Groundwater Withdrawals Prediction in Semi-arid Basins Using Machine Learning Algorithms and Integrated Water Management Models

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Abstract

The use of modeling tools for integrated water resources management is a complex task due to the large number of processes involved in a basin. Moreover, these modeling tools commonly require information that is not readily available, such as illegal water withdrawals, or other data difficult to obtain, which results in groundwater models that fail to capture the aquifer dynamics. In recent years, machine learning algorithms have shown outstanding performance as prediction tools. Despite being questioned for not having a physical basis, they have been used in areas such as hydrology and hydrogeology (e.g., for flow prediction, rain forecast). Thus, the objective of this research is to estimate groundwater withdrawals using machine learning algorithms and integrated water management models. To achieve this objective, ensembles of groundwater levels were generated with a previously calibrated groundwater/surface water integrated model. Then, these ensembles were used as input parameters for Gaussian process regression (GPR) and artificial neural network (ANN) models to construct time series of water withdrawals throughout a basin. This method was applied in the Petorca and La Ligua basins, in central Chile, as they exhibit a contrasting reality in terms of water availability even when they have geographical proximity. Also, these basins are within an effective extraction monitoring program lead by the Chilean water authority that can be used to validate the users' water withdrawal. Our results show that the GPR model, compared to ANNs, adequately estimates the spatiotemporal distribution of groundwater withdrawals in the pilot basins. Thus, the use of machine learning algorithms improves the performance of integrated water resources management models.

Groundwater withdrawals prediction in semi-arid basins using machine learning algorithms and integrated water management models

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Integrated Management of Water Resources **(IMWR)**

problems related to

- Resources availability
- Institutional capacities
- Represent systems through **models**

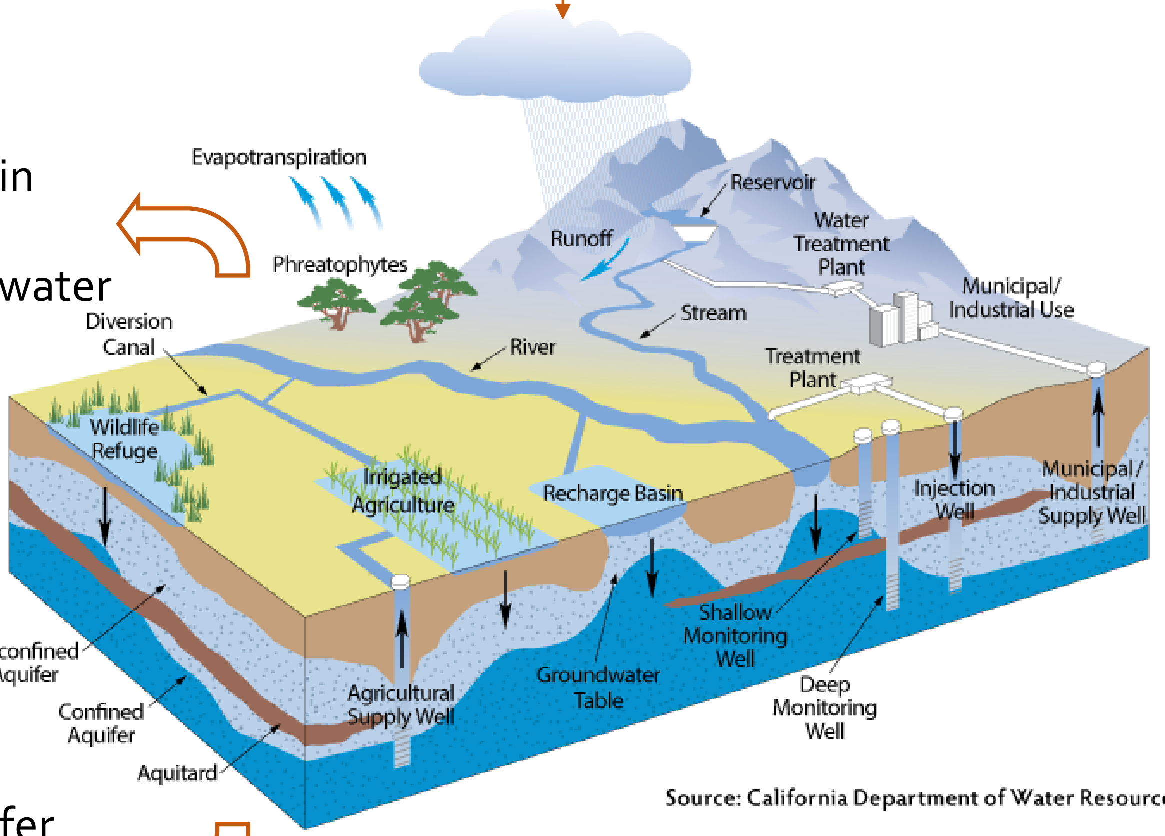
Problems?

Lack of data

Groundwater models that fail to capture the aquifer dynamics

Basin

Surface water



Source: California Department of Water Resources

Aquifer

Groundwater

Machine Learning Algorithms

Supervised Learning

Regression

Analysis of continuous variables

- Lineal Regression Models
- Regression Trees
- Support Vector Machines Regression (SVM)
- Gaussian Process Regression Model (GPR)
- Kernel Approximation Regression Models
- Ensembles of Trees
- Artificial Neural Networks (ANN)

- Streamflow prediction
- Rain forecast
- Short-term groundwater level prediction

(Wang, et al., 2006;
Lange y Sippel, 2020;
Band et al., 2021)

Classification

Objective

Estimate groundwater withdrawals using machine learning algorithms and integrated water management models.

