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Transición energética en la 4ta revolución industrial

Universidad Tecnológica de Pereira

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Prediction Model Of Primary Solar Resource With The Use Of Machine Learning, Current Results

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Contents

I. Introduction

--Design of photovoltaic systems based on solar radiation atlases.

- There is climate information that is not recognized as important in the long-term planning of photovoltaic systems.

-Due to the high variability of the primary resource, there are problems to ensure the long-term photovoltaic electricity supply.

PROPOSED SOLUTION

Prediction of primary resource with the use of techniques based on Machine Learning (ML).

I. Introduction

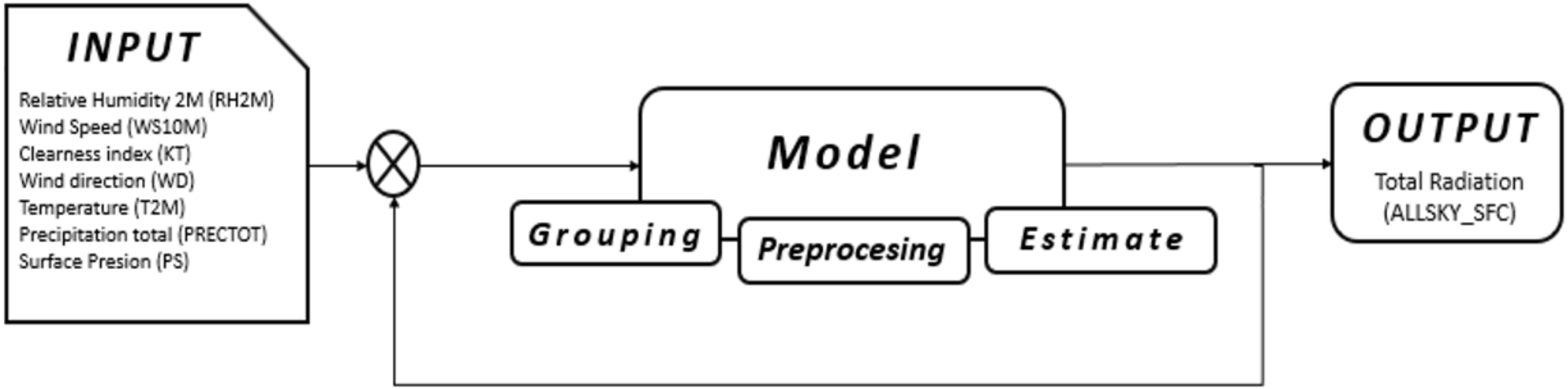
Table I. Classification of unit predictors using established criteria.

Criteria					
Predictors	**Treatment of no linearity**	**Behavior when using multiple inputs.**	**Error**	**Model flexibility**	**Horizon forecast**
NN					Variable
SVM					Variable
Fuzzy					A day ahead
k-NN					A day ahead
(ARIMA)					Variable
Decision tree					Hour
k-means					Hour

