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Development of a Quantile Regression Model for Replicating Extreme Precipitation in Different Climatic Zones of Morocco

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ABSTRACT

In Morocco, where floods represent the most frequent risk, the modeling of this phenomenon primarily relies on precipitation data. Given the dispersion and scarcity of meteorological stations in the country, as well as gaps in the recorded series, many researchers turn to satellite data to obtain this crucial information. However, the direct use of satellite data can introduce biases, necessitating research efforts to correct them. Several studies have proposed solutions, such as the merging of satellite products or the use of arithmetic corrections like averaging, but these focus mainly on the central part of the data (low to moderate precipitation), leaving extreme events, which cause floods, uncorrected.

Our contribution is divided into two parts: first, we evaluated the reliability of different satellite data sources, including GPM, ERA5, TRMM, and PERSIANN. Then, we developed a quantile regression (QR) model tailored to each homogeneous region (five regions) in terms of climatic factors responsible for generating extreme events. This model was designed to accurately reproduce extreme events, even in areas lacking measurement stations. We used the Kullback-Leibler (KL) distance to determine the rate that best reproduces ground precipitation. Subsequently, a comparison of the selected model with the linear regression model was made to demonstrate that the latter cannot accurately inform about extreme precipitation.

The results reveal a variation in the rate of the selected regression model from one area to another, as well as the coefficients defining the contribution of each satellite product, depending on the specific rainfall regime of each homogeneous region. We validated our model through different approaches: validation using extreme precipitation, validation using other stations outside the DGM network, and another validation using extreme events beyond the period [2000-2018] used to construct the QR model.

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Abbreviations

QR: Quantile Regression LR: Linear Regression
KL: Kullback-Leibler Distance
DGM: General Directorate of Meteorology
DRPE: Directorate of Water Research and Planning

Introduction

Based on climatic factors responsible for generating extreme events, a delineation of homogeneous zones was performed [1]. Moreover, the quality of rainfall estimates by remote sensing has significantly improved, following the evolution of measurement devices. The need for a very dense measurement network to assess the spatial variability of precipitation and the emergence of satellite products have driven many researchers and scientists to conduct comparative studies of these products to evaluate their reliability before using them in various calculations and modeling.

Satellite products must be validated before their potential use in hydrological modeling to evaluate water resource forecasting and in climate models to predict flood or drought risks [2]. Studies have been conducted both nationally and internationally to assess the reliability of satellite measurements over different geographical areas. For example, conducted a study on the comparison of high-resolution satellite precipitation products in Central Asia; studied the comparison between satellite-gauge adjusted precipitation estimates and their applicability for effective water resource management in the transboundary Meghna River basin; evaluated the performance of the TRMM 3B42 V7 rainfall product over the Oum Er Rbia watershed in Morocco; and assessed remote sensing precipitation estimates in Saudi Arabia [3-6].

International reinsurances require the use of satellite data to evaluate and insure climate risks. These institutions need reliable and consistent data to determine insurance premiums and potential compensations in the event of a disaster. The validation and integration of satellite data into forecasting and risk management models allow for meeting international standards and ensuring adequate coverage against climate risks. This is particularly crucial in a context where the variability and intensity of extreme weather events are increasing.

The objective of this study is to construct a quantile regression model to accurately estimate precipitation at any point in a watershed, using satellite-measured precipitation data. Various types of satellite precipitation data are available, but for this study, we opted to use data from GPM, ERA5, TRMM, and PERSIANN, which have been identified through several statistical analyses as the most appropriate or closest to ground measurements.

