atypical periods (years with climatic anomalies). The statistical test used to compare the three climatic series found through the model with the values recorded in the period of interest is selected based on the nature of the probability distribution of the data and prediction target.

The software development phase implemented the method for constructing the backend and frontend of the open-source software (SIE-Climate), according to the following stages:

Analysis stage: functional and non-functional requirements are determined, establishing the refinement tree, wherein three functional groups are identified:

- *Basic Administration*;
- *Configuration*;
- *Management Data*.

Design stage: The general use case diagram of the system and the sequence diagram are established for each component. The component diagram is developed, and the entity-relationship model is developed.

Programming stage: The software SIE-Climate is constructed, implementing the previous analysis and design, in the form of the following tools: BACKEND: API REST, and Django (Python); DB: PostgreSQL; and FRONTEND: Angular 8, HTML 5 and CSS 3.

Lastly, in the *evaluation phase*, internal (unit, integration) and external tests are performed to analyse the reliability, efficiency, usability, maintainability, portability, security, and relevance of the software and to identify future challenges for its optimisation.

3.2 | Software development of the SIE-Climate prediction model

The software development phase made it possible to implement the method described above and to construct the backend and frontend of the open-source software (SIE-Climate) through the above-described analysis, design, and programming stages.

As a result of the analysis stage, the climate prediction software consists of three modules (Figure 5): (a) Administration: user and role management for managing the software and implementing security and administration requirements. (b) Configuration (setting): Through its options, the basic information is entered to

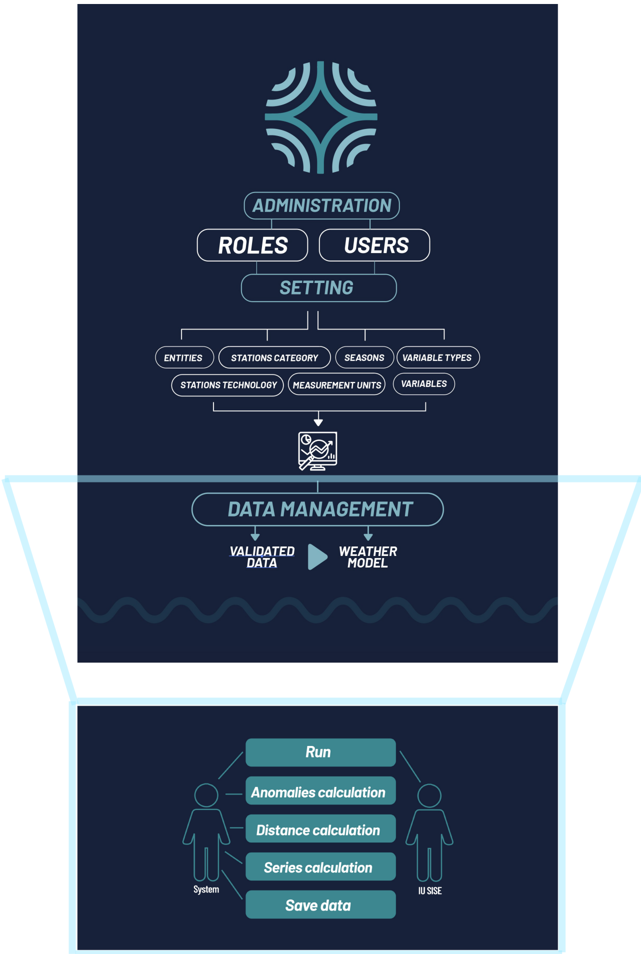


FIGURE 5 General diagram of the modules and use case of the SIE-climate model [Colour figure can be viewed at wileyonlinelibrary.com]

operate the climate model, such as the types of variables, the variables themselves, the units of measure, the entities, the technology used, the categories of stations, and the names of the stations themselves. (c) Data management: processing data, managing previously validated data in Microsoft Excel, and running the SIE-Climate prediction model.

In the *design stage*, the general use case diagram of the system and the sequence diagram are established for each component. The actors to target are identified (System and IU SISE); the System is the application programming interface (API), which is responsible for executing all business logic operations, and the IU SISE is the API user, who is responsible for making all requests to it. For each component of the general use case, its use case and sequence diagram are determined, which identifies the actions and functions of each actor in the functional requirements.

The design includes the class diagram of the system with the classes and their attributes, methods, and relationships.

Lastly, the component diagram that contains the functionalities of the system is designed, and the entity-relationship model is elaborated, describing the tables, attributes, and relationships needed to manage the software data and to move on to the programming stage.

The software of the SIE-Climate prediction model can forecast the behaviour of two climate variables simultaneously in a reference station or area, during a maximum period of 1 year from the date of interest. This period is selected in the interface of the climate model of the management data module.

The climate series are predicted from local historical information and from the characterization of the climate variability phenomenon on a global scale, which are linked to the SIE-Climate model through the configuration module. This method identifies in the DB, meteorological events before the prediction period, thereby finding three data series of the climatic variables, which represent their forecasts (behaviours) for the period of interest and for the reference station.

The response of the climate prediction model is displayed graphically, both on a daily and on a monthly scale, and offers an application for data searching. The Oceanic Niño Index (ONI) and the local climate DB have been parameterised to enable users to update them: http://www.sie.org.co/sie/index.php/descargas

3.3 | SIE-Climate software evaluation

The agro-meteorological station closest to Lake Sochagota (the Tunguavita station, operated by the Institute of Hydrology, Meteorology, and Environmental Studies *Instituto de Hidrología, Meteorología y Estudios Ambientales*—IDEAM) was used as a reference for the methodology and software evaluation. The DB was design combining records from the conventional station (from 1 January 1985 to 14 December 2004) and from the DHIME platform (Instituto de Hidrologia M. y E.A, 2019; up to December 31, 2018). Missing data was estimated on a daily scale using historical records from 33 stations located in the study area and applying the multiple imputation statistical method (Gao *et al*., 2018) with Amelia II software (Honaker *et al*., 2011). This method has been widely used and validated to complete climatological series (Schneider, 2001). The results were verified by over-imputation (Honaker *et al*., 2011). The resulting DB provides a continuous series of daily climatic records, which were validated using historical regional and national records.

3.3.1 | Internal tests

Unit and integration tests were performed for each software component. The API's Postman testing software was used in the tests to send HTTP REST requests through a graphical interface. In this method, collections are created in which all requests are stored in an organized way, and these collections can be shared for collaboration work. Postman can generate invocation codes for different backend development languages, in this case, Python.

The reliability of the model was evaluated for typical years and extreme climatic anomalies as benchmark (see Figure 2). The daily rainfall data recorded at the Tunguavita station was compared with the predicted series (three series for year) in each case. The predicted and observed series comparison during calibration and validation process was carry out with percentile analysis.

The percentiles (0.25, 0.5, 0.55, 0.65, 0.75, 0.85, 0.95, 0.975, 0.99, and 0.999) of daily rainfall data observed and predicted were obtained. These percentiles were matched to represent a linear regression model. This data set (2000–2018) was evaluated using statistical metrics to evaluate the SIE-Climate suitability for water management purposes (Curve-fitting to the linear regression model (R^2); Root Mean squared error (RMSE); Percent bias (PBIAS); and Nash–Sutcliffe efficiency coefficient (EFF)).

3.3.2 | External tests

The methodology and software for climate prediction were tested and validated by 34 regional actors (Corpoboyacá Environmental Agency, IDEAM Institute of Hydrology, Meteorology and Environmental Studies, Paipa Department of Agriculture, engineering professionals, and related professionals).

The methodology for selecting the climatic stations, the identification of missing data, the filling of the DB (Multiple Imputation method) and the interpolation of data between stations to consolidate the regional DB were explained to the regional actors. Likewise, the climate prediction methodology and statistical analyses carried out in the calibration stage were explained for the evaluation.

