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Spatio-Temporal Forecasting Model of Water Balance Variables in the San Diego Aquifer, Venezuela

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Abstract

In this paper, a spatio-temporal forecasting model of water balance variables in the San Diego aquifer, Venezuela is proposed combining tools of GIS as the geostatistical analyst tool to make prediction of variables using statistical spatial prediction models based on the Ordinary Krigging followed by the application of forecasting models including those as: linear trend, quadratic trend, exponential trend, moving average, simple exponential smoothing, Brown's linear exponential smoothing, quadratic exponential smoothing and autoregressive integrated moving average (ARIMA). The spatio-temporal forecasting models of water balance variables in the San Diego aquifer have been calibrated and validated showing a successful adjustment to the water balance variables as the following five variables: 1) precipitation, 2) evapotranspiration, 3) pumping flow, 4) infiltration and 5) volume stored. In the calibration stage, the statistical spatial prediction model selected has been J-Bessel and the forecasting model selected has been Brown's quadratic exp. smoothing with constant alpha. In the validation stage, the correlation coefficient has taken values upper to 0.98 and the determination coefficient upper to 0.96 confirming that the method used to generate the spatio-temporal forecasting model to achieve good predictions to the water balance variables.

Keywords: *Spatio-Temporal Forecasting Model, Water Balance, Statistical Spatial Prediction Model*

INTRODUCTION

Using the technology of Geographic Information System (GIS), only two methods have been reported for forecasting, which are Markovian chains (Jianping et al., 2005; Yin et al, 2007; Kumar et al., 2014; Han et al., 2015; Padonou et al., 2017) and neural networks focused in multi-layer perceptron (Pijanowski et al., 2002; Mishra et al., 2014). These two methods have been applied mainly for predicting changes in land use and land cover. The water balance model mainly used to estimate a current, concentrated and averaged value of the water balance variables has been developed from 1940's by Thornthwaite (1948) and later revised by Thornthwaite and Mather (1955). In this paper, it is proposed a hybrid method to generate a spatio-temporal forecasting model of water balance variables using as study unit the San Diego aquifer, Venezuela. The proposed method combines tools of GIS as the geostatistical analyst tool to make prediction of variables using statistical spatial prediction models based on the Ordinary Krigging followed by the application of forecasting models including those as: linear trend, quadratic trend, exponential trend, moving average, simple exponential smoothing, Brown's linear exponential smoothing, quadratic exponential smoothing and autoregressive integrated moving average (ARIMA).

STUDY AREA

The study area is the San Diego aquifer,

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located in the north region of Venezuela (Figure 1). The aquifer limits in geographic coordinates are the following: latitude: N 10°22'00", N 10°09'00", longitude: W67°52'00", W68°00'00". The San Diego aquifer is belonging to the Carabobo State. The north region is part of the mountain zone of the "Cordillera de la Costa", which is in front of the Caribbean sea (Figure 1).

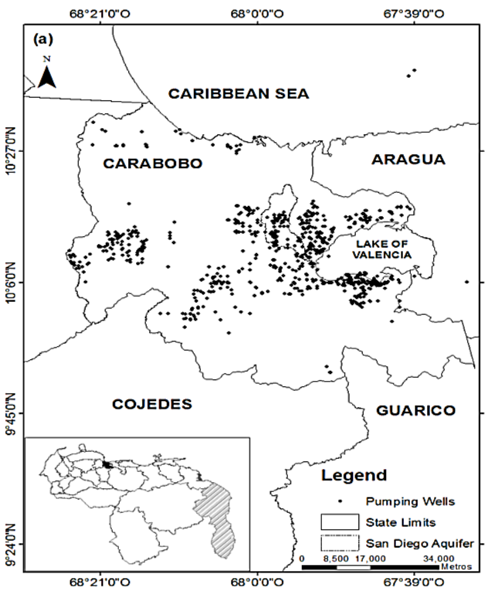


Fig: 1. *Location of the study area: a) Relative position of the San Diego aquifer regarding to the Carabobo State in Venezuela, showing the spatial distribution of the 925 pumping wells founded into the Carabobo State; whose monitoring variables are used to predict the hydrogeological parameters from the San Diego aquifer*

METHOD

The applied method incudes the three steps following (Figure 2): 1) collection of information, 2) processing of information and 3) generation of results. In the first step, the database used in this study has been provided by four information sources, which are 1) Ministry of the Environment, 2) National Institute of Meteorology and Hydrology belonging to Ministry of the Environment, 3) the Hydrological Company "Hidrologica Del Centro C.A.", 4) Center of Hydrological and environmental Research. The information has been gotten as it is described in the following two aspects : 1) Meteorological information corresponding to the period between 2015 and 2017, which are measured by the telemetric network of 31 climate monitoring stations close to San Diego aquifer managed by the National Institute of Meteorology and Hydrology belonging to Ministry of the Environment. The information is available at no cost in the following web page: http://estaciones.inameh.gob.ve/estaciones/estaciones_home.php.2) The database Of the pumping flow is provided by three sources: a) the Hydrological Company "Hidrologica del Centro C.A.", consisting of 200 pumping wells in the Carabobo State, b) Ministry of the Environment, consisting of 1201 pumping wells in the Carabobo State and c) Center of Hydrological and Environmental Research of University of Carabobo based on 24 pumping wells into the San Diego aquifer. The second step implies: 1) calibration of geostatistical models, 2) validation of geostatistical models, 3) calibration of forecast models, and 4) validation of forecast models. The third step is the generation of spatio-temporal prediction maps of water balance variables.

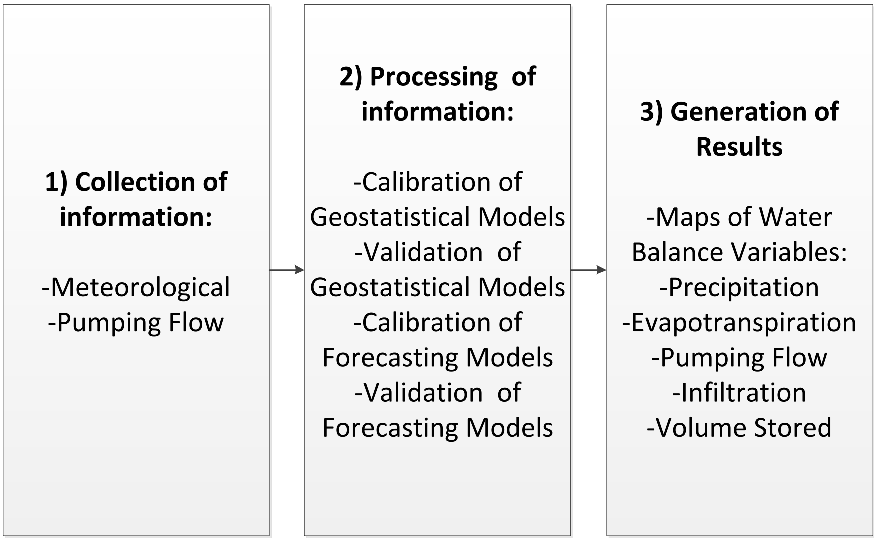


Fig: 2. *Workflow for spatio-temporal geostatistical modeling of hydrogeochemical parameters in the San Diego aquifer, Carabobo State, Venezuela.*

MODELING OF STATISTICAL SPATIAL PREDICTION

It will be applied models of statistical spatial prediction (SSPM) for estimating of the hydrogeochemical parameters. A spatial prediction model estimates the values of the target variable (z) at some new location s_0; being a set of observations of a target variable z denoted as $z(s_1)$, $z(s_2)$,. . . , $z(s_n)$, where $s_i = (x_i, y_i)$ is a location and xi and yi are the coordinates (primary locations) in geographical space and n is the number of observations. The geographical domain of interest (area, land surface, object) can be denoted as A. It defines inputs, outputs and the computational procedure to derive outputs based on the given inputs (Hengl, 2007):

$$\hat{z}(s_0) = E\{Z/z(s_i)\,, q_k(s_0), \gamma(h), s \in A\}$$

Where $z(s_i)$ is the input point dataset, $q_k(s_0)$ is the list of deterministic predictors and $\gamma(h)$ is the covariance model defining the spatial autocorrelation structure. The type of SSPM used is the statistical model called Ordinary Krigging (OK); whose technique was developed by Krige (1951). The predictions are based on the model:

$$Z(s) = \mu + \varepsilon'(s) \quad (1)$$

Where μ is the constant stationary function (global mean) and ε'(s) is the spatially correlated stochastic part of variation. The predictions are made as in Matheron (1963) and Gandin (1960) introduced to the analysis of point data is the derivation and plotting of the so-called semivariances — differences between the neighbouring values:

$$\gamma(h) = \frac{1}{2}\, E\left[\left(z(s_i) - z(s_i + h\,)\right)^2\right] \quad (2)$$

where $z(s_i)$ is the value of target variable at some sampled location and z(si +h) is the value of the neighbour at distance $s_i + h$. The semivariances versus their distances produce a standard experimental variogram. From the experimental variogram, it can be fitted using some of the authorized variogram models, such as linear, spherical, exponential, circular, Gaussian, Bessel, power and similar (Isaaks and Srivastava, 1989; Goovaerts, 1997).

FORECASTING MODEL

One of the models used for forecasting is the ARIMA models, which express the observation at time t as a linear function of previous observations, a current error term, and a linear combination of previous error terms. ARIMA(p,d,q)x(P,D,Q)s model consists of several terms: 1. A nonseasonal autoregressive term of order p, 2. Nonseasonal differencing of order d, 3. A nonseasonal moving average term of order q, 4. A seasonal autoregressive term of order P, 5. Seasonal differencing of order D, and 6. A seasonal moving average term of order Q. As a reference, AR(1) is an autoregressive of order 1; where the observation at time t is expressed as a mean plus a multiple of the deviation from the mean at the previous time period plus a random shock (Box, 1994; Hamilton 1994)

$$Y_t = \mu + \phi_1\left(Y_{(t-1)} - \mu\right) + \phi_2\left(Y_{(t-2)} - \mu\right) + a_t \quad (3)$$

Where a_t is a random error or shock to the system at time t, usually assumed to be random observations from a normal distribution with mean 0 and standard deviation σ_a. For a stationary series, μ represents the process mean.

RESULTS

Forecasting of Precipitation

The forecasting of SSPM coefficients of the monthly precipitation semivariances based on the time series between 2015 and 2017 are shown in Table 1; where it is observed that the tested models are the five following: A) ARIMA (autoregressive integrated moving average), B) Linear Trend, C) Simple exponential smoothing with constant alpha, D) Brown's linear exp. smoothing with constant alpha, E) Brown's quadratic exp. smoothing with constant alpha. As a sample, the results found for the coefficient “a” are as follows: A) ARIMA(1,0,0) with constant, B) Linear trend = -65584.6 + 83.4519 t, C) Simple exponential smoothing with alpha = 0.1857, D) Brown's linear exp. smoothing with alpha = 0.1322 and E) Brown's quadratic exp. smoothing with alpha = 0.085.

The error statistics by fitting the forecasting models to the SSPM coefficients of the monthly precipitation semivariances based on the time series between 2015 and 2017 are shown in Table 2, which are expressed in terms of three statistics of errors: 1) RMSE = root mean squared error, 2) MAE = mean absolute error, and 3) ME = mean error. As a sample, the results found for the coefficient “a” are as follows: for model A: 1) RMSE:1582.65, 2) MAE: 1083.43, and 3) ME: 10.2435. For model B: 1) RMSE: 1429.98, 2) MAE: 985.879, and 3) ME: -5.66E-12. For model C: 1) RMSE: 1554.13, 2) MAE: 916.51, and 3) ME: 320.584. For model D: 1) RMSE: 1588.26, 2) MAE: 1066.55, and 3) ME: 334.38. For model E: 1) RMSE: 1583.11, 2) MAE: 1091.45, and 3) ME: 241.615. In general, the model selected for forecasting of coefficients of semivariances SSPM of monthly precipitation is the model D corresponding to Brown's linear exp. smoothing with constant alpha because of the error statistics are in the group of lower values.