Part I - Integrated model of water resources

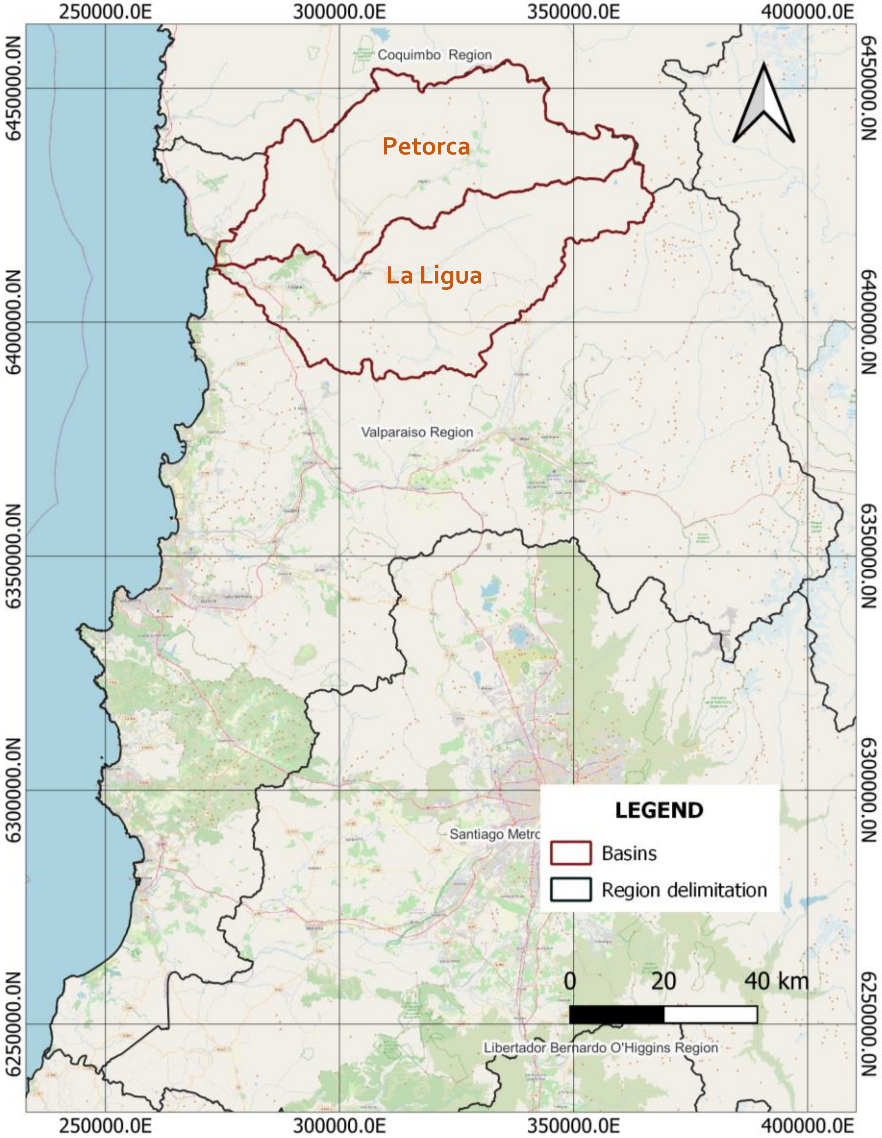


Figure: Pilot basins.