Source: Authors

II. Materials and methods

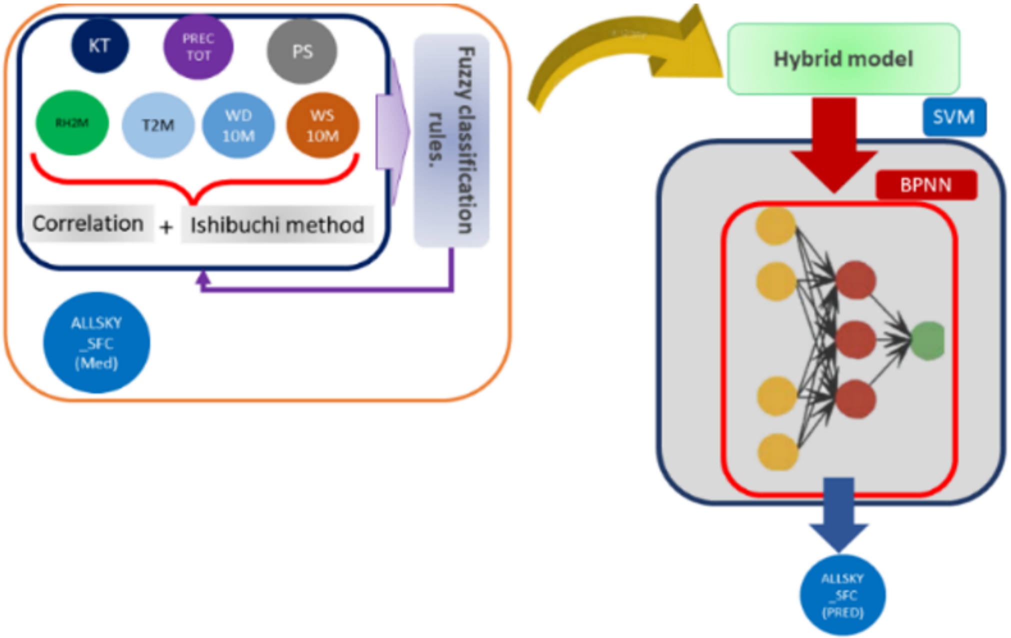
Fig. 1. Hybrid predictor topology.



Source: Authors.

I. Materials and methods

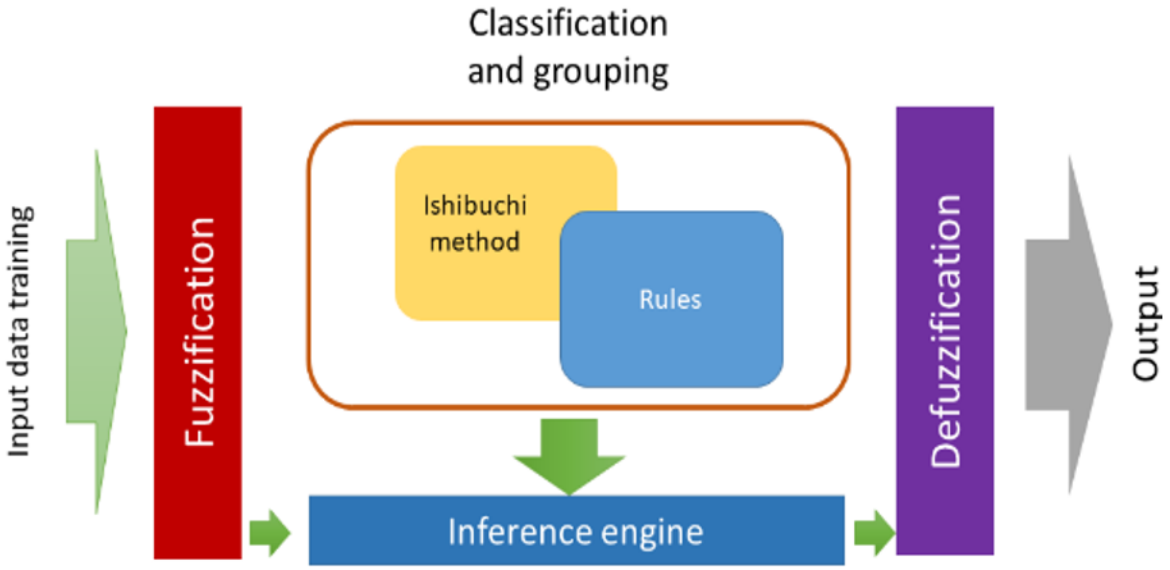
Fig. 2. Proposed ML model.



Source: Authors.