The forecasting of SSPM coefficients of the monthly precipitation semivariances based on the time series between 2015 and 2017 using Brown's quadratic exp. smoothing with constant alpha are shown in Table 3, the period for forecasting of monthly precipitation covers from 8/17 (August 2017 to 12/18 (December, 2018). For each coefficient are included the following three values: 1) forecast, 2) Lower 95.0% limit, 3) Upper 95.0% limit. The values of coefficients have been selected for forecasting of monthly precipitation for 12/18 as follows*: for coefficient a:* 1) forecast: 5812.25, 2) Lower 95.0% limit: 1692.19, 3) Upper 95.0% limit: 9932.3. *For coefficient b:* 1) forecast: 3497.94, 2) Lower 95.0% limit: -3681.11, 3) Upper 95.0% limit: 10677.0. *For coefficient c:* 1) forecast: 169761, 2) Lower 95.0% limit: -188724, 3) Upper 95.0% limit: 528246. *For coefficient d:* 1) forecast: 0.713961, 2) Lower 95.0% limit: -2.01368, 3) Upper 95.0% limit: 3.4416. In Figure 3 is shown the map of forecasting of monthly precipitation, which varies between 255 and 279 mm/month. For this month, the maximum precipitation occurs between the north and middle region of the

San Diego aquifer.

The calibration of SSPM of the monthly precipitation semivariances with forecasted coefficients for 2017 based on the time series between 2015 and 2017; which will be used in the validation stage is shown in Table 4, using the forecasted coefficients for the months of august 2017 and October 2017 and obtaining the correlation statistics between the monthly precipitation spatial prediction and the measured values from the precipitation map for August 2016 and October 2016, respectively: for August 2017: 1) *Precipitation semivariance SSPM* is 2605.74*Nugget+2749.48*J-Bessel(170522, 0.803972), 2) *PMRF*: Predicted versus Measured Regression Function: 0.998736192687617 * x + 0.372881835725707, 3) *EMRF:* -0.00126380731238643 * x + 0.372881835726463 and 4) *SEMRF:* Standardized Error versus Measured Regression Function: -0.0000284879536300382 * x + 0.00840874839905042. The statistics of prediction error are: 1) Mean Error: 0.14737273353673505, 2) Root-Mean-Square Error: 0.22413627021079577, 3) Mean Standardized Error: 0.0033252776322928944, 4) Root-Mean-Square Standardized Error: 0.00505251238223869 and 6) Average Standard Error: 44.32340688814414.

The calibration of SSPM of the monthly precipitation semivariances for August 2017 and October 2017 based on the observed time series between 2015 and 2017; which will be used in the validation stage is shown in Table 5, obtaining the correlation statistics between the monthly precipitation spatial prediction and the measured values from the precipitation map for August 2016 and October 2016, respectively: for August 2017: 1) *Precipitation semivariance SSPM* is 4555.3*Nugget+10834*J-Bessel(72869,0.01), 2) *PMRF*: 0.445997193775157 * x + 72.8387182689694, 3) *EMRF:* -0.554002806224843 * x + 72.8387182689694 and 4) *SEMRF:* -0.00671600747345756 * x + 0.797998950155083. The statistics of prediction error are: 1) Mean Error: -20.983851180100107, 2) Root-Mean-Square Error: 109.64527742491912, 3) Mean Standardized Error: -0.18307542156759835, 4) Root-Mean-Square Standardized Error: 0.8977035001318255 and 6) Average Standard Error: 119.41009406720504.

The validation of the forecasting of SSPM corresponding to the observed monthly precipitation for 2018 and the monthly precipitation estimated with forecasted coefficients of the monthly precipitation based on the time series between 2015 and 2017 is carried on using Brown's linear exp. smoothing with constant alpha, as it is indicated in Table 6 and Figure 4; observing that the extracted values from the forecasted precipitation map in August 2017 are correlated to the extracted values from the observed precipitation map in August 2017, finding the following statistical parameters: PMRF: Predicted versus Measured Regression function: Forecasted = 1.18948*Measured, CC: Correlation Coefficient: 0.995675, R-squared: Determination Coefficient: 0.991369, R^2adjusted: R-squared (adjusted): 0.991369, SEE: Standard Error of Estimation: 9.98084, MAE: Mean absolute error: 7.51386, DWs: Durbin-Watson statistic: 0.263242. In Figure 4a and Figure 4b, it is possible to observe the graphics of observed versus predicted in water balance variables to assess the performance of the spatio – temporal hybrid model, the dots are close to the line of slope 1:1, indicating a successful adjustment between monthly precipitation predicted values and monthly precipitation observed values.

Forecasting of Evapotranspiration

The forecasting of SSPM coefficients of the monthly evapotranspiration semivariances based on the time series between 2015 and 2017 are shown in Table 7; where it is observed that the tested models are the five, as a sample, the results found for the coefficient "a" are as follows: A) ARIMA(1,0,0) with constant, B) Linear trend = 308.828 + -7.63053 t, C) Simple exponential smoothing with alpha = 0.0942, D) Brown's linear exp. smoothing with alpha = 0.062 and E) Brown's quadratic exp. smoothing with alpha = 0.0488.

Table: 1. *Forecasting of SSPM Coefficients of the monthly precipitation semivariances based on the time series between 2015 and 2017*

	Coefficient a	b	c	d
(A)	ARIMA(1,0,0) with constant	ARIMA(1,0,0) with constant	ARIMA(1,0,0) with constant	ARIMA(1,0,0) with constant
(B)	Linear trend = -65584.6 + 83.4519 t	Linear trend = -33193.7 + 44.5936 t	Linear trend = -443333. + 748.781 t	Linear trend = 61.4333 - 0.0759959 t
(C)	Simple exponential smoothing with alpha = 0.1857	Simple exponential smoothing with alpha = 0.0585	Simple exponential smoothing with alpha = 0.0112	Simple exponential smoothing with alpha = 0.2334
(D)	Brown's linear exp. smoothing with alpha = 0.1322	Brown's linear exp. smoothing with alpha = 0.0205	Brown's linear exp. smoothing with alpha = 0.0052	Brown's linear exp. smoothing with alpha = 0.1054
(E)	Brown's quadratic exp. smoothing with alpha = 0.085	Brown's quadratic exp. smoothing with alpha = 0.0125	Brown's quadratic exp. smoothing with alpha = 0.0034	Brown's quadratic exp. smoothing with alpha = 0.0149

Table: 2. *Error statistics by fitting the forecasting models to the SSPM coefficients of the monthly precipitation semivariances based on the time series between 2015 and 2017*

Model	a			b			c			d		
	RMSE	MAE	ME	RMSE	MAE	ME	RMSE	MAE	ME	RMSE	MAE	ME
(A)	1582.65	1083.43	10.2435	2988.75	1943.26	28.3926	186848	115654	-4.1367	1.38864	1.03044	-0.005462
(B)	1429.98	985.879	-5.6E-12	3084.13	2053.7	1.65E-12	186721	114237	-8.63E-11	1.23324	0.91895	3.438E-16
(C)	1554.13	916.51	320.584	3148.47	2172.48	-77.0617	185893	120163	-19681.3	1.30458	1.03367	-0.249325
(D)	1588.26	1066.55	334.38	3163.1	2173.51	53.9117	185848	120215	-19787.6	1.37795	1.06146	-0.310107
(E)	1583.11	1091.45	241.615	3173.36	2177.88	93.8822	185833	120224	-19775.1	1.40359	1.12649	-0.268706

RMSE = root mean squared error, MAE = mean absolute error, ME = mean error

Table: 3. *Forecasting of SSPM coefficients of the monthly precipitation semivariances based on the time series between 2015 and 2017 using Brown's quadratic exp. smoothing with constant alpha*

Period	a			b			c			d		
	Forecast	Lower 95.0% Limit	Upper 95.0% Limit	Forecast	Lower 95.0% Limit	Upper 95.0% Limit	Forecast	Lower 95.0% Limit	Upper 95.0% Limit	Forecast	Lower 95.0% Limit	Upper 95.0% Limit
8/17	2605.74	-446.643	5658.13	2749.48	-3687.04	9186.0	170522.	-187850.	528894.	0.803972	-1.90229	3.51024
9/17	2769.23	-326.952	5865.41	2786.29	-3684.29	9256.86	170475.	-187904.	528854.	0.798528	-1.90894	3.50599
10/17	2937.63	-205.447	6080.72	2824.42	-3681.79	9330.64	170428.	-187958.	528814.	0.79306	-1.91562	3.50174
11/17	3110.97	-82.1435	6304.07	2863.89	-3679.56	9407.34	170380.	-188012.	528773.	0.787567	-1.92235	3.49749
12/17	3289.22	42.9522	6535.49	2904.69	-3677.62	9487.0	170333.	-188067.	528733.	0.782051	-1.92912	3.49322
1/18	3472.4	169.844	6774.95	2946.81	-3675.99	9569.61	170286.	-188121.	528693.	0.77651	-1.93594	3.48896
2/18	3660.49	298.546	7022.44	2990.27	-3674.68	9655.21	170238.	-188176.	528652.	0.770945	-1.94279	3.48468
3/18	3853.52	429.076	7277.96	3035.05	-3673.7	9743.8	170191.	-188230.	528612.	0.765355	-1.94969	3.4804
4/18	4051.46	561.461	7541.46	3081.16	-3673.06	9835.39	170143.	-188285.	528571.	0.759742	-1.95663	3.47611
5/18	4254.33	695.736	7812.92	3128.61	-3672.78	9929.99	170096.	-188339.	528531.	0.754104	-1.96361	3.47182
6/18	4462.12	831.937	8092.3	3177.38	-3672.85	10027.6	170048.	-188394.	528490.	0.748442	-1.97063	3.46752
7/18	4674.83	970.107	8379.56	3227.48	-3673.29	10128.3	170000.	-188449.	528449.	0.742755	-1.9777	3.46321
8/18	4892.47	1110.29	8674.65	3278.91	-3674.1	10231.9	169953.	-188504.	528409.	0.737045	-1.98481	3.4589
9/18	5115.03	1252.54	8977.52	3331.68	-3675.29	10338.6	169905.	-188559.	528368.	0.73131	-1.99196	3.45458
1018	5342.51	1396.91	9288.12	3385.77	-3676.85	10448.4	169857.	-188614.	528328.	0.725551	-1.99916	3.45026
1118	5574.92	1543.44	9606.4	3441.19	-3678.79	10561.2	169809.	-188669.	528287.	0.719768	-2.00639	3.44593
12/18	5812.25	1692.19	9932.3	3497.94	-3681.11	10677.0	169761.	-188724.	528246.	0.713961	-2.01368	3.4416

***Table: 4.** Calibration of SSPM of the monthly precipitation semivariances with forecasted coefficients for 2017 based on the time series between 2015 and 2017; which will be used in the validation stage.*