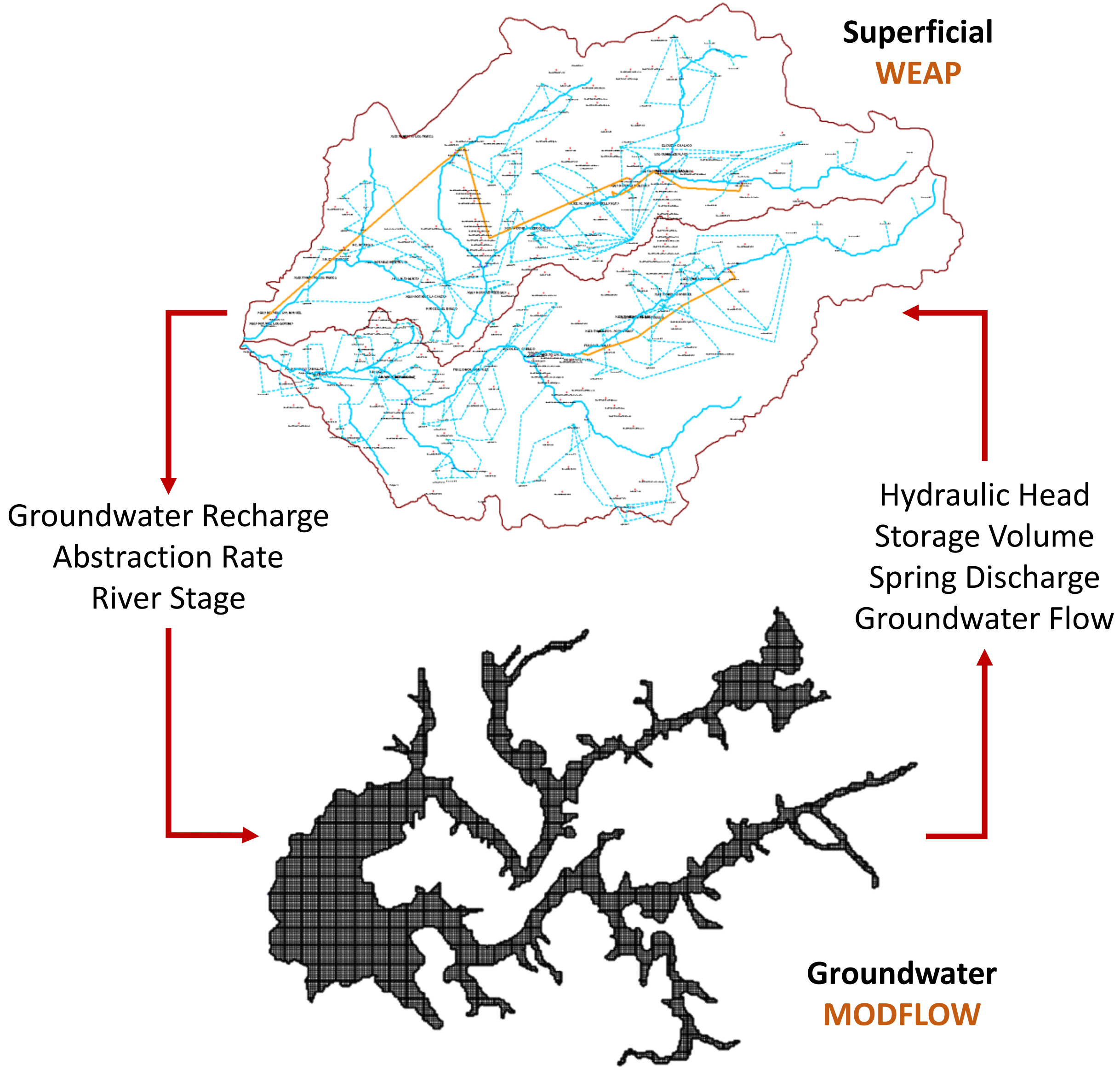


Figure: Schematic configuration of the integrated model of WEAP-MODFLOW.

Part II – Machine Learning algorithms - Training

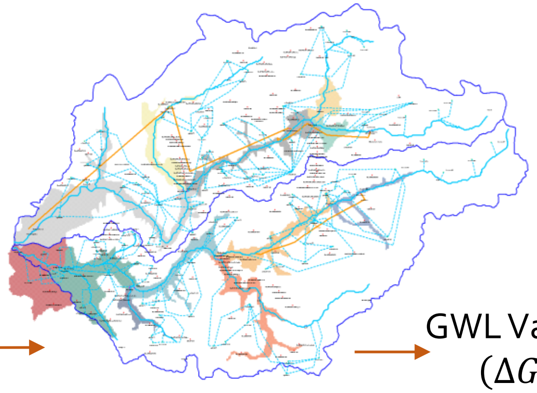
Obtaining data within WEAP – MODFLOW model

Demand sites

Water Use Rights

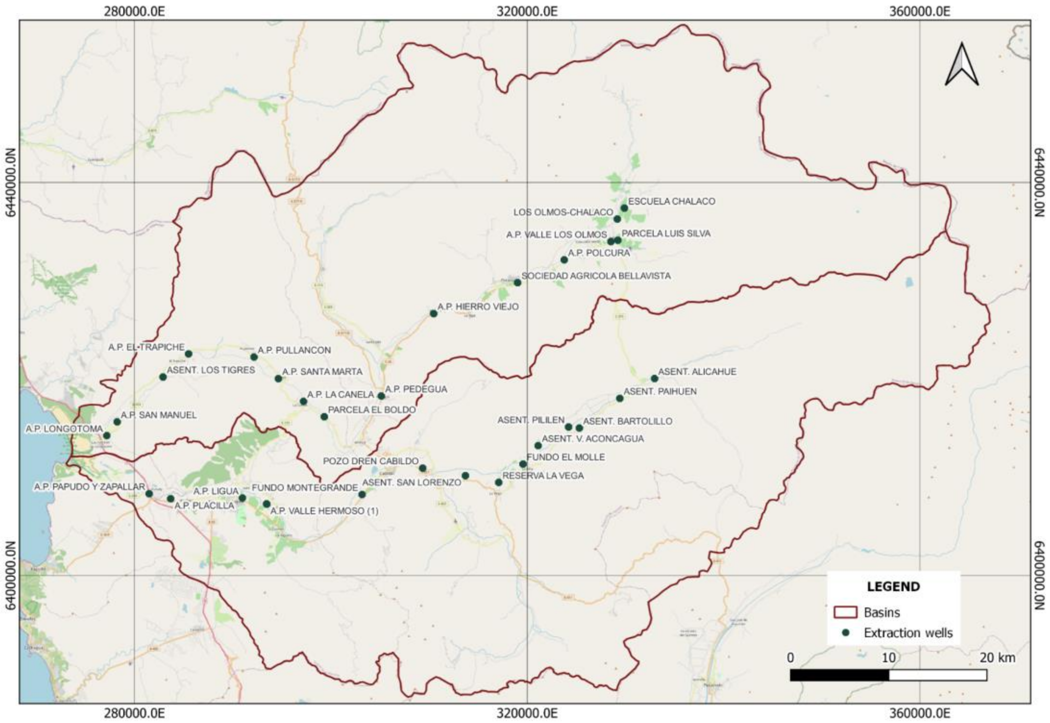
Demand Variations (ΔWUR)