Study Area

In order to account for the spatio-temporal variation of precipitation prevailing from North to South of Morocco and to reproduce precipitation at any point based on satellite precipitation data, we used 38 rain gauge stations covering all climatic regions of Morocco. The study area corresponds to the Moroccan territory. Figure 1 illustrates the boundaries of the area as well as the geographical locations of the rain gauge stations:

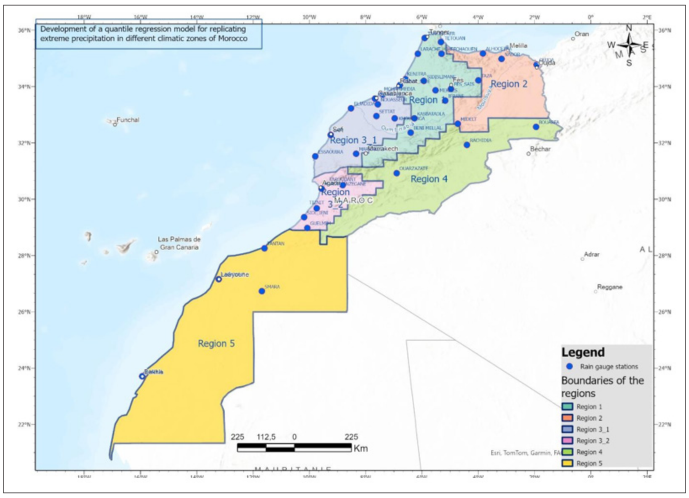


Figure 1: Study Area

Data, Materials, and Methods

Methodology

The methodology adopted in this work is based on five main axes:

Data Preparation

We began by preparing the precipitation data for each homogeneous climatic region defined in the article by [2]. Each region was analyzed separately to ensure the relevance of the results.

Downloading Satellite Precipitation Data

The satellite precipitation data were downloaded from the Climate Engine platform (https://app.climateengine.org/climateEngine). This platform provides access to high-resolution satellite data, which is essential for our analysis.

Development of Quantile Regression (QR) Models

For each region, we developed a Quantile Regression (QR) model for different quantiles (0.1, 0.2, 0.3, ..., 0.9). A rainfall threshold of 20 mm was used for all regions except regions 4 and 5, where the threshold was set to 10 mm. This threshold helps improve the performance of our model in reproducing extreme events and minimizes the impact of low rainfall values on model construction.

Calculation of KL Distance

We calculated the Kullback-Leibler (KL) distance between the developed quantile regression models and the observed rainfall data. The regression model with the smallest KL distance was selected as the most effective.

Model Validation

The selected model was validated using extreme events recorded in locations different from those used for model construction. This allowed us to verify the robustness and reliability of our model under real conditions.

Data

The data used in this study are grouped into three categories: Satellite Precipitation Data: ERA5, GPM, TRMM, and PERSIANN are the primary sources of satellite precipitation studied.

Ground-Measured Precipitation by DGM: These data are assumed to be accurate and serve as a reference.
Ground-Measured Precipitation by DRPE: Used to validate the obtained results.

ERA5 is a climate reanalysis model developed by the European Centre for Medium-Range Weather Forecasts (ECMWF). It utilizes various techniques including ground-based meteorological station measurements, satellite data to estimate real-time global precipitation, and numerical weather prediction models to produce precipitation estimates. The spatial resolution of ERA5 data is 11 km [7].

GPM (Global Precipitation Measurement): GPM measures precipitation quantity using satellites equipped with microwave and radar sensors that measure precipitation through clouds and weather conditions. Raw data are then corrected for systematic errors such as calibration errors and biases. Validated data using ground-based measurements are used to produce a variety of precipitation products [8]. The spatial resolution of GPM data is 9.6 km.

TRMM (Tropical Rainfall Measuring Mission): This satellite provides precipitation estimates based on microwave and radar sensor measurements. TRMM data are corrected for biases and validated with ground-based precipitation data, offering global coverage of tropical and subtropical precipitation with a spatial resolution of 0.25° x 0.25° [9].

PERSIANN (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks): This product uses artificial neural networks to estimate precipitation from satellite data. Infrared data are combined with ground-based precipitation observations to improve estimation accuracy. PERSIANN has a spatial resolution of 0.25° x 0.25° [10].

Materials

The software R was employed for performing all necessary calculations, leveraging its extensive documentation, package availability, and performance in handling complex and repetitive operations [11].