The regional actors interacted with the software to create new stations and variables as well as carried out exercises to (a) obtain the temperature and precipitation series for the Tunguavita station in historical periods (2018, 2015, and 2011) and, (b) in the projected period 1 January 2020–31 December 31 2020.

The evaluation of the SIE-Climate prediction software was carry out in order to inquire about the quality of the information (accuracy, timeliness, complete, relevant, and consistent), the quality of the system (reliability, easiness, and response speed), the quality of the service (response to user needs) and innovation degree. The questionnaire was implemented in a Google form, using five qualitative assessment categories (1—not satisfactory, 2—not so satisfactory, 3—somewhat satisfactory, 4—satisfactory to 5—Very satisfactory). It also allowed to give additional comments and suggestions.

4 | RESULTS

The SIE-Climate method and technological tool is illustrated by its application to the socio-ecological system of Lake Sochagota, Paipa, Boyacá, Colombia. The exploration, development, and evaluation phases of the seasonal prediction of time series for the variables temperature and rainfall are presented below. These variables were chosen for their association with hydrological and hydrodynamic dynamics, an association that is required for managing the system of interest.

The meetings with local institutional and community actors in the exploratory stage made it easier to identify regional dynamics, reference stations, technological infrastructure, and developments in and the current scope of existing prediction models at the national scale developed by IDEAM, along with their projection periods (daily and semi-annual). The meetings also helped identify the macro- and mesoscale phenomena with the strongest impacts on the region.

4.1 | Analysis of the macro-climate index

ENSO events have been related to rainfall, soil moisture, and river flows in Colombia. Quarterly cross-correlation studies have identified strong associations with rainfall and streamflow for the December–January–February (DJF) quarter and the weakest for the March–April–May (MAM) period (Poveda *et al*., 2011; Enciso *et al*., 2016; Kim *et al*., 2019; Canchala *et al*., 2020). These physical processes reflect a well-defined degree of inertia between the components of the local and global climate system (ocean and atmosphere). The index selected to represent the interannual macro-climatic variability in the study area is the ONI (NOAA National Weather Service, 2020).

In the Boyacá Department or Colombia, the climatic variability with the strongest relationships with the variables of interest is the ONI. It has a direct relationship with maximum temperature and an indirect relationship with rainfall, mainly in the DJF and September–October–November quarters (Díaz and Villegas, 2015). This index represents ENSO (Poveda *et al*., 1998, 2002, 2011) and is calculated as the quarterly moving average of the anomalies of the SST, measured by ERSST.v3b (NOAA PSL, 2020; 2020b) in the region Niño 3.4, based on 30-year periods and updated every 5 years. Values above 0.5 for five consecutive months are linked to El Niño events and below −0.5 to La Niña events (NOAA CPC, 2015).

The ONI is mainly directly correlated with temperature and negatively correlated with rainfall anomalies (Table 1). The synchronous (Figure 6) and lagged cross-correlation in the study area showed that the most appropriate correlation between the local variables of interest and the ONI occurred with a lag of one to five quarters, therefore two quarters was adopted for the present study ($m = 2$). The phenomenon occurs first in the Pacific Ocean and, about two quarters later, at the local level. The period of repercussion of the phenomenon was set to five quarters ($n = 5$); consequently, the total period over which to search for the target matrix in the DB transformed on a quarterly scale is seven quarters ($m + n = 7$). This time span considers the minimum consecutive evaluation period to declare the existence of the phenomena El Niño and La Niña, and it considers previous studies in the South American context, in which the lag, spread, and impact times are sometimes shorter than or close to seven quarters, depending on the geographical location and proximity to the Pacific coast (Poveda *et al.*, 1998; Poveda *et al.*, 2002; Hoyos *et al.*, 2013; Córdoba-Machado *et al.*, 2015; Díaz and Villegas, 2015; NOAA CPC, 2015; Canchala *et al.*, 2020; NOAA PSL, 2020a; NOAA PSL, 2020b; NOAA PSL, 2020c).

TABLE 1 Pearson correlation between ONI, rainfall, and temperature anomalies

Lag period (month)	*N*	Rainfall anomaly and ONI	Temperature anomaly and ONI
0	407	−.325**	.216**
1	406	−.322**	.247**
2	405	−.305**	.276**
3	404	−.274**	.303**
4	403	−.232**	.320**
5	402	−.182**	.325**

**The correlation is significant at the .01 level (bilateral), *p*-value <.001. Database 1985–2018.

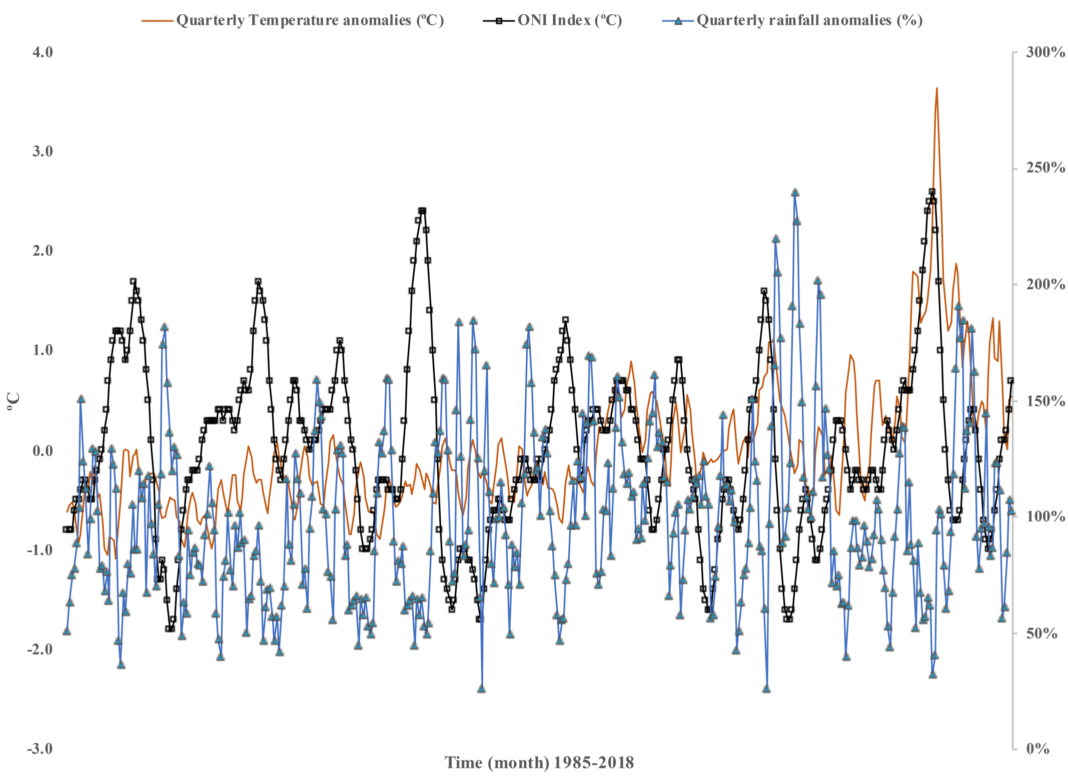


FIGURE 6 Graphical relationship between ONI and the rainfall and temperature anomalies without lag time [Colour figure can be viewed at wileyonlinelibrary.com]

4.2 | Application of the KNN method to the Lake Sochagota socio-ecological system

In the development phase, the KNN method is applied for seasonal climate prediction by identifying the three time-series (S1–S3) after the period in which the matrices similar to the target are found. The calibration and validation processes included in the development phase are performed in typical and atypical climatic prediction periods (2000–2018).

Rainfall can be grouped into three categories: normal range (typical years), deficit conditions associated with the macroclimatic phenomenon El Niño (as shown in 1989, 1992, 1995, 1997, and 2015), and excessive rainfall associated with La Niña phenomenon (in 1988, 2003, 2010, 2011, and 2017). The greatest rainfall excess and deficit within the last 15 years occurred in 2011 (157% anomaly) and 2015, respectively.