II. Materials and methods

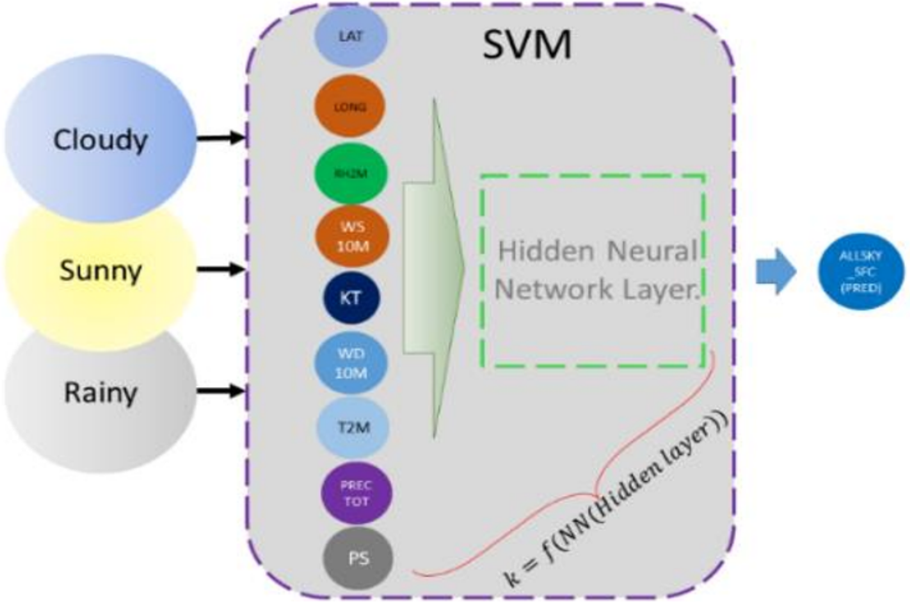
Fig. 3. Fuzzy logic classifier components.



Source: Authors

II. Materials and methods

Fig. 4. Hybrid main predictor components.