WEAP – MODFLOW Execution



GWL Variations (ΔGWL)

Output ← **Input**



Training process

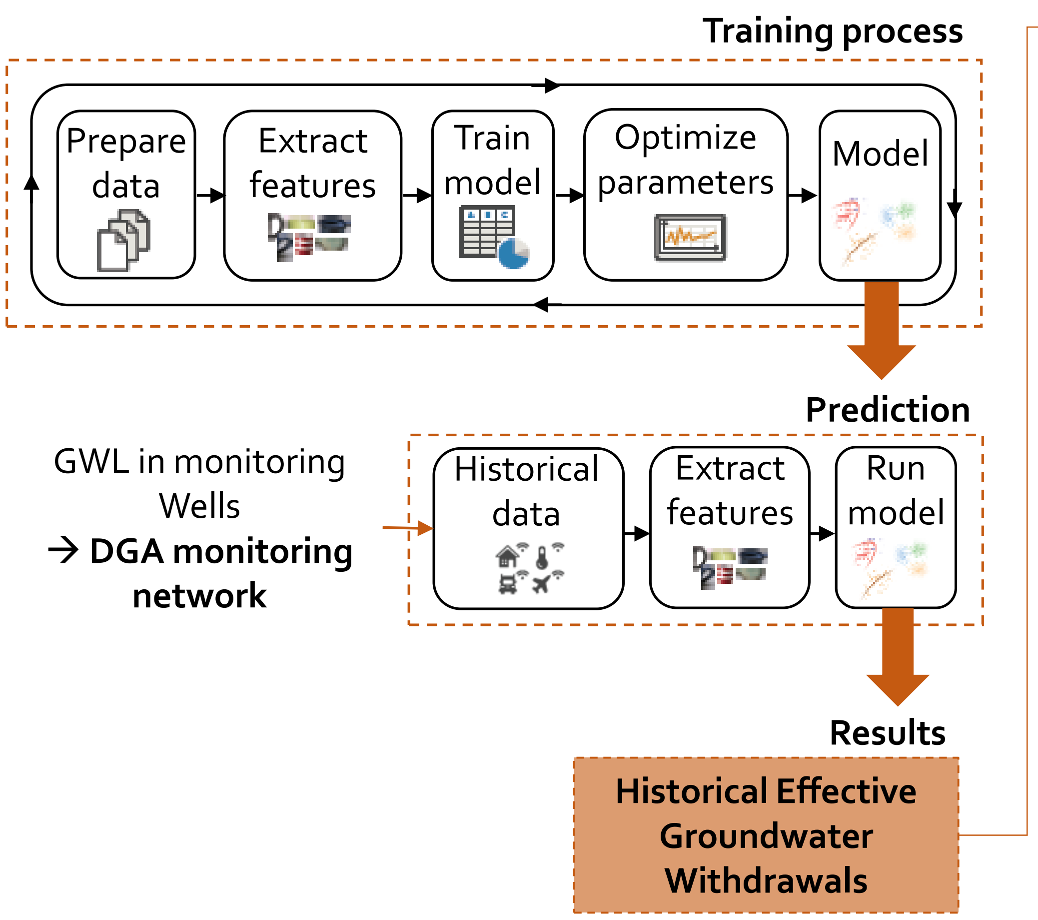
Prepare data → Extract features → Train model → Optimize parameters → Model

Metrics:

- R^2
- RMSE
- MSE
- MAE

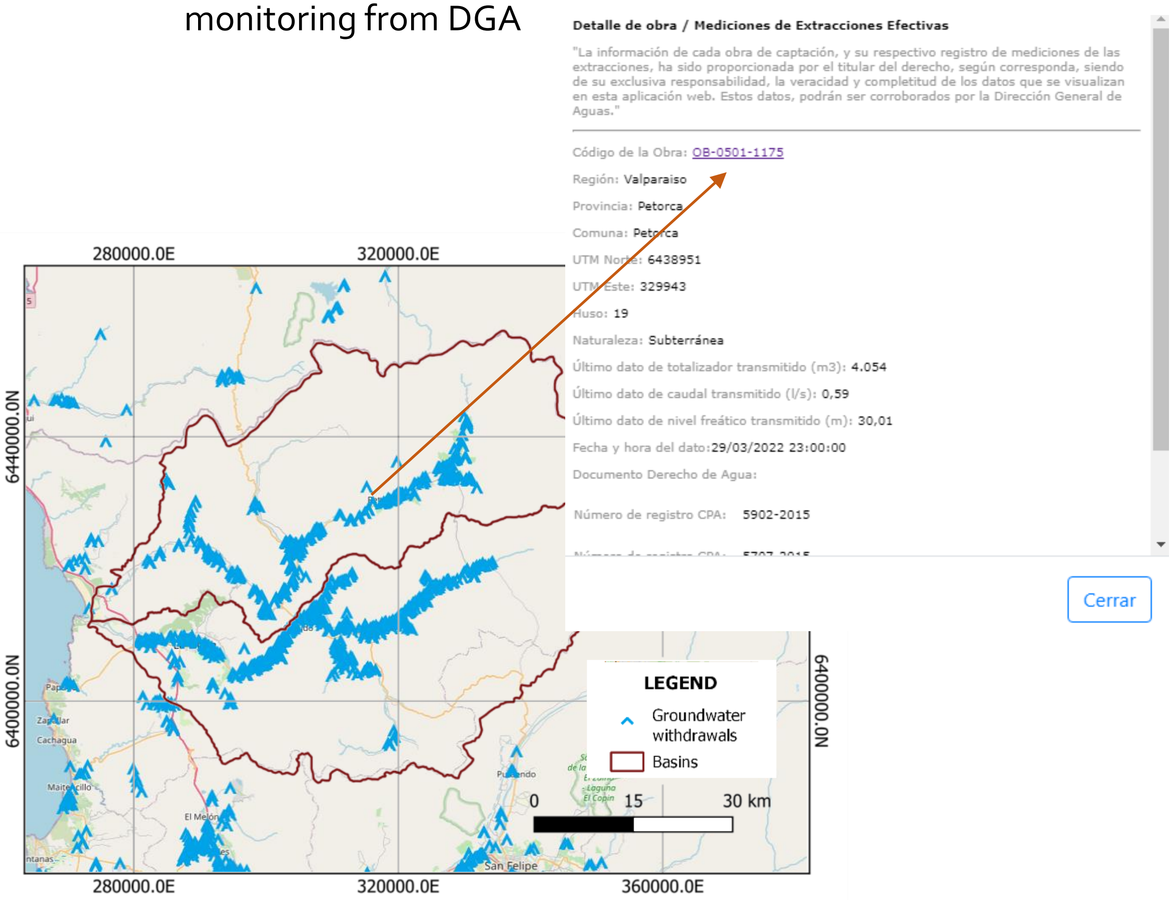
- *Gaussian Process Regression Model* (*GPR*)
- *Artificial Neural Networks* (*ANN*)