- Model calibration (typical-year and normal conditions)

The reliability of the model is evaluated for the typical year 2018. The three climatic series found (KNN: 1, 2, and 3) by applying the SIE-Climate method correspond to 2014 (S1), 2002 (S2), and 1990 (S3).

The daily rainfall data recorded at the Tunguavita station is compared with the predicted series (Figure 7).

The scatter plot between the percentiles (0.25, 0.5, 0.55, 0.65, 0.75, 0.85, 0.95, 0.975, 0.99, and 0.999) of daily rainfall data predicted for S1–S3 and recorded in 2018 show that the SIE-Climate model accurately predicts the data. Curve-fitting to the linear regression model indicates R^2 values of 0.9419, 0.9678, and 0.9824 (mean: 0.96) for 2014, 2002, and 1990, respectively, showing a good match between the predicted and recorded series in terms of magnitude (maxima, average, and minima) and in the distribution of the periods with the highest and lowest rainfall in 2018.

- Model validation (years with climatic anomalies)

The extremely dry year 2015 (El Niño phenomenon) and the high-rainfall year 2011 (La Niña phenomenon) are used to illustrate the model validation process. The three climatic series found (KNN: 1, 2, and 3) for the dry year (2015) correspond to 1994 (S1), 1991 (S2), and 2013 (S3).

The daily rainfall data recorded at the Tunguavita station is compared with the series predicted for 2015 (Figure 8).

The scatter plot between the percentiles (0.25, 0.5, 0.55, 0.65, 0.75, 0.85, 0.95, 0.975, 0.99, and 0.999) of daily rainfall data predicted for S1–S3 and recorded in 2015 show that the SIE-Climate model accurately predicted the data. Curve-fitting to the linear regression model indicates R^2 values of 0.8336, 0.8611, and 0.7248 (mean: 0.81) for 1994, 1991, and 2013, respectively, meaning there was a good match between the predicted and recorded series in terms of magnitude (minima and average and, to a lesser extent, maxima) and in the distribution of the periods with the highest and lowest rainfall in 2015.

The daily rainfall data recorded at the Tunguavita station is compared with the series predicted for 2011 (Figure 9).

The scatter plot between the percentiles (0.25, 0.5, 0.55, 0.65, 0.75, 0.85, 0.95, 0.975, 0.99, and 0.999) of daily rainfall data predicted for S1–S3 and recorded in 2011 show that the SIE-Climate model accurately predicts the data. Curve-fitting to the linear regression model indicates R^2 values of 0.9873, 0.9608, and 0.9967 (mean: 0.98) for 1989, 2000, and 2008, respectively, meaning there was a good match between the predicted and recorded series in terms of magnitude (minima, average and maxima) and in the distribution of the periods with the highest and lowest rainfall in 2011. The Comparison of climate series from the SIE-Climate model with benchmark data (2000–2018) is shown in Table 2 using as statistical metrics, root mean squared error (RMSE), percent bias (PBIAS), and the Nash-Sutcliffe efficiency coefficient (EFF).

4.3 | Results from the SIE-Climate prediction software

The SIE-Climate software plots, on a monthly and daily scale, the rainfall and temperature at the selected reference stations. The model is sensitive to the selection of the simulation start date, with differences of up to 1 month (before and after the simulation start). The predicted series change, but they retain at least one of the series found in the original simulation. To illustrate the application of the software, the results of the typical year 2018 are presented for two stations (Tunguavita and Surbatá) in Figure 10 (rainfall) and Figure 10 (temperature).

Figure 11 (Tunguavita) and Figure 12 (Surbatá) present the rainfall results, on a daily and monthly scale, for the stations of interest. The series predicted for the Surbatá station (2014, 2015, and 2002) match those found for the Tunguavita station in 2018, except for the 2015 series, which indicates that the model is sensitive to the specific location and records of each weather station. The map shows that the total rainfall records of the stations range from 900 to 1,100 mm·year^{-1} and that the predictions for Tunguavita (853.3–1,053.2 mm·year^{-1}) and Surbatá (598.5–783.8 mm·year^{-1}) on average differ

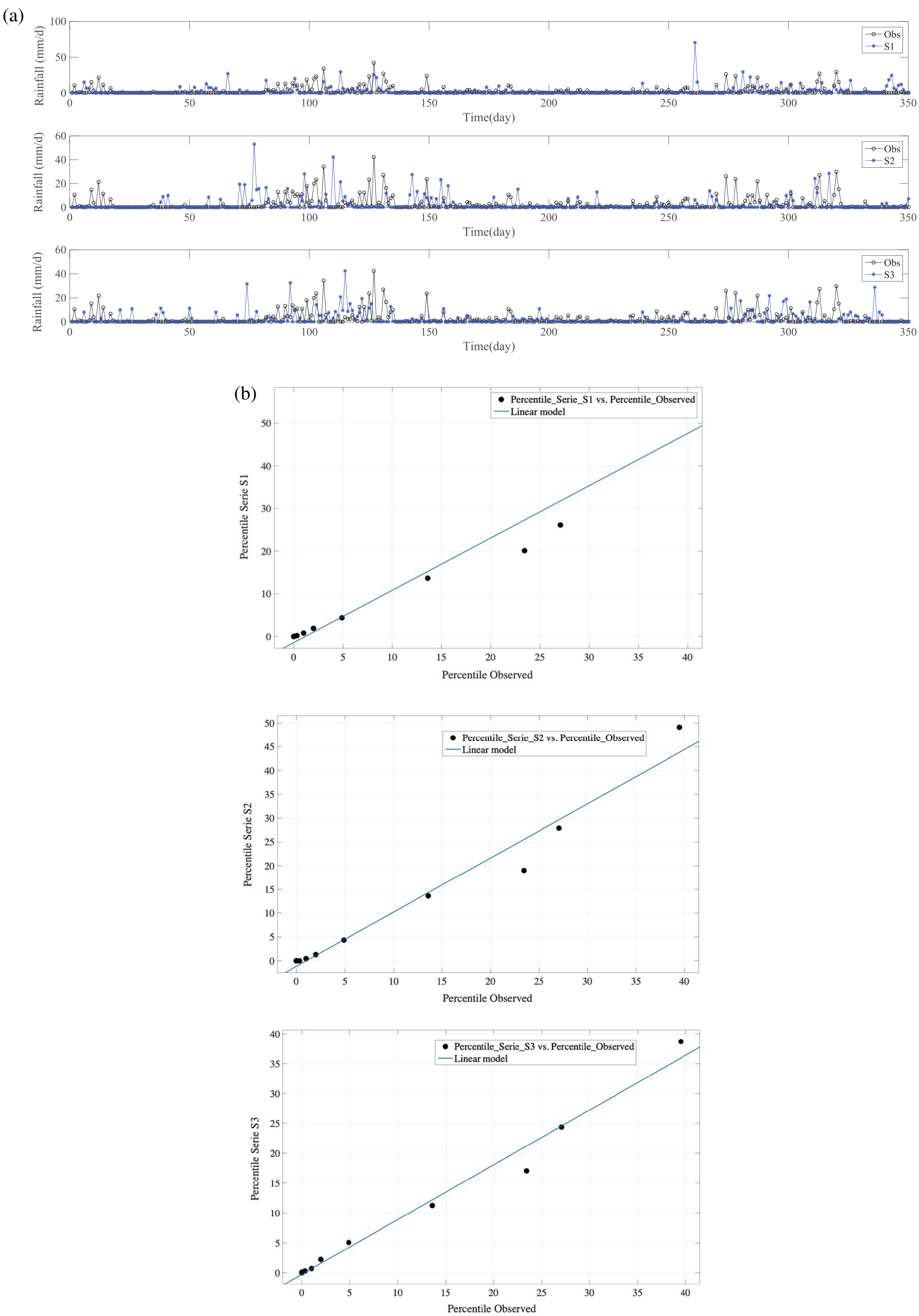


FIGURE 7 (a) 2014 (S1), 2002 (S2), and 1990 (S3) series of rainfall recorded in the typical year 2018 and rainfall predicted by the KNN method. (b) Scatter plot of the percentiles of rainfall recorded [Colour figure can be viewed at wileyonlinelibrary.com]