Source: Authors

II. Materials and methods

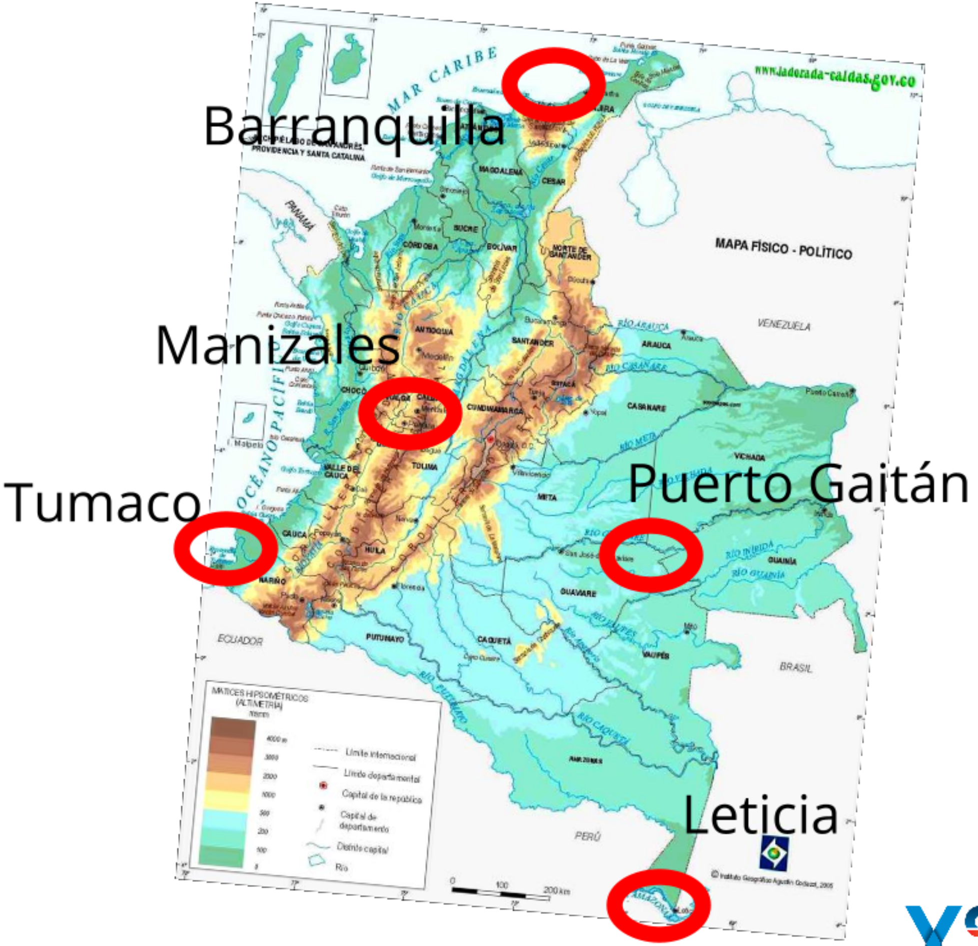
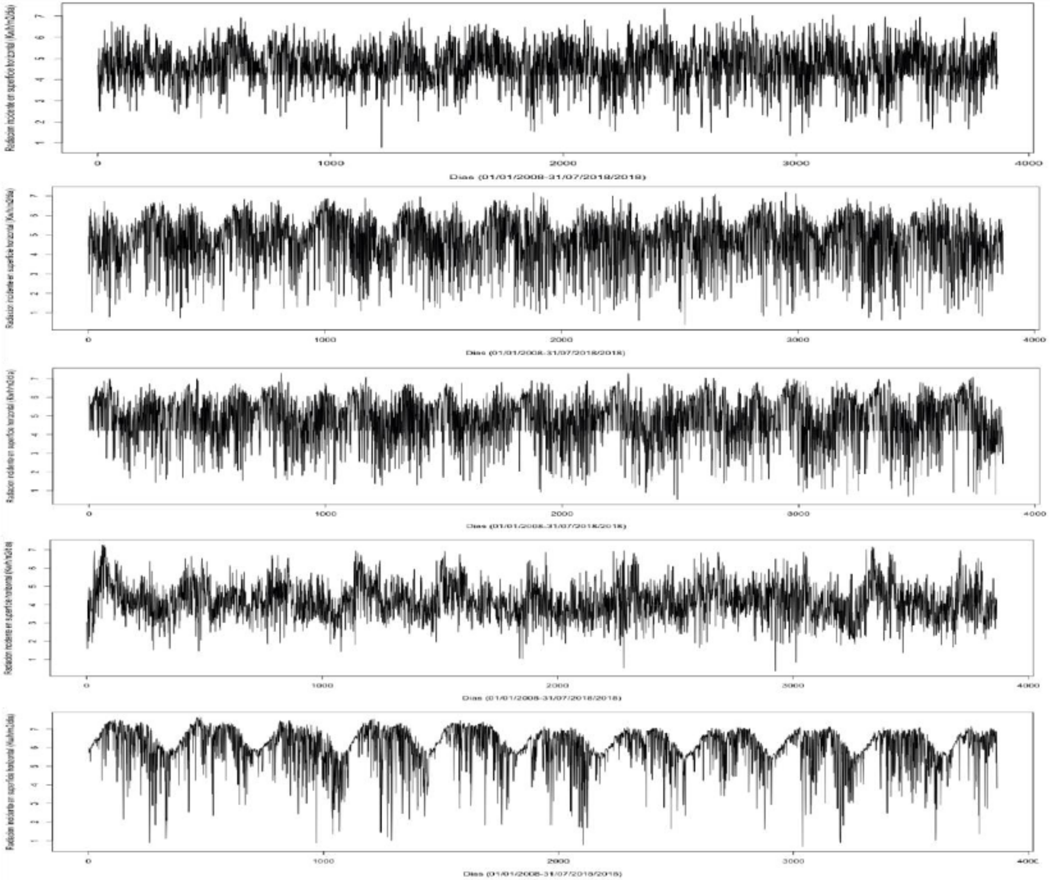


Fig. 5. Study cities.

II. Materials and methods

Fig. 6. Solar raditaion in Study cities.