Image Date	SSPM	Ordinary Kriging	Independent Variable
August 2017	Precipitation semivariance SSPM	2605.74*Nugget+2749.48*J-Bessel(170522, 0.803972)	Precipitation Map in August 2016
	PMRF	0.998736192687617 * x + 0.372881835725707	
	EMRF	-0.001263807312386 * x + 0.372881835726463	
	SEMRF	-0.00002848795363 * x + 0.00840874839905042	
	Samples	11709	
	Mean Error	0.14737273353673505	
	Root-Mean-Square Error	0.22413627021079577	
	Mean Standardized Error	0.0033252776322928944	
	Root-Mean-Square Standardized Error	0.00505251238223869	
	Average Standard Error	44.32340688814414	
October 2017	Precipitation semivariance SSPM	2937.63*Nugget+2824.42*J-Bessel(170428, 0.79306)	Precipitation Map in October 2016
	PMRF	1.00092117531462 * x + -0.0940326806877039	
	EMRF	0.000921175314636 * x + -0.094032680689529	
	SEMRF	0.000029414137948 * x + -0.0030035385528645	
	Samples	11709	
	Mean Error	0.01622753032847511	
	Root-Mean-Square Error	0.04393955657243635	
	Mean Standardized Error	0.0005173438693785862	
	Root-Mean-Square Standardized Error	0.001392919866632191	
	Average Standard Error	31.389318696102922	

SSPM: Statistical Spatial Prediction Model, PMRF: Predicted versus Measured Regression Function, EMRF: Error versus Measured Regression Function, SEMRF: Standardized Error versus Measured Regression Function, PE: Prediction Errors

***Table: 5.** Calibration of SSPM of the monthly precipitation semivariances for August 2017 and October 2017 based on the observed time series between 2015 and 2017; which will be used in the validation stage.*

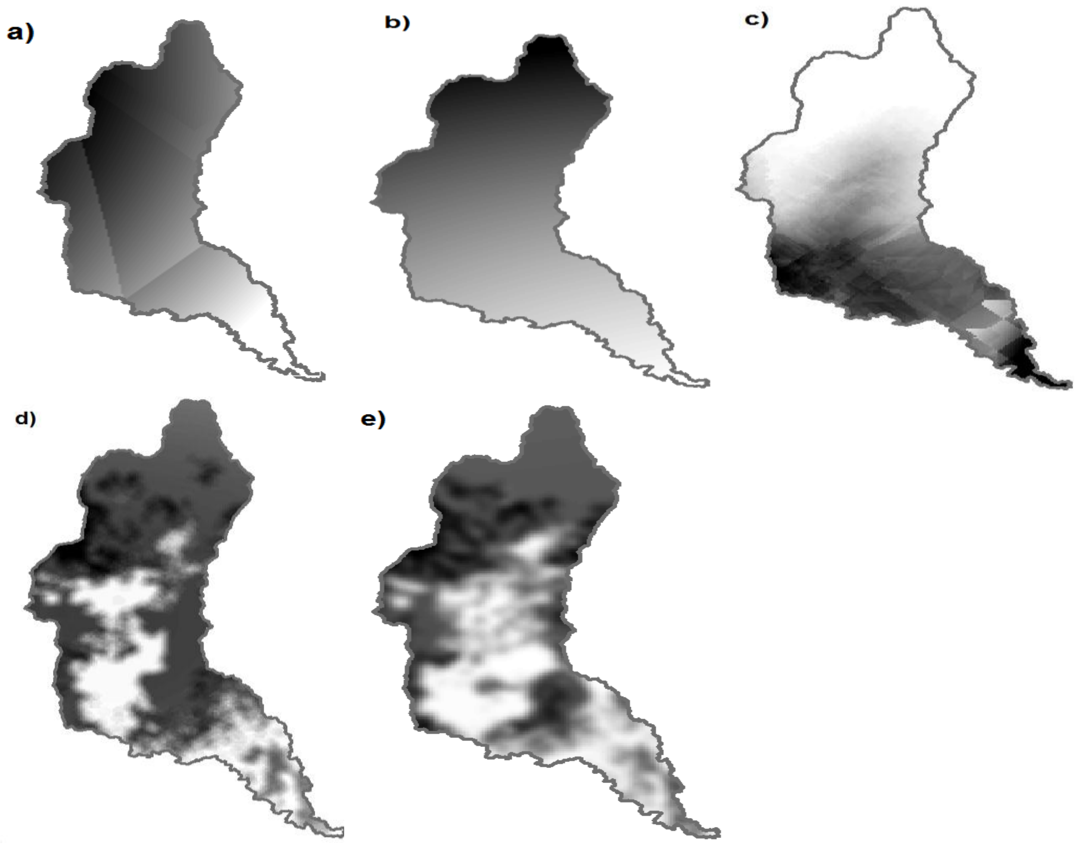
Image Date	SSPM	Ordinary Kriging
August 2017	Precipitation semivariance SSPM	4555.3*Nugget+10834*J-Bessel(72869,0.01)
	PMRF	0.445997193775157 * x + 72.8387182689694
	EMRF	-0.554002806224843 * x + 72.8387182689694
	SEMRF	-0.00671600747345756 * x + 0.797998950155083
	Samples	15
	Mean Error	-20.983851180100107
	Root-Mean-Square Error	109.64527742491912
	Mean Standardized Error	-0.18307542156759835
	Root-Mean-Square Standardized Error	0.8977035001318255
	Average Standard Error	119.41009406720504
October 2017	Precipitation semivariance SSPM	69.566*Nugget+4502.5*J-Bessel(343190,2.7017)
	PMRF	0.575441427566573 * x + 44.0901349376733
	EMRF	-0.424558572433427 * x + 44.0901349376734
	SEMRF	-0.0164616260498862 * x + 1.8141364901493
	Samples	11
	Mean Error	7.218086715869637
	Root-Mean-Square Error	38.63193432456264
	Mean Standardized Error	0.05483761885418889
	Root-Mean-Square Standardized Error	1.960909710160917
	Average Standard Error	22.185509063836722

SSPM: Statistical Spatial Prediction Model, PMRF: Predicted versus Measured Regression Function, EMRF: Error versus Measured Regression Function, SEMRF: Standardized Error versus Measured Regression Function, PE: Prediction Errors

***Table: 6.** Validation of the forecasting of SSPM corresponding to the observed precipitation for 2018 and the precipitation estimated with forecasted coefficients of the monthly precipitation based on the time series between 2015 and 2017 using Brown's linear exp. smoothing with constant alpha*

Dependent Variable	SSPM	Statistics	Independent Variable
Forecasted Precipitation Map in August 2017	PMRF	Forecasted = 1.18948*Measured	Observed Precipitation Map in August 2017
	Samples	532	
	CC	0.995675	
	R^2	0.991369	
	$R^2_{adjusted}$	0.991369	
	SEE	9.98084	
	MAE	7.51386	
	DW	0.263242	
Forecasted Precipitation Map in October 2017	PMRF	Forecasted = 0.923415* Measured	Observed Precipitation Map in October 2017
	Samples	133	
	CC	0.999997	
	R^2	0.999994	
	$R^2_{adjusted}$	0.999994	
	SEE	0.279439	
	MAE	0.221791	
	DW	0.357667	

PMRF: Predicted versus Measured Regression function, CC: Correlation Coefficient, R-squared: Determination Coefficient, $R^2_{adjusted}$: R-squared (adjusted), SEE: Standard Error of Estimation, MAE: Mean absolute error, DWs: Durbin-Watson statistic, x: observed value



	a	b	c	d	e
Min.	255	120	0	30	-110
Máx.	279	121	20	61	-77

***Fig: 3.** Maps of forecasting of water balance variables using spatio – temporal hydrid model for December 2018: a) Precipitation (mm/month), b) Evapotranspiration (mm/month), c) Pumping flow (l/s), d) Infiltration (mm/month), e) Volume Stored (mm/month).*

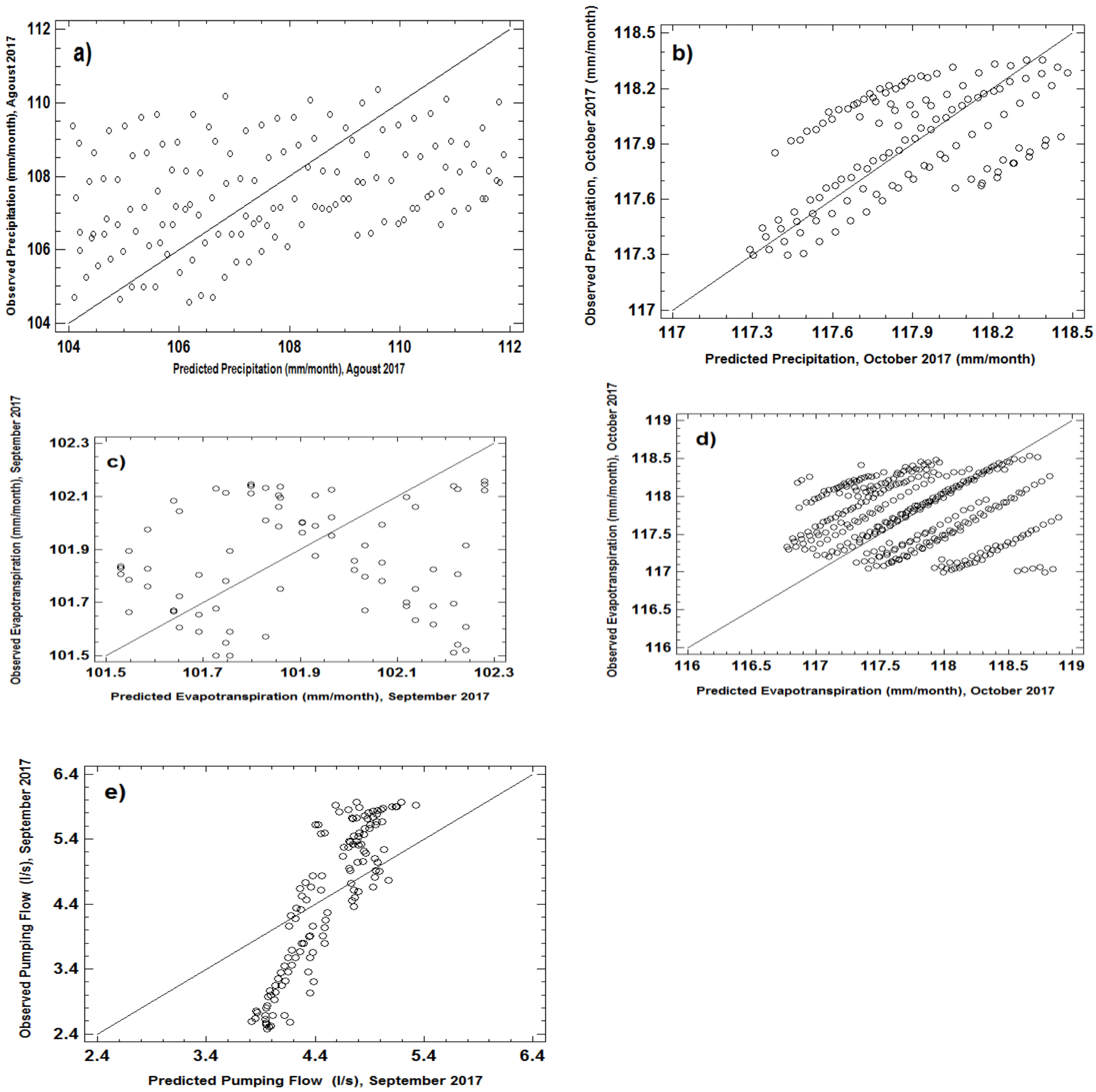


Fig: 4. *Graphics of Observed versus Predicted in water balance variables to assess the performance of the spatio – temporal hybrid model*

The error statistics by fitting the forecasting models to the SSPM coefficients of the monthly evapotranspiration semivariances based on the time series between 2015 and 2017 are shown in Table 8, which are expressed in terms of three statistics of errors, as a sample, the results found for the coefficient “a” are as follows: for model A: 1) RMSE: 238.791, 2) MAE: 184.844, and 3) ME: 0.387769. For model B: 1) RMSE: 245.74, 2) MAE: 195.605, and 3) ME: -4.92796E-14. For model C: 1) RMSE: 255.946, 2) MAE: 219.035, and 3) ME: -33.2113. For model D: 1) RMSE: 260.086, 2) MAE: 226.631, and 3) ME: -49.4012. For model E: 1) RMSE: 262.117, 2) MAE: 229.284, and 3) ME: -52.3767. In general, the model selected for forecasting of coefficients of semivariances SSPM of monthly evapotranspiration is the model D corresponding to Brown's linear exp. smoothing with constant alpha because of the error statistics are in the group of lower values.