Part II – Machine Learning algorithms - Prediction

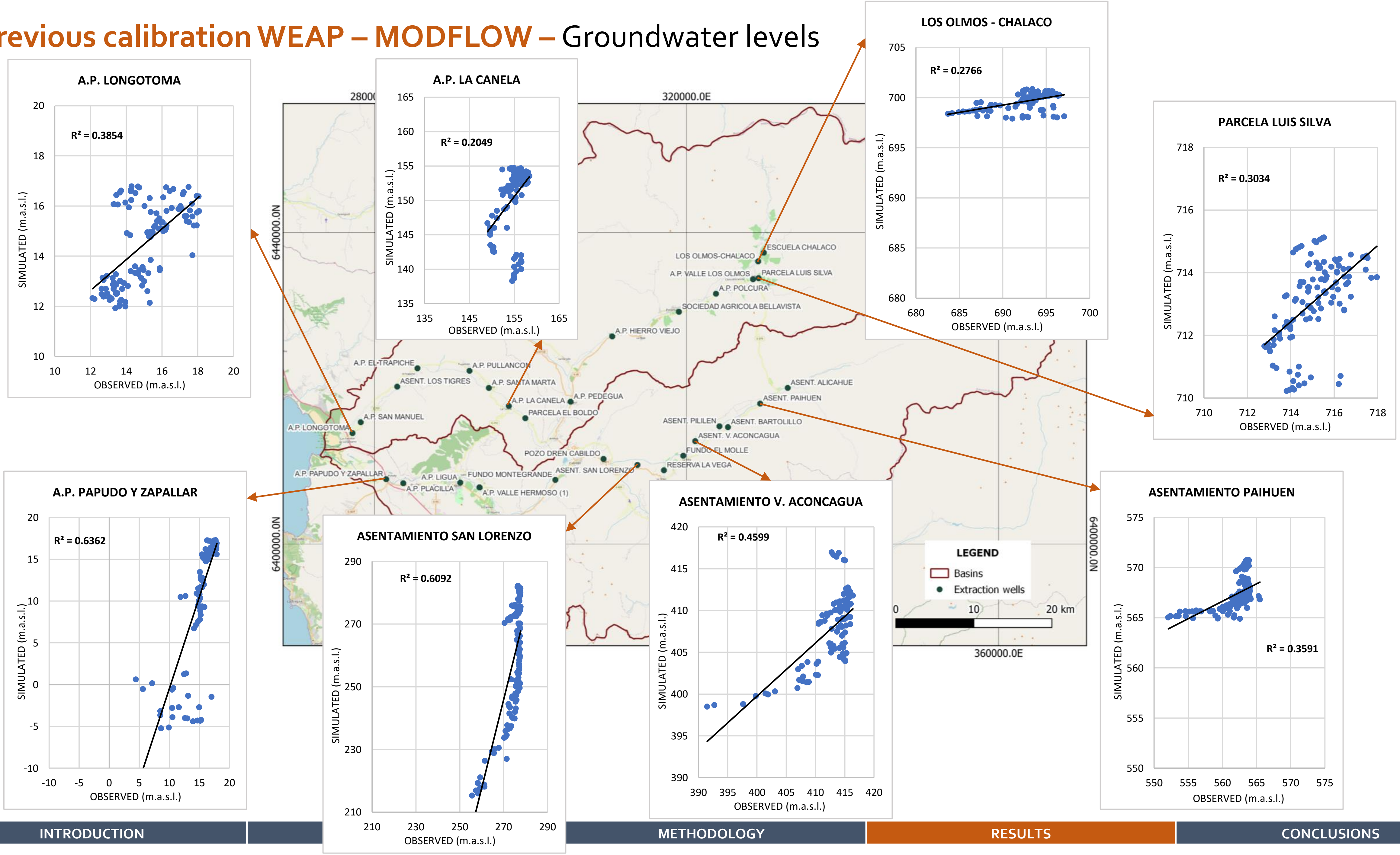


Calibration → WEAP – MODFLOW model
Historic period: 1980 – 2021

Validation → Record of effective extraction monitoring from DGA



Previous calibration WEAP – MODFLOW – Groundwater levels



Metrics – Training algorithms

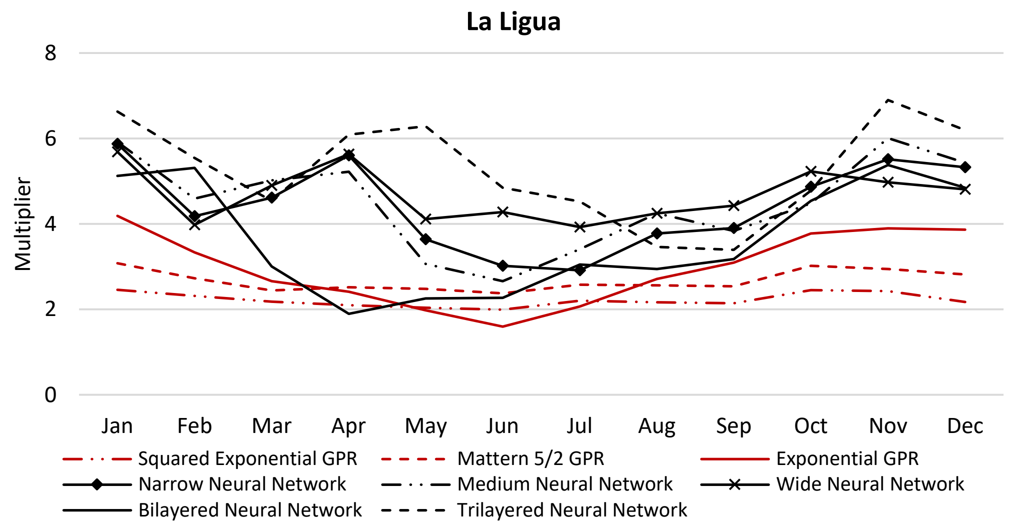
Table. Metrics obtained from the training algorithms process in **La Ligua** river basin.

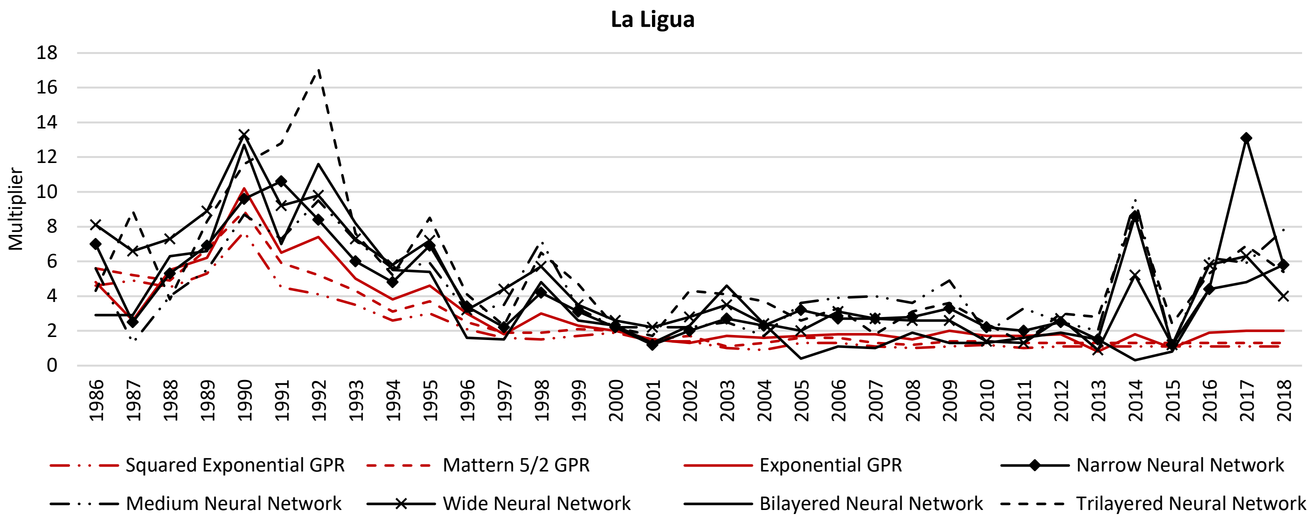
Algorithm	Configuration	Training results			
		RMSE	R^2	MSE	MAE
GPR model	Squared Exponential GPR	0.3768	0.95	0.1420	0.2318
	Matern 5/2 GPR	0.3426	0.96	0.1174	0.1977
	Exponential GPR	0.2895	0.97	0.0838	0.1342
Artificial Neural Network	Narrow Neural Network	0.4357	0.93	0.1898	0.2841
	Medium Neural Network	0.3999	0.94	0.1599	0.2514
	Wide Neural Network	0.3627	0.95	0.1316	0.2235
	Bilayered Neural Network	0.3961	0.94	0.1569	0.2518
	Trilayered Neural Network	0.3840	0.95	0.1474	0.2387