Mountain

Forest

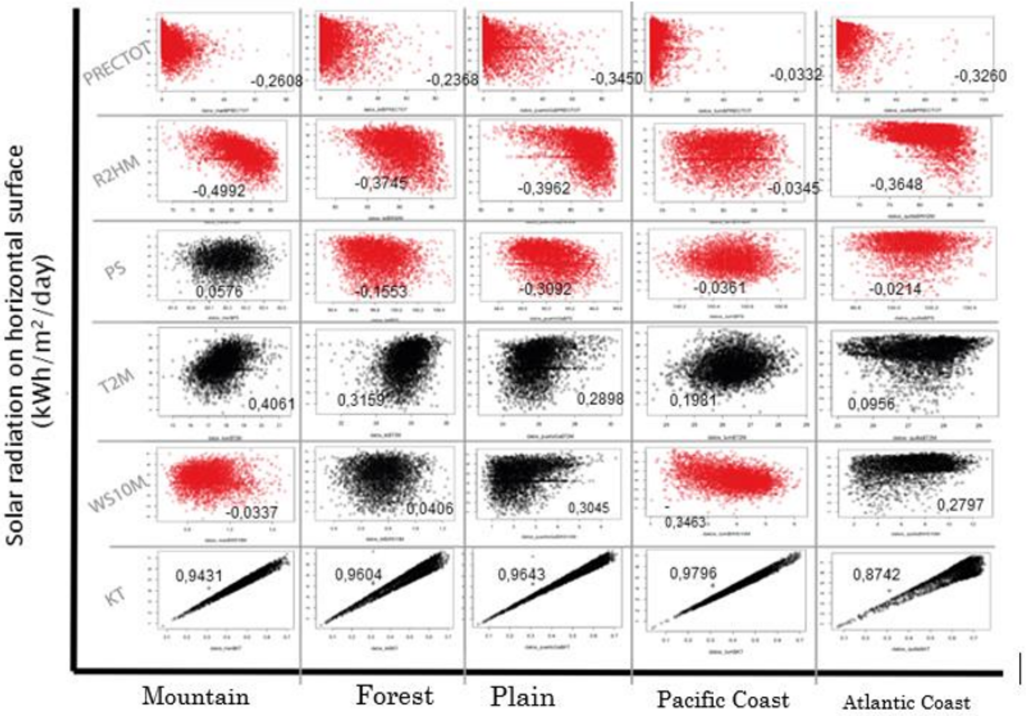
Plain

Pacific Coast

Atlantic Coast

III. Results

Fig. 7. Daily radiation correlation graphs and climate data from 01/10/2009 to 07/31/2020



Source: Authors

III. Results

Table II. Results of the SVM model in the cities evaluated.

Natural Regions	Parameter			
	ε	Support vectors	Value objective function	Training Error
Mountain	0.3	1770	-367.481	0.1133
Plain	0.2	1439	-463.437	0.3014
Forest	0.17	1646	-233.756	0.0472
Pacific Coast	0.5	1553	-1005.49	10.61
Atlantic coast	0.21	2215	-743.441	0.2165

Source: Authors

III. Results

Table III. Model metric values evaluated in cities.

Natural Region	r	U^M	U^S	U^C	$\sum U^M + U^S + U^C$	$RMSE$	MSE
Mountain	0.937	0.00781082	0.00677162	0.986269	1,00085235	0.0480485	0.0023086
Forest	0,958	0.00708421	0.00214435	0.991624	1,00085297	0.0446628	0.0019947
Plain	0.963	0,03978723	0.00260174	0.958436	1,00082497	0,0987763	0.0097567
Pacífic Coast.	0.481	0,02433792	0.68385410	0.292646	1,00083812	0.7167485	0.5137284
Atlantic Coast	0.913	0.07505674	0,01250164	0.913236	1,00079450	0,0686814	0.0047171

Source: Authors

IV. Conclusions

The model that is designed in this paper considers geographical conditions for the quantification-prediction of primary solar resource.

The model is a contribution to the development and visibility of computational techniques, which will be taken as tools to help in decision-making in the face of the reality of the growth of Distributed Generation with PV sources and data as resources that inform the way of working with energy.

Thanks!

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IV. Questions