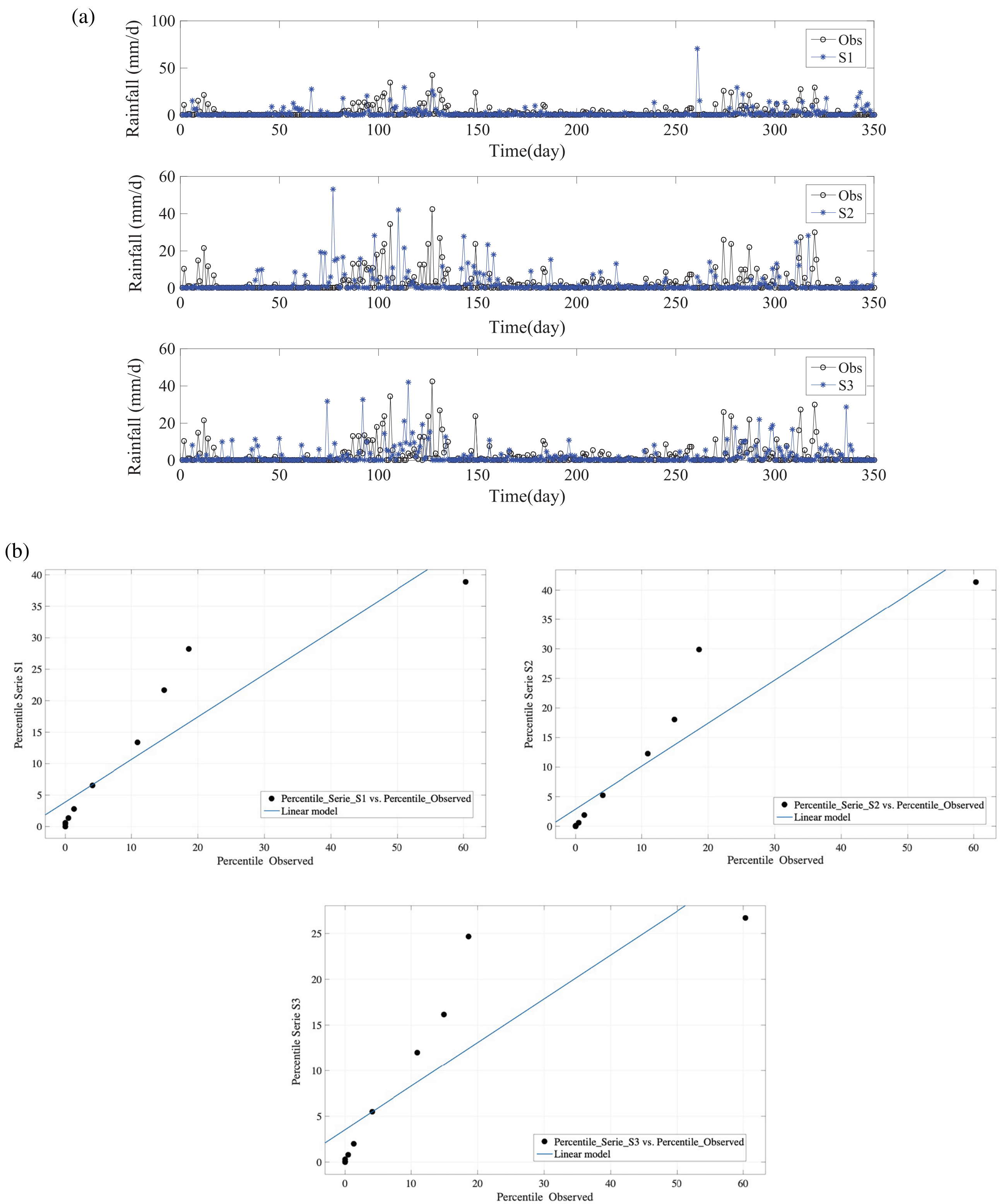


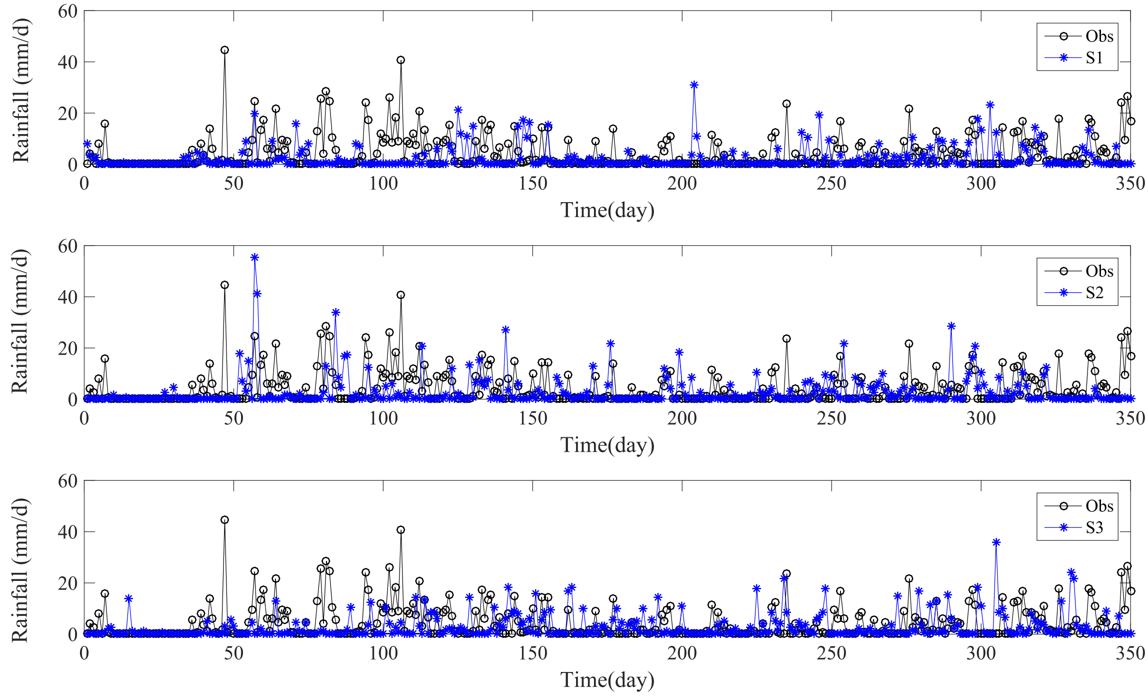
FIGURE 8 (a) The 1994 (S1), 1991 (S2), and 2013 (S3) series of rainfall recorded in the atypical year 2015 and rainfall predicted by the KNN method. (b) Scatter plot of the percentiles of rainfall recorded [Colour figure can be viewed at wileyonlinelibrary.com]

from the measured values by 10 and 30%, respectively. Figures 10–12 show that the annual average temperatures range from 14 to 14.6°C at both stations, thus highlighting a good match with the recorded values.