The forecasting of SSPM coefficients of

the monthly evapotranspiration semivariances based on the time series between 2015 and 2017 using Brown's quadratic exp. smoothing with constant alpha are shown in Table 9, the period for forecasting of monthly evapotranspiration covers from 8/17 (August 2017 to 12/18 (December, 2018). The values of coefficients have been selected for forecasting of precipitation for 12/18 as follows*: for coefficient a:* 1) forecast: 179.391, 2) Lower 95.0% limit: -314.38, 3) Upper 95.0% limit: 673.162. *For coefficient b:* 1) forecast: 1578.28, 2) Lower 95.0% limit: -766.658, 3) Upper 95.0% limit: 3923.22. *For coefficient c:* 1) forecast: 648143, 2) Lower 95.0% limit: -106531, 3) Upper 95.0% limit: 1.40282E6. *For coefficient d:* 1) forecast: 2.67126, 2) Lower 95.0% limit: -5.01121, 3) Upper 95.0% limit: 10.3537. In Figure 3 is shown the map of forecasting of monthly evapotranspiration, which varies between 120 and 121 mm/month. For this month, the maximum monthly evapotranspiration occurs between the north and middle region of the San Diego aquifer.

The calibration of SSPM of the monthly evapotranspiration semivariances with forecasted coefficients for 2017 based on the time series between 2015 and 2017; which will be used in the validation stage is shown in Table 10, using the forecasted coefficients for the months of august 2017 and September 2017 and obtaining the correlation statistics between the monthly evapotranspiration spatial prediction and the measured values from the monthly evapotranspiration map for August 2016 and September 2016, respectively: for August 2017: 1) *monthly evapotranspiration semivariance SSPM* is 176.043*Nugget+1505.47*J-Bessel(650930, 2.43295), 2) *PMRF*: 1.00003858791842 * x + -0.00877499054303144, 3) *EMRF:* 0.0000385879178285533 * x + -0.00877499047065942 and 4) *SEMRF:* 0.00000293273326722762 * x + -0.000666505665. The statistics of prediction error are: 1) Mean Error: -0.004002294030264697, 2) Root-Mean-Square Error: 0.005188808075072052, 3) Mean Standardized Error: -0.00030372741268137047, 4) Root-Mean-Square Standardized Error: 0.0003925714187172654 and 6) Average Standard Error: 13.180938969970756.

The calibration of SSPM of the monthly evapotranspiration semivariances for August 2017 and October 2017 based on the observed time series between 2015 and 2017; which will be used in the validation stage is shown in Table 11, obtaining the correlation statistics between the monthly evapotranspiration spatial prediction and the measured values from the monthly evapotranspiration map for August 2016 and October 2016, respectively: for August 2017: 1) *Monthly evapotranspiration SSPM* is 280.78*Nugget+1496.8*J-Bessel(1380800,0.01), 2) *PMRF*: 0.540279168262678 * x + 53.5961726423937, 3) *EMRF:* -0.459720831737321 * x + 53.5961726423936 and 4) *SEMRF:* -0.0225043030693121 * x + 2.59282615084186. The statistics of prediction error are: 1) Mean Error: 1.3412381015847903, 2) Root-Mean-Square Error: 22.528504964545103, 3) Mean Standardized Error: 0.0348370352967245, 4) Root-Mean-Square Standardized Error: 0.9867032032596413 and 6) Average Standard Error: 22.039174662732194.

The validation of the forecasting of SSPM corresponding to the observed monthly evapotranspiration for 2018 and the monthly evapotranspiration estimated with forecasted coefficients of the monthly evapotranspiration based on the time series between 2015 and 2017 is carried on using Brown's linear exp. smoothing with constant alpha, as it is indicated in Table12 and Figure 4; observing that the extracted values from the forecasted monthly evapotranspiration map in August 2017 are correlated to the extracted values from the monthly evapotranspiration map in August 2017, finding the following statistical parameters: PMRF: Predicted versus Measured Regression function: Forecasted = 1.02574*Measured, CC: Correlation Coefficient: 0.999928, R-squared: Determination Coefficient: 0.999856, R^2adjusted: R-squared (adjusted): 0.999856, SEE: Standard Error of Estimation: 1.22393, MAE: Mean absolute error: 1.0272, DWs: Durbin-Watson statistic: 0.845245. In Figure 4c and Figure 4d, it is possible to observe the graphics of observed versus predicted in water balance variables to assess the performance of the spatio – temporal hybrid model, the dots are close to the line of slope 1:1, indicating a successful adjustment between monthly precipitation predicted values and monthly precipitation observed values.

Forecasting of Pumping Flow

The forecasting of SSPM coefficients of the monthly pumping flow semivariances based on the time series between 2015 and 2017 are shown in Table 13; where it is observed that the tested models are the five, as a sample, the results found for the coefficient "a" are as follows: A) ARIMA(1,0,0) with constant, B) Linear trend = -8.21905 + 0.0224575 t, C) Simple exponential smoothing with alpha = 0.3166, D) Brown's linear exp. smoothing with alpha = 0.1589 and E) Brown's quadratic exp. smoothing with alpha = 0.1088.

The error statistics by fitting the forecasting models to the SSPM coefficients of the monthly pumping flow semivariances based on the time series between 2015 and 2017 are shown in Table 14, which are expressed in terms of three statistics of errors, as a sample, the results found for the coefficient "a" are as follows: for model A: 1) RMSE: 0.243571, 2) MAE: 0.18554, and 3) ME: 0.0165821. For model B: 1) RMSE: 0.215797, 2) MAE: 0.177117, and 3) ME: 3.89652E-15. For model C: 1) RMSE: 0.236881, 2) MAE: 0.187756, and 3) ME: 0.0459251. For model D: 1) RMSE: 0.240064, 2) MAE: 0.192478, and 3) ME: 0.0374056. For model E: 1) RMSE: 0.243439, 2) MAE: 0.194055, and 3) ME: 0.0181451.

Table: 7. *Forecasting of SSPM coefficients of the monthly evapotranspiration semivariances based on the time series between 2015 and 2017*

	Coefficient a	b	c	d
(A)	ARIMA(1,0,0) with constant	ARIMA(1,0,0) with constant	ARIMA(1,0,0) with constant	ARIMA(1,0,0) with constant
(B)	Linear trend = 308.828 + -7.63053 t	Linear trend = -12727.8 + 17.837 t	Linear trend = -3.81971E6 + 5581.58 t	Linear trend = -31.4643 + 0.0424819 t
(C)	Simple exponential smoothing with alpha = 0.0942	Simple exponential smoothing with alpha = 0.0427	Simple exponential smoothing with alpha = 0.0155	Simple exponential smoothing with alpha = 0.0384
(D)	Brown's linear exp. smoothing with alpha = 0.062	Brown's linear exp. smoothing with alpha = 0.0169	Brown's linear exp. smoothing with alpha = 0.0075	Brown's linear exp. smoothing with alpha = 0.0165
(E)	Brown's quadratic exp. smoothing with alpha = 0.0488	Brown's quadratic exp. smoothing with alpha = 0.0107	Brown's quadratic exp. smoothing with alpha = 0.0047	Brown's quadratic exp. smoothing with alpha = 0.0101

Table: 8. *Error statistics by fitting the forecasting models to the SSPM coefficients of the monthly evapotranspiration semi variances based on the time series between 2015 and 2017*

Model	a			b			c			d		
	RMSE	MAE	ME	RMSE	MAE	ME	RMSE	MAE	ME	RMSE	MAE	ME
(A)	238.791	184.844	0.387769	1190.43	909.033	-9.28528	391055.	299864.	-847.566	3.80627	3.05829	0.000123277
(B)	245.74	195.605	-4.92E-14	1194.52	900.803	-1.54E-13	388978.	298244.	-6.158E-10	3.9257	3.18125	2.69319E-15
(C)	255.946	219.035	-33.2113	1212.02	910.849	159.493	390699.	313866.	-31859.9	3.97308	2.96555	0.547744
(D)	260.086	226.631	-49.4012	1203.89	908.729	129.743	390666.	313661.	-29991.2	3.94586	3.02917	0.407009
(E)	262.117	229.284	-52.3767	1201.19	908.687	115.293	390675.	313966.	-31476.8	3.93933	3.03104	0.396925

RMSE = root mean squared error, MAE = mean absolute error, ME = mean error

***Table: 9.** Forecasting of SSPM coefficients of the monthly evapotranspiration semivariances based on the time series between 2015 and 2017 using Brown's linear exp. smoothing with constant alpha*

Period	a			b			c			d		
	Forecast	Lower 95.0% Limit	Upper 95.0% Limit	Forecast	Lower 95.0% Limit	Upper 95.0% Limit	Forecast	Lower 95.0% Limit	Upper 95.0% Limit	Forecast	Lower 95.0% Limit	Upper 95.0% Limit
8/17	176.043	-315.509	667.595	1505.47	-815.869	3826.81	650930.	-102312.	1.40417E6	2.43295	-5.17505	10.0409
9/17	176.252	-315.427	667.932	1510.02	-812.628	3832.67	650756.	-102571.	1.40408E6	2.44784	-5.16429	10.06
10/17	176.461	-315.347	668.27	1514.57	-809.409	3838.55	650582.	-102831.	1.40399E6	2.46274	-5.15361	10.0791
11/17	176.671	-315.269	668.61	1519.12	-806.211	3844.45	650407.	-103091.	1.40391E6	2.47763	-5.14299	10.0983
12/17	176.88	-315.192	668.951	1523.67	-803.034	3850.38	650233.	-103352.	1.40382E6	2.49253	-5.13244	10.1175
1/18	177.089	-315.116	669.294	1528.22	-799.88	3856.33	650059.	-103613.	1.40373E6	2.50742	-5.12195	10.1368
2/18	177.298	-315.042	669.638	1532.77	-796.747	3862.3	649885.	-103875.	1.40364E6	2.52232	-5.11153	10.1562
3/18	177.508	-314.969	669.984	1537.33	-793.636	3868.29	649711.	-104138.	1.40356E6	2.53721	-5.10119	10.1756
4/18	177.717	-314.897	670.331	1541.88	-790.548	3874.3	649537.	-104401.	1.40347E6	2.5521	-5.09091	10.1951
5/18	177.926	-314.828	670.68	1546.43	-787.482	3880.34	649362.	-104665.	1.40339E6	2.567	-5.0807	10.2147
6/18	178.135	-314.759	671.03	1550.98	-784.439	3886.39	649188.	-104930.	1.40331E6	2.58189	-5.07056	10.2343
7/18	178.345	-314.692	671.381	1555.53	-781.418	3892.47	649014.	-105195.	1.40322E6	2.59679	-5.06049	10.2541
8/18	178.554	-314.627	671.734	1560.08	-778.42	3898.58	648840.	-105461.	1.40314E6	2.61168	-5.05049	10.2738
9/18	178.763	-314.563	672.089	1564.63	-775.444	3904.7	648666.	-105728.	1.40306E6	2.62657	-5.04056	10.2937
10/18	178.972	-314.501	672.445	1569.18	-772.492	3910.85	648492.	-105995.	1.40298E6	2.64147	-5.0307	10.3136
11/18	179.181	-314.44	672.803	1573.73	-769.563	3917.03	648317.	-106263.	1.4029E6	2.65636	-5.02092	10.3336
12/18	179.391	-314.38	673.162	1578.28	-766.658	3923.22	648143.	-106531.	1.40282E6	2.67126	-5.01121	10.3537