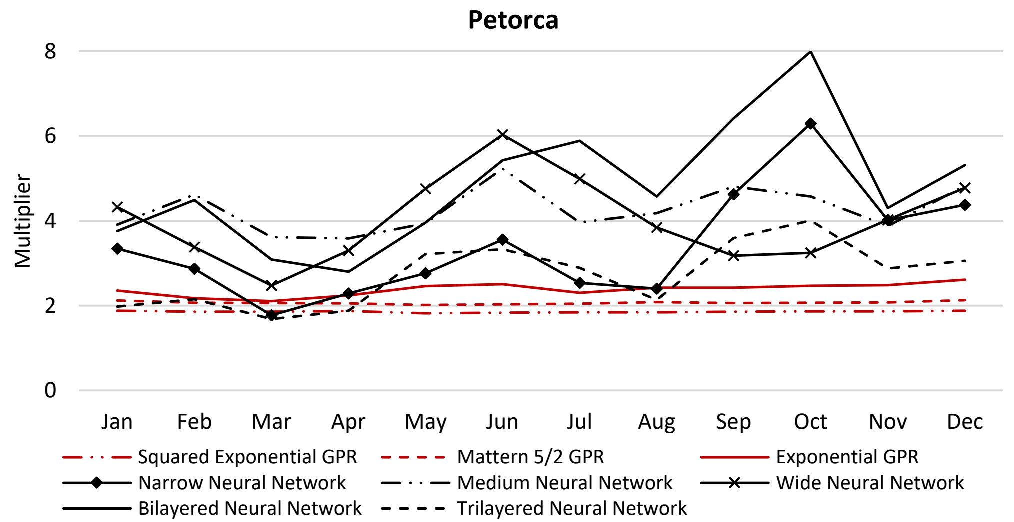
Table. Metrics obtained from the training algorithms process in **Petorca** river basin.

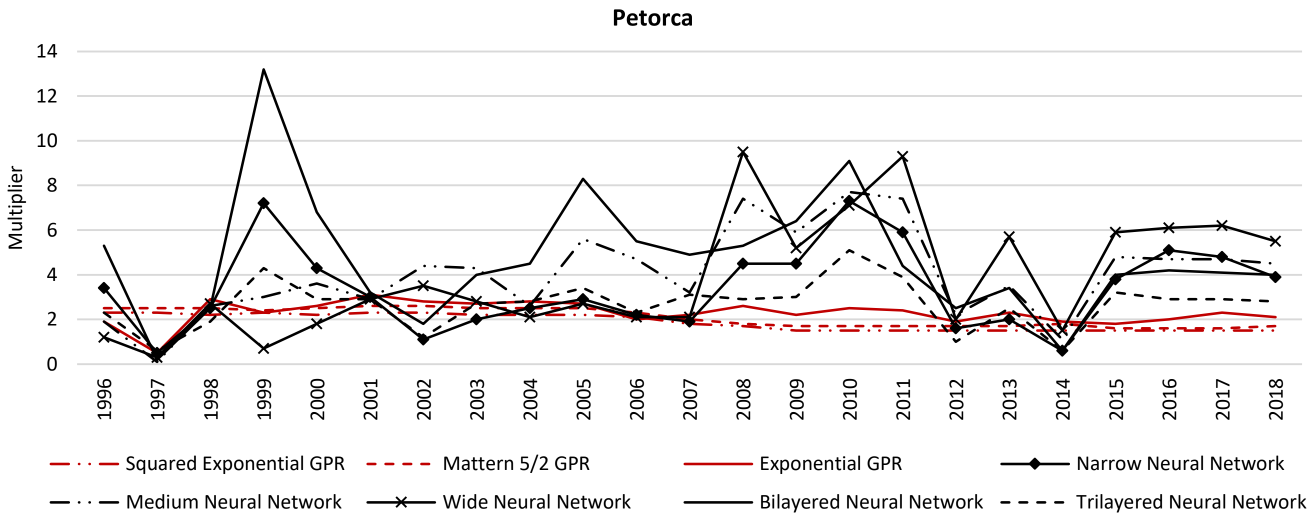
Algorithm	Configuration	Training results			
		RMSE	R^2	MSE	MAE
GPR model	Squared Exponential GPR	0.1603	0.98	0.0257	0.0749
	Matern 5/2 GPR	0.1341	0.99	0.0180	0.0599
	Exponential GPR	0.1311	0.99	0.0172	0.0618
Artificial Neural Network	Narrow Neural Network	0.2678	0.94	0.0717	0.1732
	Medium Neural Network	0.2035	0.97	0.0414	0.1306
	Wide Neural Network	0.1639	0.98	0.0268	0.1011
	Bilayered Neural Network	0.2103	0.96	0.0442	0.1329
	Trilayered Neural Network	0.2105	0.96	0.0443	0.1302

Groundwater withdrawals prediction - Effective groundwater withdrawals predictions show an increase compared to assigned water rights.