5 | DISCUSSION

The management of water systems requires planning management decisions; therefore, seasonal climate

(a)



(b)

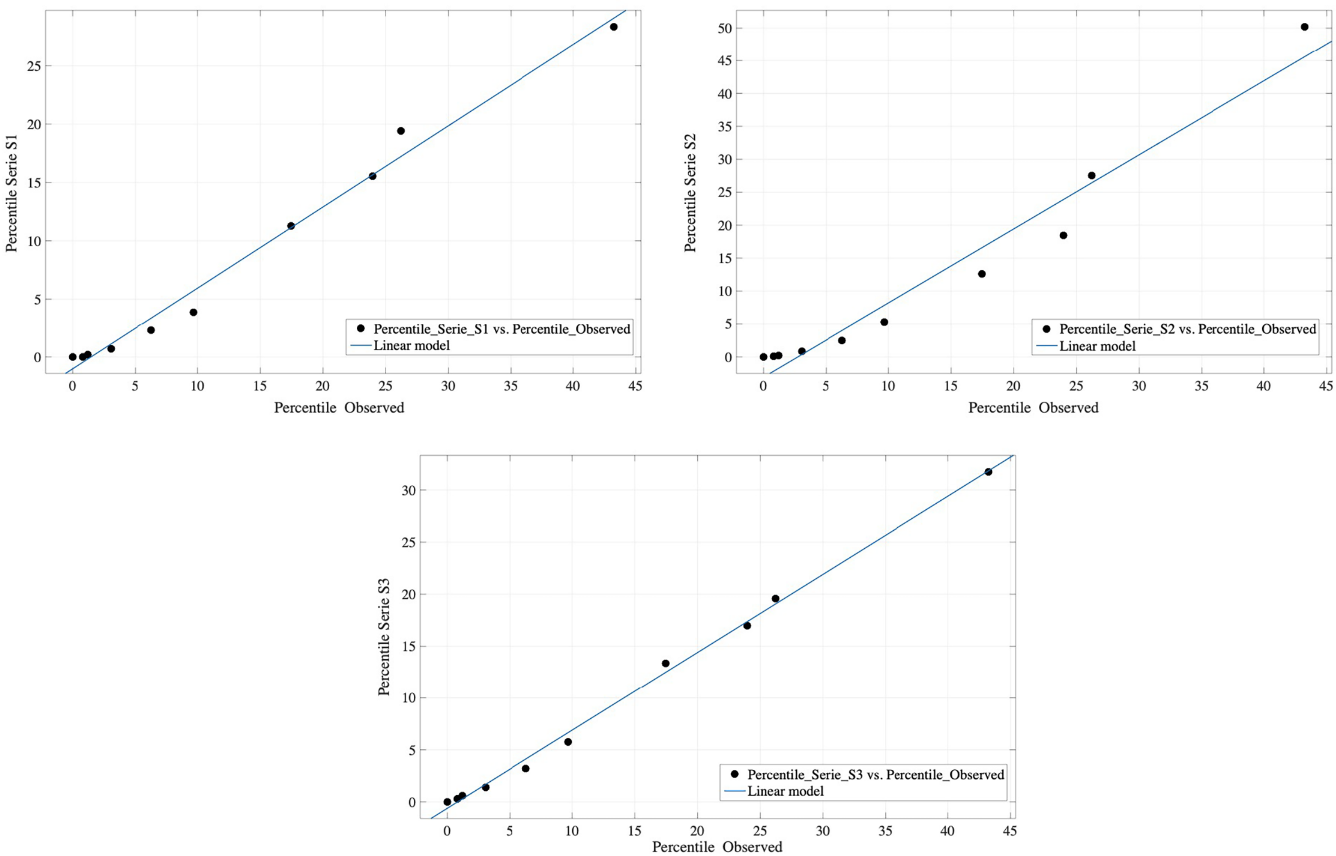


FIGURE 9 (a) The 1989 (S1), 2000 (S2), and 2008 (S3) series of rainfall recorded in the atypical year 2011 and rainfall predicted by the KNN method. (b) Scatter plot of the percentiles of rainfall recorded [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 2 Mean statistical metrics for the SIE-climate model evaluation

Prediction periods	Series	Predicted year	R^2	RMSE	PBIAS	EFF
2000	S1	1989	0.96	5.05	−8.73%	0.88
	S2	1999				
	S3	1996				
2001	S1	1990	0.94	3.24	13.11%	0.91
	S2	1997				
	S3	1986				
2002	S1	1990	0.98	3.59	−10.19%	0.94
	S2	1993				
	S3	1991				
2003	S1	1991	0.97	6.82	−26.46%	0.80
	S2	1992				
	S3	1988				
2004	S1	1994	0.98	2.85	−9.47%	0.96
	S2	1991				
	S3	2002				
2005	S1	2004	0.97	7.01	−26.29%	0.81
	S2	1992				
	S3	1991				
2006	S1	1990	0.97	3.92	−20.18%	0.90
	S2	1986				
	S3	1997				
2007	S1	1991	0.91	7.69	−17.12%	0.82
	S2	1994				
	S3	1993				
2008	S1	1997	0.98	2.75	3.82%	0.91
	S2	1996				
	S3	1986				
2009	S1	1997	0.97	2.36	8.10%	0.92
	S2	1986				
	S3	1990				
2010	S1	1991	0.97	5.60	−20.83%	0.82
	S2	1992				
	S3	2003				
2011	S1	1989	0.98	5.20	−26.14%	0.84
	S2	2000				
	S3	2008				
2012	S1	1997	0.95	5.28	−22.27%	0.85
	S2	2009				
	S3	1986				
2013**	**S1**	**1991**	**0.91**	**6.38**	**29.37%**	**0.46**
	S2	**1993**				
	S3	**2007**				

TABLE 2 (Continued)

Prediction periods	Series	Predicted year	R^2	RMSE	PBIAS	EFF
2014	S1	2002	0.96	5.38	−16.26%	0.87
	S2	1990				
	S3	1986				
2015	S1	1994	0.81	8.58	−6.16%	0.75
	S2	1991				
	S3	2013				
2016	S1	1998	0.98	5.06	−8.72%	0.86
	S2	2005				
	S3	1992				
2017*	**S1**	**2005**	**0.99**	**1.97**	**−5.39%**	**0.98**
	S2	**2004**				
	S3	**2014**				
2018	S1	2014	0.96	3.64	0.89%	0.92
	S2	2002				
	S3	1990				

Note: The statistical metrics are based on the percentiles (0.25, 0.5, 0.55, 0.65, 0.75, 0.85, 0.95, 0.975, 0.99, and 0.999) of daily rainfall (mm). Curve-fitting to the linear regression model (R^2); Root mean squared error (RMSE); Percent bias (PBIAS); Nash-Sutcliffe efficiency coefficient (EFF). The best (*) and the worst (**) predicted period. For more details see supporting information. Bold values indicate Linear model (R^2) with 95% confidence bounds.

prediction on an annual scale is a key link in the hydrological and hydrodynamic response of a basin and to water management for different activities in the socio-ecological system.

In the context of global climate change and anthropogenic stresses, extreme weather events are expected to increase in both frequency and intensity. Current climatic dynamics more frequently present extreme events (on a daily scale) and changes in the behaviour patterns of key water management variables, such as rainfall and temperature. This is a challenge for the development of non-stationary tools and numerical models, which in general do not simulate rainfall as well as they simulate temperature (Odon *et al.*, 2019) or which require a robust and complex technological development for future projection (Towler *et al.*, 2020). Satellite rainfall products with high temporal and spatial resolution offer opportunities to monitor extreme weather event intensities and trends over large areas. Some satellite rainfall products show little accuracy in capturing extreme rainfall and drought events, both in low areas of basins and in the high sections of mountainous areas. However, products with an improved reversal rainfall algorithm have been developed recently (Towler *et al.*, 2020).

Climatic variability as an element of uncertainty in water management affects community, sectoral, and individual decision-making. There is a need to identify, through applications that consider changes in local climatic conditions, the best forecasting models for effective water management and planning (Kim *et al.*, 2019). The results of the present study show that the methodological and technological tool SIE-Climate provides an alternative for local seasonal climate prediction on a daily and monthly scale for management purposes.