***Table: 10.** Calibration of SSPM of the monthly evapotranspiration semivariances with forecasted coefficients between August 2017 and April 2018 based on the time series between 2015 and 2017; which will be used in the validation stage.*

Image Date	SSPM	Ordinary Kriging	Independent Variable
August 2017	Evapotranspiration semivariance SSPM	176.043*Nugget+1505.47*J-Bessel(650930, 2.43295)	Evapotranspiration Map in August 2016
	PMRF	1.00003858791842 * x + -0.00877499054303144	
	EMRF	0.000038587917828 * x + -0.008774990470659	
	SEMRF	0.0000029327332672276 * x + -0.000666505665	
	Samples	11709	
	Mean Error	-0.004002294030264697	
	Root-Mean-Square Error	0.005188808075072052	
	Mean Standardized Error	-0.00030372741268137047	
	Root-Mean-Square Standardized Error	0.0003925714187172654	
	Average Standard Error	13.180938969970756	
September 2017	Evapotranspiration semivariance SSPM	176.252*Nugget+1510.02*J-Bessel(650756, 2.44784)	Evapotranspiration Map in September 2016
	PMRF	1.00000588733684 * x + -0.00323041380988798	
	EMRF	0.0000058873368449678 * x + -0.003230413810	
	SEMRF	4.3227555161189e-7 * x + -0.000236305309632	
	Samples	11709	
	Mean Error	-0.002808939172869688	
	Root-Mean-Square Error	0.012148184153800867	
	Mean Standardized Error	-0.00020521445930467633	
	Root-Mean-Square Standardized Error	0.0008817231141922124	
	Average Standard Error	13.687806452684532	

SSPM: Statistical Spatial Prediction Model, PMRF: Predicted versus Measured Regression Function, EMRF: Error versus Measured Regression Function, SEMRF: Standardized Error versus Measured Regression Function, PE: Prediction Errors

Table: 11. *Calibration of SSPM of the monthly observed evapotranspiration semivariances between for 2017 based on the time series between 2015 and 2017; which will be used in the validation stage.*

Image Date	SSPM	Ordinary Kriging
August 2017	Evapotranspiration semivariance SSPM	280.78*Nugget+1496.8*J-Bessel(1380800,0.01)
	PMRF	0.540279168262678 * x + 53.5961726423937
	EMRF	-0.459720831737321 * x + 53.5961726423936
	SEMRF	-0.0225043030693121 * x + 2.59282615084186
	Samples	9
	Mean Error	1.3412381015847903
	Root-Mean-Square Error	22.528504964545103
	Mean Standardized Error	0.0348370352967245
	Root-Mean-Square Standardized Error	0.9867032032596413
	Average Standard Error	22.039174662732194
September 2017	Evapotranspiration semivariance SSPM	835.07*Nugget+1970.7*J-Bessel(537800,0.01)
	PMRF	0.426725855617936 * x + 61.4134388937095
	EMRF	-0.573274144382064 * x + 61.4134388937095
	SEMRF	-0.0142833571494279 * x + 1.57091912314857
	Samples	11
	Mean Error	-2.689033614466736
	Root-Mean-Square Error	41.611003653856514
	Mean Standardized Error	-0.026219903560181054
	Root-Mean-Square Standardized Error	1.0310003001596355
	Average Standard Error	43.533813746120124

SSPM: Statistical Spatial Prediction Model, PMRF: Predicted versus Measured Regression Function, EMRF: Error versus Measured Regression Function, SEMRF: Standardized Error versus Measured Regression Function, PE: Prediction Errors

Table: 12. *Validation of the forecasting of SSPM corresponding to the observed evapotranspiration for 2017 and the evapotranspiration estimated with forecasted coefficients of the monthly evapotranspiration based on the time series between 2015 and 2017 using Brown's linear exp. smoothing with constant alpha*

Image Date	SSPM	Statistics	Independent Variable
Forecasted Evapotranspiration Map in September 2017	PMRF	Forecasted = 1.02574*Measured	Observed Evapotranspiration Map in September 2017
	Samples	360	
	CC	0.999928	
	R^2	0.999856	
	$R^2_{adjusted}$	0.999856	
	SEE	1.22393	
	MAE	1.0272	
	DW	0.845245	
Forecasted Evapotranspiration Map in October 2017	PRF	Forecasted = 0.919342*Measured	Observed Evapotranspiration Map in October 2017
	Samples	350	
	CC	0.999986	
	R^2	0.999972	
	$R^2_{adjusted}$	0.999972	
	SEE	0.626462	
	MAE	0.503439	
	DW	0.285864	

PMRF: Predicted versus Measured Regression function, CC: Correlation Coefficient, R-squared: Determination Coefficient, $R^2_{adjusted}$: R-squared (adjusted), SEE: Standard Error of Estimation, MAE: Mean absolute error, DWs: Durbin-Watson statistic, x: observed value

In general, the model selected for forecasting of coefficients of semivariances SSPM of monthly pumping flow is the model D corresponding to Brown's linear exp. smoothing with constant alpha because of the error statistics are in the group of lower values.

The forecasting of SSPM coefficients of the monthly pumping flow semivariances based on the time series between 2015 and 2017 using Brown's quadratic exp. smoothing with constant alpha are shown in Table 15, the period for forecasting of monthly pumping flow covers from 8/17

(August 2017 to 12/18 (December, 2018). The values of coefficients have been selected for forecasting of monthly pumping flow for 12/18 as follows*: for coefficient a:* 1) forecast: 10.263, 2) Lower 95.0% limit: 9.19104, 3) Upper 95.0% limit: 11.3349. *For coefficient b:* 1) forecast: 49.3878, 2) Lower 95.0% limit: 2.51383, 3) Upper 95.0% limit: 96.2618. *For coefficient c:* 1) forecast: 16999.4, 2) Lower 95.0% limit: 7745.14, 3) Upper 95.0% limit: 26253.7. *For coefficient d:* 1) forecast: 1.77918, 2) Lower 95.0% limit: 1.197, 3) Upper 95.0% limit: 2.36136. In Figure 3 is shown the map of forecasting of pumping flow, which varies between 0 and 20 l/s. For this month, the maximum monthly pumping flow occurs between the middle and south region of the San Diego aquifer.

The calibration of SSPM of the monthly pumping flow semivariances with forecasted coefficients for 2017 based on the time series between 2015 and 2017; which will be used in the validation stage is shown in Table 16, using the forecasted coefficients for the months of august 2017 and September 2017 and obtaining the correlation statistics between the monthly evapotranspiration spatial prediction and the measured values from the precipitation map for August 2016 and September 2016, respectively: for August 2017: 1) *monthly evapotranspiration semivariance SSPM* is 9.97905*Nugget+63.6095*J-Bessel(21496.9, 1.55481), 2) *PMRF*: 0.99539935584911 * x + 0.0229489632869351, 3) *EMRF:* -0.00460064415084568 * x + 0.022948963286767 and 4) *SEMRF:* -0.00142185681509449 * x + 0.007116149604344. The statistics of prediction error are: 1) Mean Error: 0.010181654684313146, 2) Root-Mean-Square Error: 0.23739405887419587, 3) Mean Standardized Error: 0.003171181756427858, 4) Root-Mean-Square Standardized Error: 0.07370419219507944and 6) Average Standard Error: 3.2201525228085703.

The calibration of SSPM of the monthly pumping flow semivariances for August 2017 and October 2017 based on the observed time series between 2015 and 2017; which will be used in the validation stage is shown in Table 17, obtaining the correlation statistics between the monthly pumping flow spatial prediction and the measured values from the monthly evapotranspiration map for August 2016 and October 2016, respectively: for August 2017: 1) *Monthly pumping flow SSPM* is 15.602*Nugget+16.264*J-Bessel(8061.5,1.3762), 2) *PMRF*: 0.434176422688513 * x + 4.30162297735632, 3) *EMRF:* -0.565823577311485 * x + 4.30162297735631 and 4) *SEMRF:* -0.126334524710947 * x + 0.970409259998791. The statistics of prediction error are: 1) Mean Error: 0.022136598959744225, 2) Root-Mean-Square Error: 4.320368124219371, 3) Mean Standardized Error: 0.0027951259984918273, 4) Root-Mean-Square Standardized Error: 0.9975122712102633and 6) Average Standard Error: 4.454346970456804.

The validation of the forecasting of SSPM corresponding to the observed monthly pumping flow for 2018 and the monthly pumping flow estimated with forecasted coefficients of the monthly pumping flow based on the time series between 2015 and 2017 is carried on using Brown's linear exp. smoothing with constant alpha, as it is indicated in Table 18 and Figure 4; observing that the extracted values from the forecasted monthly pumping flow map in August 2017 are correlated to the extracted values from the monthly pumping flow map in August 2017, finding the following statistical parameters: PMRF: Predicted versus Measured Regression function: Forecasted = 0.91709*Observed, CC: Correlation Coefficient: 0.9846, R-squared: Determination Coefficient: 0.969437, R^2adjusted: R-squared (adjusted): 0.969437, SEE: Standard Error of Estimation: 0.807491, MAE: Mean absolute error: 0.700359, DWs: Durbin-Watson statistic: 0.0302105. In Figure 4d, it is possible to observe the graphics of observed versus predicted in water balance variables to assess the performance of the spatio – temporal hybrid model, the dots are close to the line of slope 1:1, indicating a successful adjustment between monthly precipitation predicted values and monthly precipitation observed values.

Table: 13. *Forecasting of SSPM coefficients of the monthly pumping flow semivariances based on the time series between 2015 and 2017*

	Coefficient			
	a	b	c	d
(A)	ARIMA(1,0,1) with constant	ARIMA(1,0,2) with constant	ARIMA(1,0,1) with constant	ARIMA(1,0,1) with constant
(B)	Linear trend = -8.21905 + 0.0224575 t	Linear trend = -174.212 + 0.30422 t	Linear trend = 118076. + -117.407 t	Linear trend = 0.636943 + 0.000986653 t
(C)	Simple exponential smoothing with alpha = 0.3166	Simple exponential smoothing with alpha = 0.5182	Simple exponential smoothing with alpha = 0.5247	Simple exponential smoothing with alpha = 0.3663
(D)	Brown's linear exp. smoothing with alpha = 0.1589	Brown's linear exp. smoothing with alpha = 0.2668	Brown's linear exp. smoothing with alpha = 0.2287	Brown's linear exp. smoothing with alpha = 0.1829
(E)	Brown's quadratic exp. smoothing with alpha = 0.1088	Brown's quadratic exp. smoothing with alpha = 0.1836	Brown's quadratic exp. smoothing with alpha = 0.1154	Brown's quadratic exp. smoothing with alpha = 0.1242

Table: 14. *Error statistics by fitting the forecasting models to the SSPM coefficients of the monthly pumping flow semivariances based on the time series between 2015 and 2017*