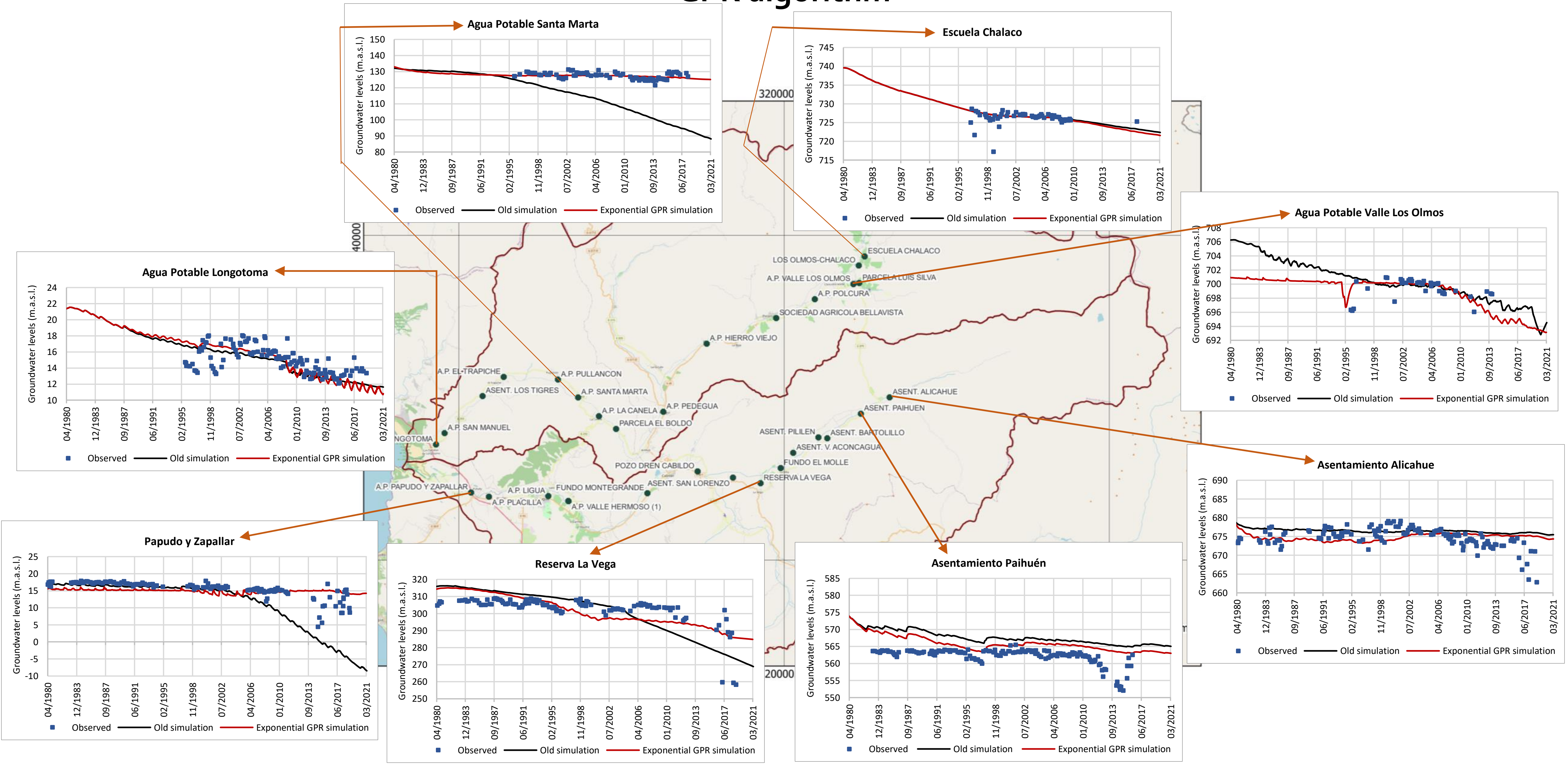








Re-calibration WEAP – MODFLOW model – Effective groundwater withdrawals obtained from **Exponential GPR algorithm**



Conclusions

- Our results show that the **GPR model**, compared to ANNs, adequately estimates the spatiotemporal distribution of groundwater withdrawals in the pilot basins.
- Thus, the use of machine learning algorithms improves the performance of integrated water resources management models.

- The initial years show a high increase in the effective groundwater withdrawals compared with the water rights in La Ligua river basin. This could be because, with time, the water rights registration has been improved.
- We can assume or deduce that the increase calculated in the effective groundwater withdrawals for the algorithms is due to the illegal extractions in those areas or to temporal water rights awarded from the DGA.

Next steps

- Disaggregated analysis by aquifer sectors.
- Application of other machine learning algorithms, e.g., Support Vector Machines Regression, Linear Regression Models, among others.
- Improve the based model with more observed data and with the support of the stakeholders (water users).

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Annex – Algorithms configuration

Table. GPR model

Algorithm	Configuration	Model Hyperparameters							
		Basis function	Kernel function	Use isotropic kernel	Kernel scale	Signal standard deviation	Sigma	Standardize	Optimize numeric parameters
GPR model	Rational Quadratic GPR	Constant	Rational Quadratic	true	Automatic	Automatic	Automatic	true	true
	Squared Exponential GPR	Constant	Squared Exponential	true	Automatic	Automatic	Automatic	true	true
	Matern 5/2 GPR	Constant	Matern 5/2	true	Automatic	Automatic	Automatic	true	true
	Exponential GPR	Constant	Exponential	true	Automatic	Automatic	Automatic	true	true

Table. Artifitial Neural Network

Algorithm	Configuration	Model Hyperparameters							
		Number of fully connected layers	First layer size	Second layer size	Third layer size	Activation	Iteration limit	Regularization strength (Lambda)	Standardize data
Artificial Neural Network	Narrow Neural Network	1	10			ReLU	1000	0	Yes
	Medium Neural Network	1	25			ReLU	1000	0	Yes
	Wide Neural Network	1	100			ReLU	1000	0	Yes
	Bilayered Neural Network	2	10	10		ReLU	1000	0	Yes
	Trilayered Neural Network	3	10	10	10	ReLU	1000	0	Yes