The application of the exploratory phase and the configuration of the technological tool offer versatility in the projection of different climatic variables and in different regions on which macro-climatic phenomena have a local effect. SIE-Climate is flexible and adaptable to different contexts in a simple way, considering regional singularities and the joint probability of macro- and micro-climate phenomena, without losing sensitivity in the representation of intra-seasonal oscillations.

The SIE prediction tool can be configured and adapted to the dynamics of each basin or region. In the case of regions with scattered or incomplete information, the availability of reliable historical climatological data is the main source of uncertainty. Therefore, in these situations the reconstruction of the climatic series can affect the design and reliability of the final DB. The use of local historical data requires efforts to record these data, consolidate DBs, fill in missing data, and validate predictions, but it also brings together complex components that are difficult to estimate or represent numerically that affect climate variability. In this study, the data

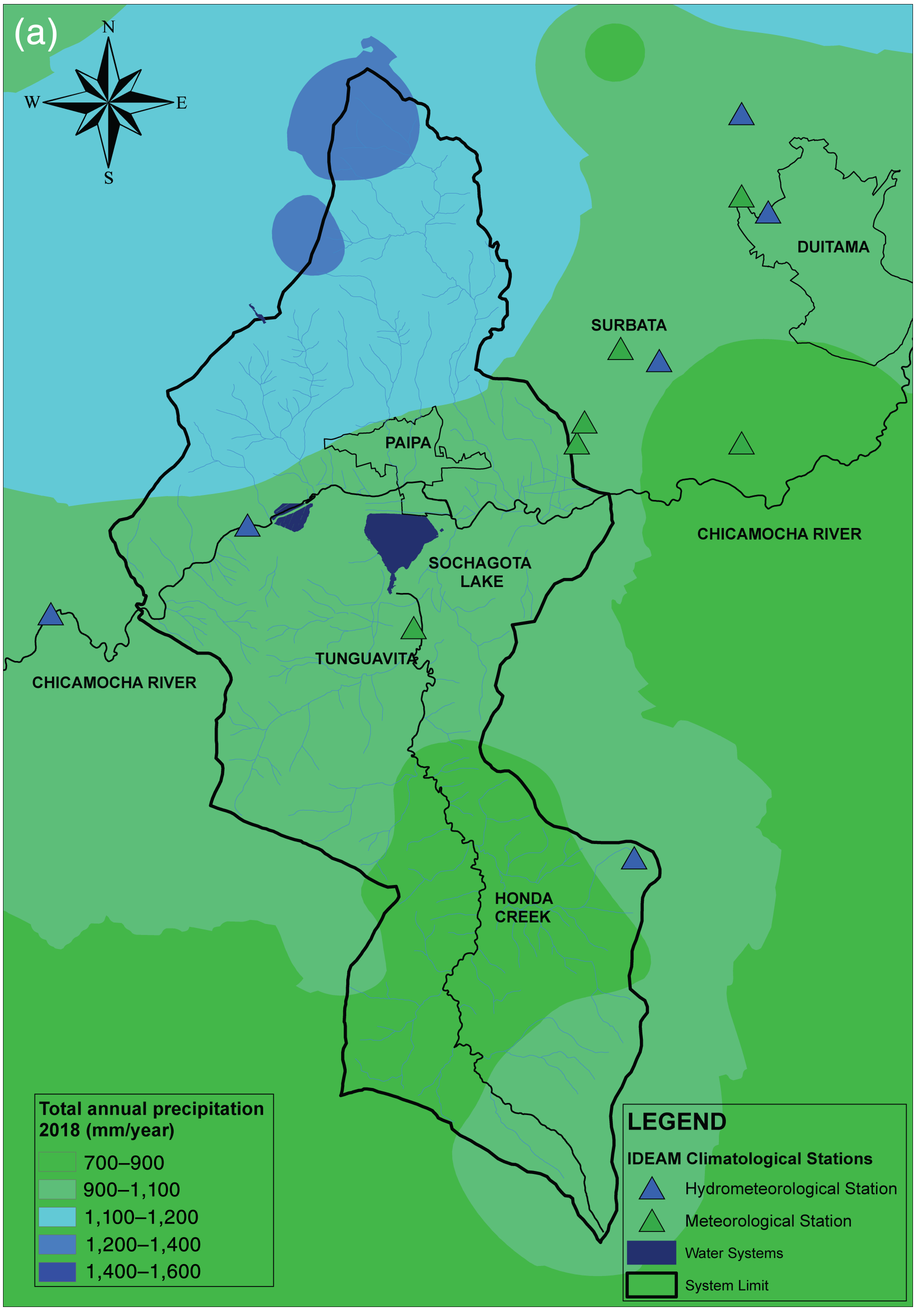


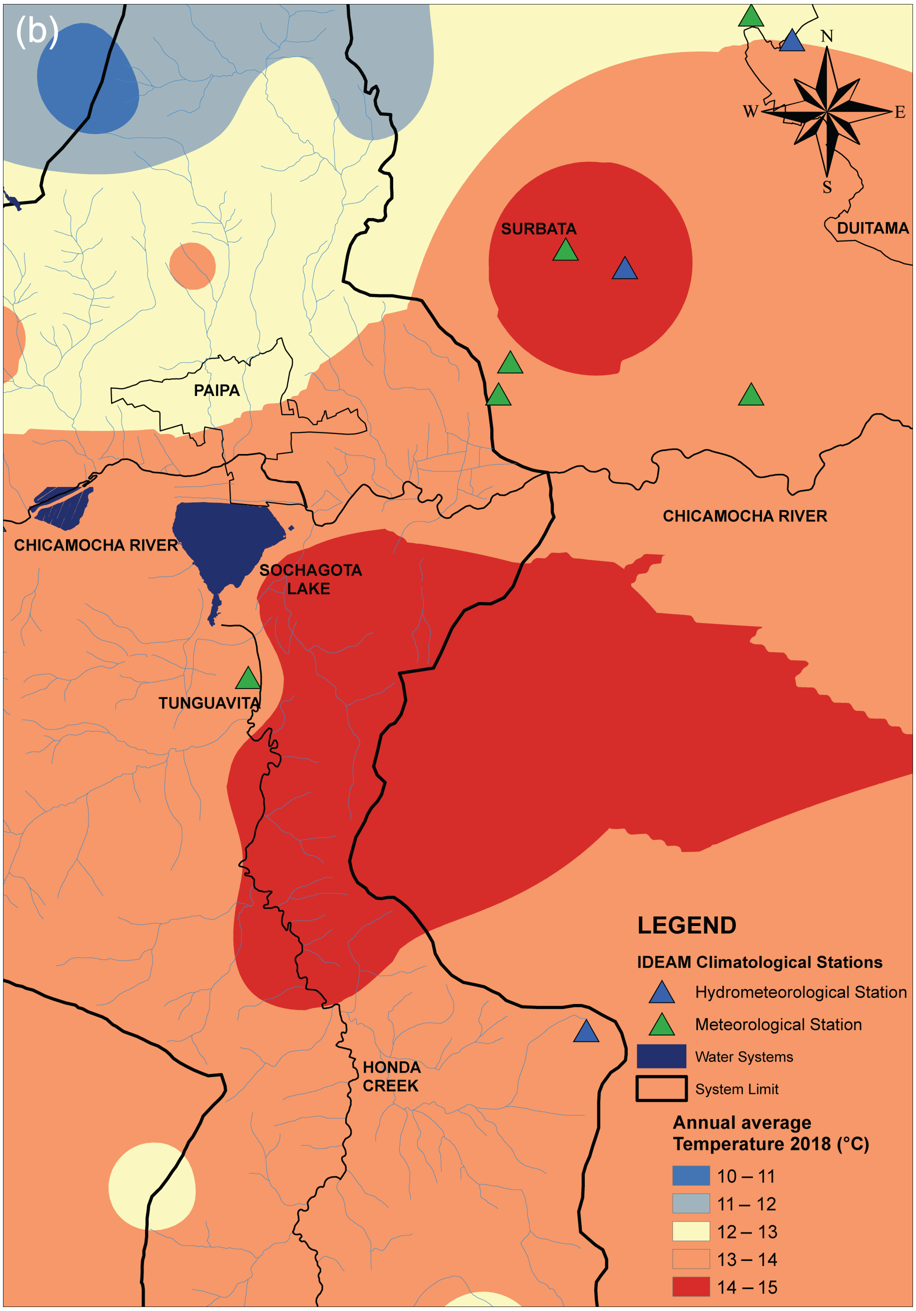
FIGURE 10 (a) Annual total rainfall in the Lake Sochagota socioecological system, 2018 [Colour figure can be viewed at wileyonlinelibrary.com]

completion and interpolation methodology that was used, recognizes this source of uncertainty and assigns a greater weight to the information from the stations that are closest to the region of interest.