Model	a			b			c			d		
	RMSE	MAE	ME	RMSE	MAE	ME	RMSE	MAE	ME	RMSE	MAE	ME
(A)	0.243571	0.18554	0.0165821	4.81715	3.68365	0.121959	1231.71	791.737	-86.7783	0.101847	0.0703192	-0.0004200
(B)	0.215797	0.177117	3.896E-15	5.84314	4.7015	-8.9E-15	1172.5	840.302	8.449E-12	0.104591	0.0776037	5.0854E-16
(C)	0.236881	0.187756	0.0459251	5.13375	3.31619	0.178013	1207.64	772.36	-227.027	0.104168	0.0732113	0.00883869
(D)	0.240064	0.192478	0.0374056	5.36387	3.51088	-0.28295	1243.87	810.895	-199.79	0.10717	0.0748443	0.011852
(E)	0.243439	0.194055	0.0181451	5.49304	3.63583	-0.62612	1250.86	824.288	-197.601	0.108773	0.0761877	0.0104421

RMSE = root mean squared error, MAE = mean absolute error, ME = mean error

Table: 15. *Forecasting of SSPM coefficients of the monthly pumping flow semivariances based on the time series between 2015 and 2017 using Brown's linear exp. smoothing with constant alpha*

Period	a			b			c			d		
	Forecast	Lower 95.0% Limit	Upper 95.0% Limit	Forecast	Lower 95.0% Limit	Upper 95.0% Limit	Forecast	Lower 95.0% Limit	Upper 95.0% Limit	Forecast	Lower 95.0% Limit	Upper 95.0% Limit
8/17	9.97905	9.51618	10.4419	63.6095	53.2674	73.9516	21496.9	19097.8	23896.0	1.55481	1.34815	1.76147
9/17	9.99679	9.511	10.4826	62.7206	51.0158	74.4255	21215.8	18561.0	23870.6	1.56884	1.34814	1.78953
10/17	10.0145	9.50332	10.5258	61.8318	48.5827	75.0809	20934.7	17991.2	23878.2	1.58286	1.34646	1.81926
11/17	10.0323	9.49324	10.5713	60.9429	45.9891	75.8968	20653.6	17391.6	23915.7	1.59688	1.34322	1.85054
12/17	10.05	9.48086	10.6192	60.0541	43.2525	76.8557	20372.5	16764.9	23980.1	1.6109	1.33853	1.88328
1/18	10.0678	9.4663	10.6692	59.1652	40.3869	77.9436	20091.4	16113.8	24069.0	1.62493	1.33247	1.91738
2/18	10.0855	9.44968	10.7213	58.2764	37.4037	79.149	19810.3	15440.3	24180.4	1.63895	1.32516	1.95275
3/18	10.1033	9.43111	10.7754	57.3875	34.3121	80.4629	19529.3	14746.1	24312.4	1.65297	1.31666	1.98929
4/18	10.121	9.41069	10.8313	56.4987	31.1196	81.8777	19248.2	14032.6	24463.7	1.667	1.30705	2.02694
5/18	10.1387	9.38852	10.889	55.6098	27.8322	83.3874	18967.1	13301.1	24633.0	1.68102	1.29641	2.06563
6/18	10.1565	9.3647	10.9483	54.721	24.4551	84.9868	18686.0	12552.6	24819.3	1.69504	1.28479	2.1053
7/18	10.1742	9.3393	11.0092	53.8321	20.9926	86.6716	18404.9	11787.9	25021.8	1.70907	1.27224	2.1459
8/18	10.192	9.31239	11.0716	52.9432	17.4484	88.4381	18123.8	11007.8	25239.8	1.72309	1.25881	2.18737
9/18	10.2097	9.28406	11.1354	52.0544	13.8258	90.283	17842.7	10212.9	25472.4	1.73711	1.24453	2.22969
10/18	10.2275	9.25435	11.2006	51.1655	10.1275	92.2036	17561.6	9403.89	25719.3	1.75114	1.22945	2.27282
11/18	10.2452	9.22333	11.2671	50.2767	6.35611	94.1973	17280.5	8581.14	25979.9	1.76516	1.2136	2.31672
12/18	10.263	9.19104	11.3349	49.3878	2.51383	96.2618	16999.4	7745.14	26253.7	1.77918	1.197	2.36136

Table: 16. *Calibration of SSPM coefficients of the monthly pumping flow semivariances with forecasted coefficients between August 2017 and April 2018 based on the time series between 2015 and 2017; which will be used in the validation stage.*

Image Date	SSPM	Ordinary Kriging	Independent Variable
August 2017	Pumping flow semivariance SSPM	9.97905*Nugget+63.6095*J-Bessel(21496.9, 1.55481)	Pumping Flow Map in August 2016
	PMRF	0.99539935584911 * x + 0.0229489632869351	
	EMRF	-0.0046006441508456 * x + 0.022948963286767	
	SEMRF	-0.0014218568150944 * x + 0.007116149604344	
	Samples	11709	
	Mean Error	0.010181654684313146	
	Root-Mean-Square Error	0.23739405887419587	
	Mean Standardized Error	0.003171181756427858	
	Root-Mean-Square Standardized Error	0.07370419219507944	
	Average Standard Error	3.2201525228085703	
September 2017	Pumping flow semivariance SSPM	9.99679*Nugget+62.7206*J-Bessel(21215.8, 1.56884)	Pumping Flow in September 2016
	PMRF	0.995913354587144 * x + 0.0231544580284524	
	EMRF	-0.004086645412717 * x + 0.0231544580279029	
	SEMRF	-0.00126375364501 * x + 0.00718706980210105	
	Samples	11709	
	Mean Error	0.010228743004009822	
	Root-Mean-Square Error	0.23476709072787713	
	Mean Standardized Error	0.003188871566307957	
	Root-Mean-Square Standardized Error	0.07295534999658784	
	Average Standard Error	3.21709227556127	

SSPM: Statistical Spatial Prediction Model, PMRF: Predicted versus Measured Regression Function, EMRF: Error versus Measured Regression Function, SEMRF: Standardized Error versus Measured Regression Function, PE: Prediction Errors

Table: 17. *Calibration of SSPM of the monthly observed pumping flow between for 2017 based on the time series between 2015 and 2017; which will be used in the validation stage.*

Image Date	SSPM	Ordinary Kriging
August 2017	Pumping flow semivariance SSPM	15.602*Nugget+16.264*J-Bessel(8061.5,1.3762)
	PMRF	0.434176422688513 * x + 4.30162297735632
	EMRF	-0.565823577311485 * x + 4.30162297735631
	SEMRF	-0.126334524710947 * x + 0.970409259998791
	Samples	211
	Mean Error	0.022136598959744225
	Root-Mean-Square Error	4.320368124219371
	Mean Standardized Error	0.0027951259984918273
	Root-Mean-Square Standardized Error	0.9975122712102633
	Average Standard Error	4.454346970456804
September 2017	Pumping flow semivariance SSPM	16.631*Nugget+15.428*J-Bessel(8283.3,0.69158)
	PMRF	0.425447930422264 * x + 4.29093822143496
	EMRF	-0.574552069577737 * x + 4.29093822143496
	SEMRF	-0.126544281076566 * x + 0.954839465406789
	Samples	219
	Mean Error	0.0493290389539815
	Root-Mean-Square Error	4.53649248513504
	Mean Standardized Error	0.006873206966958036
	Root-Mean-Square Standardized Error	0.006873206966958036
	Average Standard Error	4.581317158059182

SSPM: Statistical Spatial Prediction Model, PMRF: Predicted versus Measured Regression Function, EMRF: Error versus Measured Regression Function, SEMRF: Standardized Error versus Measured Regression Function, PE: Prediction Errors

***Table: 18.** Validation of the forecasting of SSPM corresponding to the observed pumping flow for 2017 and the pumping flow estimated with forecasted coefficients of the monthly pumping flow based on the time series between 2016 and 2017*

Image Date	SSPM	Statistics	Independent Variable
Forecasted Pumping Flow Map in September 2017	PRF	Forecasted = 0.91709*Observed	Observed Pumping Flow Map in September 2016
	Samples	127	
	CC	0.9846	
	R^2	0.969437	
	$R^2_{adjusted}$	0.969437	
	SEE	0.807491	
	MAE	0.700359	
	DW	0.0302105	

PRF: Predicted Regression function, CC: Correlation Coefficient, R-squared: Determination Coefficient, $R^2_{adjusted}$: R-squared (adjusted), SEE: Standard Error of Estimation, MAE: Mean absolute error, DWs: Durbin-Watson statistic, x: observed value

Forecasting of Infiltration

The forecasting of SSPM coefficients of the monthly infiltration semivariances based on the time series between 2015 and 2017 are shown in Table 19; where it is observed that the tested models are the five, as a sample, the results found for the coefficient “a” are as follows: A) ARIMA(1,0,0) with constant, B) Linear trend = -534.936 + 0.722448 t, C) Simple exponential smoothing with alpha = 0.0618, 4) Brown's linear exp. smoothing with alpha = 0.0707 and D) Brown's quadratic exp. smoothing with alpha = 0.0571.

The error statistics by fitting the forecasting models to the SSPM coefficients of the monthly infiltration semivariances based on the time series between 2015 and 2017 are shown in Table 20, which are expressed in terms of three statistics of errors, as a sample, the results found for the coefficient “a” are as follows: for model A: 1) RMSE: 38.393, 2) MAE: 31.5795, and 3) ME: 0.512365. For model B: 1) RMSE: 39.732, 2) MAE: 33.1322, and 3) ME: 5.04256E-14. For model C: 1) RMSE: 40.7103, 2) MAE: 35.9983, and 3) ME: 0.0902728. For model D: 1) RMSE: 42.5248, 2) MAE: 35.3469, and 3) ME: 9.24911. For model E: 1) RMSE: 43.0137, 2) MAE: 35.7074, and 3) ME: 8.42748. In general, the model selected for forecasting of coefficients of semivariances SSPM of monthly infiltration is the model D corresponding to Brown's linear exp. smoothing with constant alpha because of the error statistics are in the group of lower values.

The forecasting of SSPM coefficients of the monthly infiltration semivariances based on the time series between 2015 and 2017 using Brown's quadratic exp. smoothing with constant alpha are shown in Table 21, the period for forecasting of monthly infiltration covers from 8/17 (August 2017 to 12/18 (December, 2018). The values of coefficients have been selected for forecasting of monthly infiltration for 12/18 as follows*: for coefficient a:* 1) forecast: 49.622, 2) Lower 95.0% limit: -50.6999, 3) Upper 95.0% limit: 149.944. *For coefficient b:* 1) forecast: 44.3168, 2) Lower 95.0% limit: -47.9117, 3) Upper 95.0% limit: 136.545. *For coefficient c:* 1) forecast: 4874.01, 2) Lower 95.0% limit: -1463.89, 3) Upper 95.0% limit: 11211.9. *For coefficient d:* 1) forecast: 5.01916, 2) Lower 95.0% limit: -0.47252, 3) Upper 95.0% limit: 10.5108. In Figure 3 is shown the map of forecasting of monthly infiltration, which varies between 30 and 61 mm/month. For this month, the maximum monthly infiltration occurs between the north and south region of the San Diego aquifer, the middle region is the urban zone where the infiltration takes the lower values.

Forecasting of Volume Stored

The forecasting of SSPM coefficients of the monthly volume stored semivariances based on the time series between 2015 and 2017 are shown in Table 22; where it is observed that the tested models are the five, as a sample, the results found for the coefficient "a" are as follows: A) ARIMA(1,0,0) with constant, B) Linear trend = -534.936 + 0.722448 t, C) Simple exponential smoothing with alpha = 0.0618, D) Brown's linear exp. smoothing with alpha = 0.0707 and E) Brown's quadratic exp. smoothing with alpha = 0.0571.

The error statistics by fitting the forecasting models to the SSPM coefficients of the monthly volume stored semivariances based on the time series between 2015 and 2017 are shown in Table 23, which are expressed in terms of three statistics of errors, as a sample, the results found for the coefficient "a" are as follows: for model A: 1) RMSE: 24.8233, 2) MAE: 15.9137, and 3) ME: -0.0170661. For model B: 1) RMSE: 24.2663, 2) MAE: 15.3826, and 3) ME: -1.20334E-15. For model C: 1) RMSE: 24.97, 2) MAE: 15.9582, and 3) ME: 0.413056. For model D: 1) RMSE: 25.1666, 2) MAE: 15.9134, and 3) ME: 0.803444. For model E: 1) RMSE: 26.4411, 2) MAE: 14.8449, and 3) ME: 5.60892. In general, the model selected for forecasting of coefficients of semivariances SSPM of monthly volume stored is the model D corresponding to Brown's linear exp. smoothing with constant alpha because of the error statistics are in the group of lower values.

The forecasting of SSPM coefficients of the monthly volume stored semivariances based on the time series between 2015 and 2017 using Brown's quadratic exp. smoothing with constant alpha are shown in Table 24, the period for forecasting of monthly volume stored covers from 8/17 (August 2017 to 12/18 (December, 2018). The values of coefficients have been selected for forecasting of monthly volume stored for 12/18 as follows*: for coefficient a:* 1) forecast: 11.3475, 2) Lower 95.0% limit: -37.8087, 3) Upper 95.0% limit: 60.5038.

***Table: 19.** Forecasting of SSPM coefficients of the monthly infiltration (mm/month) semivariances based on the time series between 2015 and 2017*

	Coefficient a	b	c	d
(A)	ARIMA(1,0,0) with constant	ARIMA(1,0,0) with constant	ARIMA(1,0,0) with constant	ARIMA(1,0,0) with constant
(B)	Linear trend = -534.936 + 0.722448 t	Linear trend = -840.005 + 1.11164 t	Linear trend = 28874.4 + -30.1244 t	Linear trend = 36.4871 + -0.0393274 t
(C)	Simple exponential smoothing with alpha = 0.0618	Simple exponential smoothing with alpha = 0.0381	Simple exponential smoothing with alpha = 0.0352	Simple exponential smoothing with alpha = 0.0179
(D)	Brown's linear exp. smoothing with alpha = 0.0707	Brown's linear exp. smoothing with alpha = 0.0147	Brown's linear exp. smoothing with alpha = 0.0152	Brown's linear exp. smoothing with alpha = 0.0085
(E)	Brown's quadratic exp. smoothing with alpha = 0.0571	Brown's quadratic exp. smoothing with alpha = 0.0094	Brown's quadratic exp. smoothing with alpha = 0.0096	Brown's quadratic exp. smoothing with alpha = 0.0054

***Table: 20.** Error statistics by fitting the forecasting models to the SSPM coefficients of the monthly infiltration (mm/month) semivariances based on the time series between 2015 and 2017*

Model	a			b			c			d		
	RMSE	MAE	ME	RMSE	MAE	ME	RMSE	MAE	ME	RMSE	MAE	ME
(A)	38.393	31.5795	0.512365	47.2907	36.5492	0.0509439	3233.37	2520.43	-7.26632	2.7214	2.14172	-0.00253684
(B)	39.732	33.1322	5.04256E-14	46.2048	34.7704	-2.0628E-14	3259.3	2569.56	8.80156E-14	2.82666	2.12034	-4.34061-15
(C)	40.7103	35.9983	0.0902728	47.3493	37.2951	-0.0299189	3289.4	2578.28	256.381	2.84185	2.13461	0.233241
(D)	42.5248	35.3469	9.24911	47.4695	37.6039	-0.37612	3284.07	2593.1	181.053	2.84125	2.1415	0.217685
(E)	43.0137	35.7074	8.42748	47.5149	37.6708	-0.15157	3283.32	2597.03	164.26	2.84123	2.13993	0.223722

RMSE = root mean squared error, MAE = mean absolute error, ME = mean error

Table: 21. *Forecasting of SSPM coefficients of the monthly infiltration (mm/month) semivariances based on the time series between 2015 and 2017*

Period	a			b			c			d		
	Forecast	Lower 95.0% Limit	Upper 95.0% Limit	Forecast	Lower 95.0% Limit	Upper 95.0% Limit	Forecast	Lower 95.0% Limit	Upper 95.0% Limit	Forecast	Lower 95.0% Limit	Upper 95.0% Limit
8/17	46.6564	-35.3257	128.638	45.8805	-45.6453	137.406	4855.35	-1476.65	11187.4	4.99118	-0.487024	10.4694
9/17	46.8417	-35.9263	129.61	45.7828	-45.7826	137.348	4864.68	-1470.25	11199.6	4.99293	-0.486067	10.4719
10/17	47.0271	-36.5742	130.628	45.685	-45.9204	137.291	4874.01	-1463.89	11211.9	4.99468	-0.485116	10.4745
11/17	47.2124	-37.2698	131.695	45.5873	-46.0589	137.233	4883.33	-1457.58	11224.2	4.99643	-0.484172	10.477
12/17	47.3978	-38.0136	132.809	45.4896	-46.1978	137.177	4892.66	-1451.31	11236.6	4.99817	-0.483235	10.4796
1/18	47.5831	-38.8056	133.972	45.3918	-46.3374	137.121	4901.99	-1445.08	11249.1	4.99992	-0.482305	10.4822
2/18	47.7685	-39.6462	135.183	45.2941	-46.4775	137.066	4911.31	-1438.9	11261.5	5.00167	-0.481381	10.4847
3/18	47.9538	-40.5354	136.443	45.1964	-46.6183	137.011	4920.64	-1432.76	11274.0	5.00342	-0.480464	10.4873
4/18	48.1392	-41.4732	137.752	45.0986	-46.7596	136.957	4929.97	-1426.67	11286.6	5.00517	-0.479554	10.4899
5/18	48.3245	-42.4594	139.108	45.0009	-46.9015	136.903	4939.29	-1420.62	11299.2	5.00692	-0.478651	10.4925
6/18	48.5099	-43.494	140.514	44.9032	-47.044	136.85	4948.62	-1414.62	11311.9	5.00867	-0.477754	10.4951
7/18	48.6952	-44.5767	141.967	44.8054	-47.1871	136.798	4957.95	-1408.66	11324.6	5.01041	-0.476865	10.4977
8/18	48.8806	-45.7072	143.468	44.7077	-47.3308	136.746	4967.27	-1402.75	11337.3	5.01216	-0.475982	10.5003
9/18	49.0659	-46.8852	145.017	44.61	-47.4751	136.695	4976.6	-1396.88	11350.1	5.01391	-0.475106	10.5029
10/18	49.2513	-48.1102	146.613	44.5122	-47.62	136.644	4855.35	-1476.65	11187.4	5.01566	-0.474237	10.5056
11/18	49.4367	-49.382	148.255	44.4145	-47.7655	136.595	4864.68	-1470.25	11199.6	5.01741	-0.473375	10.5082
12/18	49.622	-50.6999	149.944	44.3168	-47.9117	136.545	4874.01	-1463.89	11211.9	5.01916	-0.47252	10.5108

For coefficient b: 1) forecast: 40.6372, 2) Lower 95.0% limit: -62.6986, 3) Upper 95.0% limit: 143.973. *For coefficient c:* 1) forecast: 4996.3, 2) Lower 95.0% limit: -1581.23, 3) Upper 95.0% limit: 11573.8. *For coefficient d:* 1) forecast: 6.4323, 2) Lower 95.0% limit: 0.39153, 3) Upper 95.0% limit: 12.4731.

In Figure 3 is shown the map of forecasting of monthly volume stored, which varies between -110 and -77 mm/month. For this month, the monthly volume stored takes negative values because of the monthly infiltration value is lower than the monthly evapotranspiration and the monthly pumping flow, as well as, the San Diego aquifer is a confined aquifer; which contains clay and silt layers alternating with well graded sand and gravel. This composition of lithological profile reduces the possibility that the San Diego aquifer can obtain direct water recharge by hydrological processes as infiltration. The water recharge might be provided by rivers and other groundwater sources, being an indirect water research.

Table: 22. *Forecasting of SSPM coefficients of the monthly volume stored semivariances based on the time series between 2015 and 2017*

	Coefficient a	b	c	d
(A)	ARIMA(1,0,0) with constant	ARIMA(1,0,0) with constant	ARIMA(1,0,0) with constant	ARIMA(1,0,0) with constant
(B)	Linear trend = -441.672 + 0.572825 t	Linear trend = -1456.53 + 1.89218 t	Linear trend = -44903.9 + 63.7966 t	Linear trend = 18.3775 + -0.0153342 t
(C)	Simple exponential smoothing with alpha = 0.0549	Simple exponential smoothing with alpha = 0.1048	Simple exponential smoothing with alpha = 0.0707	Simple exponential smoothing with alpha = 0.0049
(D)	Brown's linear exp. smoothing with alpha = 0.0193	Brown's linear exp. smoothing with alpha = 0.0215	Brown's linear exp. smoothing with alpha = 0.0219	Brown's linear exp. smoothing with alpha = 0.0064
(E)	Brown's quadratic exp. smoothing with alpha = 0.048	Brown's quadratic exp. smoothing with alpha = 0.0721	Brown's quadratic exp. smoothing with alpha = 0.0594	Brown's quadratic exp. smoothing with alpha = 0.004

Table: 23. *Error statistics by fitting the forecasting models to the SSPM coefficients of the monthly volume stored semivariances based on the time series between 2015 and 2017*

Model	a			b			c			d		
	RMSE	MAE	ME	RMSE	MAE	ME	RMSE	MAE	ME	RMSE	MAE	ME
(A)	24.8233	15.9137	-0.0170661	50.9443	38.7057	0.250558	3273.69	2703.85	1.09668	2.79456	2.47705	0.0682554
(B)	24.2663	15.3826	-1.20334E-15	48.3873	37.3104	-2.796E-14	3221.57	2646.78	-1.951E-12	3.14316	2.74403	2.14882E-16
(C)	24.97	15.9582	0.413056	51.1079	41.3342	7.72181	3298.33	2778.76	53.9417	3.13796	2.76214	-0.478747
(D)	25.1666	15.9134	0.803444	52.8838	42.6312	6.21051	3355.51	2785.06	230.213	3.12905	2.77503	-0.331947
(E)	26.4411	14.8449	5.60892	54.2384	41.908	8.89848	3399.17	2742.38	506.203	3.12875	2.77373	-0.338518

RMSE = root mean squared error, MAE = mean absolute error, ME = mean error

Table: 24. *Forecasting of SSPM coefficients of the monthly volume stored semivariances based on the time series between 2015 and 2017*