The method is highly sensitive to monthly changes; therefore, the prediction depends entirely on the ability to update the local climate data and the indicators of climatic phenomena used for such purposes. The missing data are filled in considering regional time dynamics, giving greater weight to the stations near the area of interest, which favours the projection of the time series to annual cycles (on a daily scale), without affecting their distribution or the range of variation observed in the region, and which carries an appropriate technological and computational time cost for water management in the system.

The method reliably reflects the average conditions and the distribution of the rainfall series in periods without climatic anomalies and in atypical dry or wet years, which is very useful when water management includes the evaluation of conditions of water deficit or oversupply in a socio-ecological system. In atypically humid periods (extreme rainfall), the prediction results entail high uncertainty, but the KNN method can be refined in future research to include an additional factor that

FIGURE 10 (b) Annual average temperature in the Lake Sochagota socioecological system, 2018 [Colour figure can be viewed at wileyonlinelibrary.com]



represents the dynamics in the Atlantic Ocean and in the Intertropical Convergence Zone, which are highly important to South America (Sánchez *et al.*, 2016), in addition to ocean–atmosphere interaction processes in the Pacific. Nevertheless, in regions where ENSO presents a strong effect (tropical Pacific and Latin America, in general; (Barnston *et al.*, 2019; Oertel *et al.*, 2020)), no other macroclimatic index may be necessary for SIE-Climate to provide useful forecasts.

However, other regions such as Europe, may require the inclusion of additional indices such as NAO (Tyrrell and Karpechko, 2020) to increase the skill of the model predictions (Iles and Hegerl, 2017). Indeed, areas where variability may not be strongly correlated with synoptic atmospheric patterns may require more elaborate schemes, where time series analysis of anomalies are constructed to extrapolate the recent past and current behaviour to the near future. Time series forecasting methods are among the most commonly used methods for long-range projections. The resulting climate data can be used by water managers in different climate software products, but the data must be relevant, understandable, and available to the various users and sectors (i.e., for crop models and their probable yields in a future season) (Organización Meteorológica Mundial, 2004).

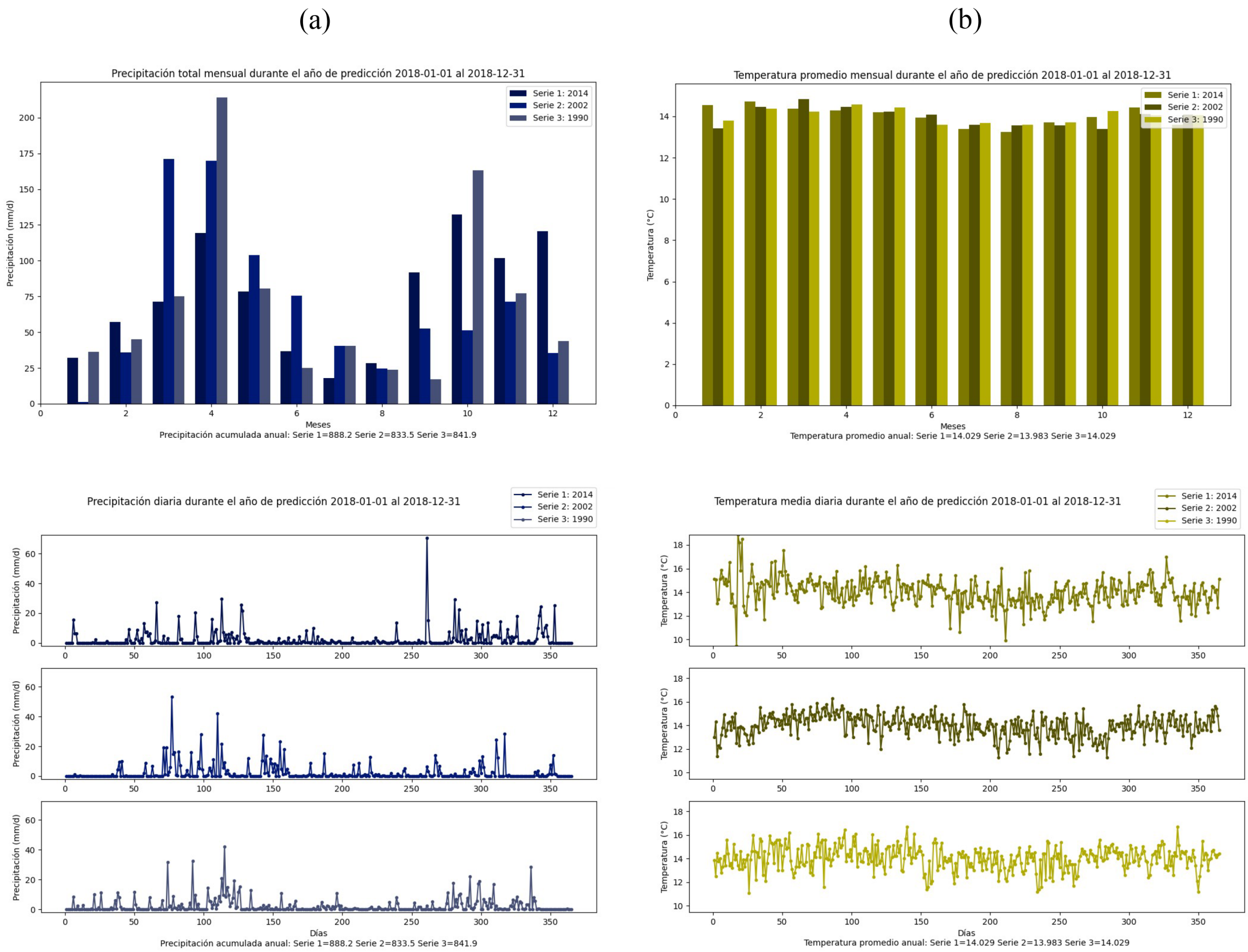


FIGURE 11 Graphical representation on a monthly and daily scale of the rainfall (a) and temperature (b) series at the Tunguavita station. Output of the SIE-climate software for 2018 [Colour figure can be viewed at wileyonlinelibrary.com]

Representing the average or monthly climate behaviour may not suffice to assess permanent effects or extreme events for management purposes. SIE-Climate is an open-access software tool and is linked to the SIE project, which aims to associate the climatic variability of annual cycles on a daily scale with the hydrological, hydraulic, and hydrodynamic responses of a water system and to represent water deficit, salinization, and eutrophication effects using socio-ecological indicators and the overall susceptibility index (Perilla *et al.*, 2012; Usaquén-Perilla, 2017). These indices are publicly available from the webpage (http://www.sie.org.co) and after a process of capacity building and social appropriation, the state of the socio-ecological system is evaluated for management purposes at the institutional, community, and individual levels by its stakeholders.