Period	a			b			c			d		
	Forecast	Lower 95.0% Limit	Upper 95.0% Limit	Forecast	Lower 95.0% Limit	Upper 95.0% Limit	Forecast	Lower 95.0% Limit	Upper 95.0% Limit	Forecast	Lower 95.0% Limit	Upper 95.0% Limit
8/17	13.5063	-35.0099	62.0226	47.0431	-54.7788	148.865	5555.58	-912.047	12023.2	6.44509	0.410403	12.4798
9/17	13.3714	-35.1798	61.9226	46.6427	-55.2614	148.547	5520.63	-952.923	11994.2	6.44429	0.409239	12.4793
10/17	13.2365	-35.3504	61.8234	46.2424	-55.7456	148.23	5485.67	-993.921	11965.3	6.44349	0.408072	12.4789
11/17	13.1016	-35.5216	61.7248	45.842	-56.2314	147.915	5450.72	-1035.04	11936.5	6.44269	0.406904	12.4785
12/17	12.9666	-35.6935	61.6268	45.4416	-56.7189	147.602	5415.76	-1076.29	11907.8	6.44189	0.405733	12.4781
1/18	12.8317	-35.8661	61.5295	45.0413	-57.2079	147.29	5380.81	-1117.66	11879.3	6.44109	0.404561	12.4776
2/18	12.6968	-36.0393	61.4328	44.6409	-57.6986	146.98	5345.85	-1159.15	11850.9	6.44029	0.403386	12.4772
3/18	12.5619	-36.2131	61.3368	44.2405	-58.191	146.672	5310.9	-1200.77	11822.6	6.43949	0.40221	12.4768
4/18	12.4269	-36.3877	61.2415	43.8402	-58.685	146.365	5275.94	-1242.52	11794.4	6.4387	0.401031	12.4764
5/18	12.292	-36.5629	61.1469	43.4398	-59.1807	146.06	5240.99	-1284.4	11766.4	6.4379	0.399851	12.4759
6/18	12.1571	-36.7388	61.0529	43.0394	-59.6781	145.757	5206.03	-1326.41	11738.5	6.4371	0.398668	12.4755
7/18	12.0222	-36.9154	60.9597	42.6391	-60.1772	145.455	5171.08	-1368.55	11710.7	6.4363	0.397483	12.4751
8/18	11.8872	-37.0926	60.8671	42.2387	-60.678	145.155	5136.12	-1410.82	11683.1	6.4355	0.396297	12.4747
9/18	11.7523	-37.2706	60.7752	41.8383	-61.1805	144.857	5101.17	-1453.22	11655.6	6.4347	0.395108	12.4743
10/18	11.6174	-37.4493	60.684	41.4379	-61.6848	144.561	5066.21	-1495.76	11628.2	6.4339	0.393917	12.4739
11/18	11.4824	-37.6286	60.5935	41.0376	-62.1908	144.266	5031.26	-1538.43	11600.9	6.4331	0.392724	12.4735
12/18	11.3475	-37.8087	60.5038	40.6372	-62.6986	143.973	4996.3	-1581.23	11573.8	6.4323	0.39153	12.4731

DISCUSSION OF RESULTS

The statistical spatial prediction models of semivariances for water balance variables predicted for December 2018: a) Precipitation, b) Evapotranspiration, c) Pumping flow, d) Infiltration and e) Volume Stored are shown in Figure 5 observing that the binned (red dots) and averaged values (blue cross) are located close to the line corresponding to the J-Bessel function; which is the geostatistical model applied in the water balance variables. The adjustment to the semivariances of each water balance variable to the geostatistical model is based on the semivariances trends to be small for groups of values located in a small distance and the semivariances are increased in a value identified as sill trending to be constant as the distance of the predicted values is increased. The characteristics of the semivariograms shown in Figure 5 are three: 1) Nugget, 2) Sill and 3) Range; which are represented by the predicted coefficients given in the Tables 3, 9, 15, 21 and 24 identified as a, b and c for the predictions corresponding to December, 2018.

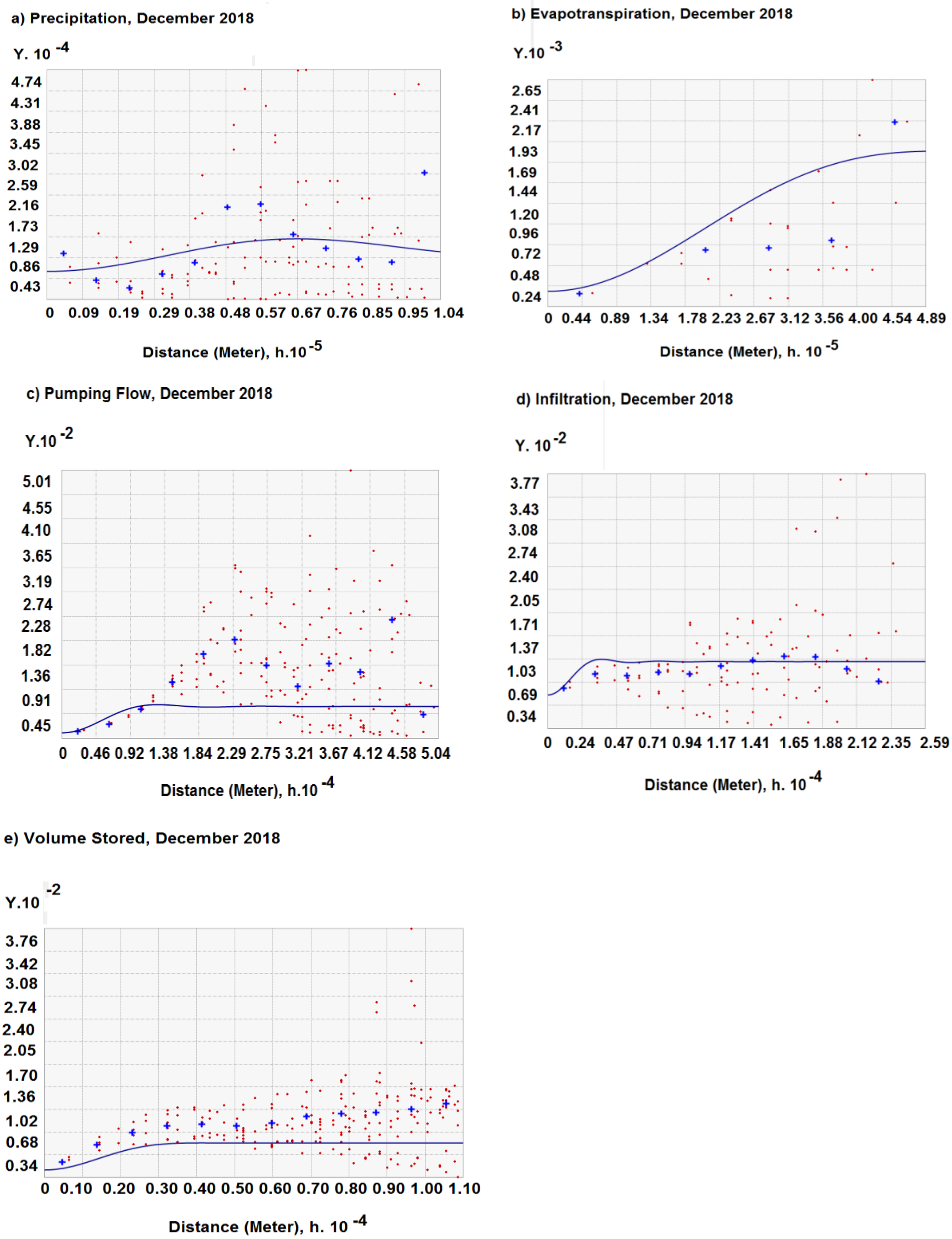


Fig: 5. *Statistical spatial prediction model of semivariances for water balance variables predicted for December 2018: a) Precipitation, b)Evapotranspiration, c) Pumping flow, d) Infiltration and e) Volume Stored*

As a sample, the coefficients for the precipitation semivariances are shown in Table as follows: 1) a: 5812.25, 2) b: 3497.94 and 3) c: 4996.3; where the nugget is the semivariogram model intercept with the y-axis, it is associated to spatial sources of variation at distances smaller than the sampling interval.

The sill is the value where the semivariogram model attains at the range (the value on the y-axis). The partial sill is the sill minus the nugget. The distance where the model first flattens out is known as the range.

CONCLUSION

The spatio-temporal forecasting models of water balance variables in the San Diego aquifer have been calibrated and validated showing a successful adjustment to the water balance variables as the following five variables: 1) precipitation, 2) evapotranspiration, 3) pumping flow, 4) infiltration and 5) volume stored. In the calibration stage, the statistical spatial prediction model selected has been J-Bessel and the forecasting model selected has been Brown's quadratic exp. smoothing with constant alpha. In the validation stage, the correlation coefficient has taken values upper to 0.98 and the determination coefficient upper to 0.96 confirming that the method used to generate the spatio-temporal forecasting model to achieve good predictions to the water balance variables.

REFERENCES

1. Box, G.E.P. Jenkins, G. M. Reinsel, G. C. and Ljung G. M. (2015) *"Time series analysis: forecasting and control".* John Wiley & Sons, 2015.
2. Gandin, L.S., (1960). On optimal interpolation and extrapolation of meteorological fields. Trudy Main Geophys. Obs. 114, 75–89.
3. Goovaerts, P., Webster, R., & Dubois, J. P. (1997). Assessing the risk of soil contamination in the Swiss Jura using indicator geostatistics. Environmental and ecological Statistics, 4(1), 49-64.
4. Hadi, S. J., Shafri, H. Z. and Mahir, M. D. (2014), "Modelling LULC for the period 2010-2030 using GIS and Remote sensing: a case study of Tikrit, Iraq," In IOP conference series: earth and environmental science. IOP Publishing, pp. 012053, 10.1088/1755-1315/20/1/012053.
5. Han, H., Yang, C., Song, J. (2015). "Scenario simulation and the prediction of land use and land cover change in Beijing, China," Sustainability, vol. 7, no. 4, pp. 4260-4279, 10.3390/su7044260.
   Hamilton, J. D. (1994) *Time series analysis*, vol. 2. Princeton: Princeton university press.
6. Isaaks, E. H., & Srivastava, M. R. (1989). Applied geostatistics (No. 551.72 ISA).
7. Jianping, L. Bai, Z. and Feng, G., (2005) "RS-and-GIS-supported forecast of grassland degradation in southwest Songnen Plain by Markov model," Geo-spatial Information Science, vol. 8, no. 2, pp. 104-109, 10.1007/BF02826848.
8. Kumar, S., Radhakrishnan, N. Mathew, S. (2014) "Land use change modelling using a Markov model and remote sensing. Geomatics," Natural Hazards and Risk, vol. 5, no. 2, pp. 145-156, 10.1080/19475705.2013.795502.
9. Krige, D. G. (1951). A statistical approach to some basic mine valuation problems on the Witwatersrand. Journal of the Southern African Institute of Mining and Metallurgy, 52(6), 119-139.
10. Matheron, G. (1963). Principles of geostatistics. Economic Geology, 58, 1246–1266.
11. Mishra, V. N. Rai, P. K. and Mohan, K. (2014) "Prediction of land use changes based on land change modeler (LCM) using remote sensing: a case study of Muzaffarpur (Bihar), India, " Journal of the Geographical Institute" Jovan Cvijic", SASA, vol. 64, no. 1, pp. 111-127, 10.2298/IJGI1401111M
12. Padonou, E. A. Lykke, A. Bachmann, M., Idohou, Y., and Sinsin, B. (2017) "Mapping changes in land use/land cover and prediction of future

extension of bowé in Benin, West Africa," Land Use Policy, vol. 69, pp. 85-92, 10.1016/j.landusepol.2017.09.015.

13. Pijanowski, B. C. Brown, D. G. . Shellito, B. A and. Manik, G. A. (2002), "Using neural networks and GIS to forecast land use changes: a land transformation model," Computers, environment and urban systems, vol. 26, no. 6, pp. 553-575, 10.1016/S0198-9715(01)00015-1.
14. Thornthwaite,C . W., (1948). An approach toward a rational classification of climate, Geogr. Rev., 38(1), 55-94.
15. Thornthwaite, C. W., and J. R. Mather, (1955). The water balance, Publ. Climatol. Lab. Climatol. Drexel Inst. Technol., 8(1), 1-104.
16. Yin, D., Chen, X. Yan, L. and Huang, Z. (2007) "The research and realization of the land-use change forecasting model in development zones based on RS and GIS". In Geoscience and Remote Sensing Symposium, IGARSS 2007. IEEE International. IEEE, pp. 3429-3432, 10.1109/IGARSS.2007.4423582.