Following the evaluation test of the methodological and technological tool SIE-Climate, external users remarked on the positive aspects of the tool, including its simplicity, quality, and usefulness, not only in environmental management, but also in disaster risk matters, energy generation, agriculture, human consumption, and guiding public and private investments. The evaluation test also highlighted opportunities for improvement and future challenges regarding its graphical interface, its interactivity, its connection with other components and environmental matrices, validation for other variables and stations (in the region and in Latin America), and its amenability to online collaborative work to facilitate real-time data updates.

6 | CONCLUSIONS

This methodological and technological tool offers an alternative for seasonal local climate prediction on a daily and monthly scale. SIE-Climate is flexible and adaptable to different regional contexts and considers macroclimatic phenomena, regional weather dynamics, and

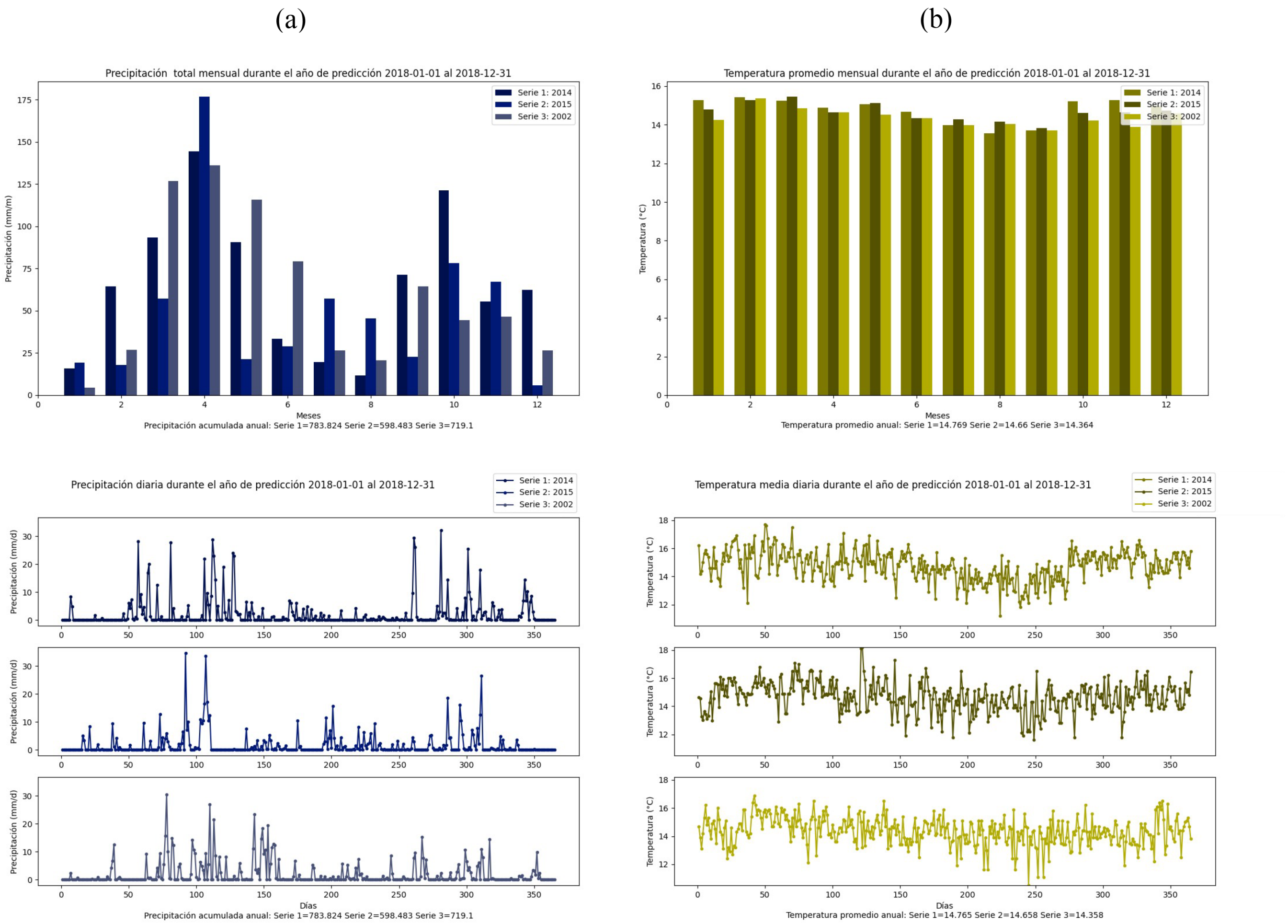


FIGURE 12 Graphical representation on a monthly and daily scale of the rainfall (a) and temperature (b) series at the Surbata station. Output of the SIE-climate software for 2018 [Colour figure can be viewed at wileyonlinelibrary.com]

interannual and interdecadal climate variability without losing sensitivity in the representation of intra-seasonal oscillations.

The SIE-Climate model was applied, calibrated, and validated to predict, on a daily and/or monthly scale, climatic variables (rainfall and temperature) over a 1-year horizon, and it categorized these variables based on the probability of occurrence of climatic anomalies (El Niño, La Niña, normal year), all as part of the ultimate goal of designing management measures for a socio-ecological system (Lake Sochagota).

Seasonal climate prediction at the yearly time scale is a key link in the hydrological and hydrodynamic responses of basins and water management in socio-ecological systems. The management of these water systems requires planning management decisions. Climate variability, as an element of uncertainty, must be quantified and known to guide community, sectoral, and individual decision-making. Current climate dynamic models more frequently present extreme events on a daily scale. Representing the average or monthly climate behaviour may not suffice to assess permanent effects or extreme events for management purposes. Macro-climatic dynamics affect the local climate, so they must be considered in predictions, as achieved by the SIE-Climate tool.

The use of local historical data requires efforts to record, consolidate, fill in, and validate these data, but it combines the complexity of macro- and micro-scale phenomena and dynamics in the system. The configuration of the methodological and technological tool SIE-Climate has the flexibility to make projections for different variables and for different regions. The method is highly sensitive to monthly changes, and the predictions depend entirely on the ability to update local climate data and the indicators of climatic phenomena used for such purposes. The method for filling in data considers the regional weather dynamics, giving greater weight to the stations near the area of interest.

The method is reliable for seasonal climate prediction in typical years, atypically dry and wet years are adequately projected, and predictions of extreme rainfall events show higher uncertainty in dry years. These results are adequate when gearing the prioritized management effects towards the evaluation of water deficit conditions.

The KNN method can recreate the recorded climate variability without affecting the observed distribution or behaviour, whilst incorporating, through macro-climatic indices, larger phenomena that affect the local climate at a technological and computational cost appropriate for regional water management. This methodological and the technological tool can be adapted to other contexts and temporal and spatial scales. It offers opportunities for future research on improving the reliability of the results in management cycles of atypical (wet) periods and on ways to consider, via the KNN method, more than three factors, reflecting not only Pacific Ocean processes, but also the effect of Atlantic Ocean and Intertropical Convergence Zone dynamics.

This technological solution is designed to facilitate decision-making in a timely and strategic manner when operating a socio-ecological system to anticipate the response of the system to climate variability events and to simulate the effects of the prioritized variables of socio-ecological interest for management purposes.

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AUTHOR CONTRIBUTIONS

Erika Sierra-Cárdenas: Conceptualization; formal analysis; investigation; methodology; visualization; writing-original draft. **Olga Usaquén-Perilla:** Conceptualization; formal analysis; funding acquisition; investigation; methodology; project administration; resources; supervision; visualization; writing-original draft; writing-review & editing. **Mauricio Fonseca-Molano:** Conceptualization; data curation; investigation; methodology; software; visualization. **Mauricio Ochoa-Echeverría:** Conceptualization; investigation; methodology; software; writing-original draft. **Jaime Díaz-Gómez:** Formal analysis; investigation; resources; supervision; visualization; writing-original draft; writing-review & editing. **Manuel del Jesus:** Conceptualization; methodology; validation; writing-review & editing.

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SUPPORTING INFORMATION

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