Regarding satellite data, various platforms now offer direct download options for climate parameters such as temperature and precipitation. For this study, the Climate Engine platform (https://app.climateengine.com/climateEngine) was used to download daily precipitation data measured by the three satellites [12].

Theoretical Methods

To assess the accuracy of satellite-measured precipitation compared to ground-based measurements, commonly used performance criteria were applied. These criteria include the correlation coefficient (CC), root mean square error (RMSE), normalized root mean square error (NMSE), and relative bias (BR). These crite ria have been employed in various studies, including the one conducted by [3].

Quantile Regression (QR): The objective of quantile regression is to estimate the parameters of a linear or nonlinear regression model that minimizes the sum of weighted absolute residuals, where the weights are determined by the quantile being estimated. QR provides a more comprehensive understanding of the distribution of the response variable across different quantiles. The equation is provided in the annexes.

Kullback-Leibler Distance: The Kullback-Leibler (KL) distance is a measure of divergence between two probability distributions, used to quantify the difference between observed precipitation and that modeled by quantile regression. Quantile regression models the relationships between variables by estimating different quantiles of the response variable's distribution, which is useful for precipitation data that is often asymmetric and extreme [13]. This method allowed us to measure the divergence between the distributions of observed and modeled precipitation at different quantiles, identifying potential anomalies or biases in our model. The use of KL distance to evaluate probabilistic forecasts has been validated in previous studies [14].

For continuous distributions, as is our case, the KL distance is defined as follows:

$$D_{KL}(P\|Q) = \int_{-\infty}^{\infty} p(x) \log \frac{p(x)}{q(x)}\, dx$$

Where p(x) and q(x) are the probability density functions of P and Q, respectively.

Results and Discussions

Descriptive Statistics

To highlight that a single satellite product cannot be universally applied across the five climatic regions, it is essential to understand the varying accuracy of satellite products across these regions. Studies have shown that each satellite product performs differently across different zones [15]. For instance, satellite precipitation estimation performance can vary significantly between tropical and arid regions due to differing atmospheric dynamics and surface conditions.

In order to overcome these limitations, we developed a quantile regression model that integrates multiple satellite products for each climatic region. This model leverages the strengths of each product in different zones, thereby improving the accuracy of precipitation estimates [16].

Furthermore, given that available records mostly contain very low or zero precipitation values (less than 2 mm), we chose to compute boxplots only for precipitation values strictly exceeding 2 mm in each zone. This approach better captures the variability of significant precipitation events and provides a more representative analysis of actual climatic conditions.

We did not use RMSE, MSE, R^2, and BR metrics as we believe these metrics provide relevant values primarily for the central parts of distributions, which does not align with the objectives of this study.

Development of RQ and RL Regression Models

The objective of this stage is to construct a quantile regression model and a linear regression model for the five regions, with a dual purpose: firstly, to accurately compute the coefficients of the quantile regression equation, and secondly, to model especially extreme precipitation events. We will use precipitation data measured by satellites GPM, ERA5, TRMM, and PERSIANN, which have been identified through various analyses as closest to ground- based data.

To enhance the performance of our model in reproducing extreme events, we have built our model using precipitation exceeding 20 mm for all regions except region 4 and region 5, where we lowered the threshold from 20 mm to 10 mm. This adjustment is due to the different precipitation regime in these two regions compared to others, where observed maximums are lower and events are intense but short-lived.

We also calculated the linear regression model for each region with the aim of demonstrating that our developed model is the best.

Results of the RQ Model

We built our model for each region by selecting only precipitation events (that could cause floods) above 20 mm for all regions except region 4, where we selected precipitation above 10 mm due to lower precipitation levels compared to other regions. Subsequently, when calculating the Kullback-Leibler distance between the precipitation estimated by quantile regression and the ground-measured precipitation, we chose the quantile that minimized this distance. The coefficients and quantiles obtained by region are provided in Table 1:

During the validation of the quantile regression (RQ) model developed for region 3, stretching from Mohammadia to Sidi Ifni, we observed two sub-groups of discrepancies between the RQ model and ground observations. The first group covers the area between Mohammadia and Souira, while the second extends from the Agadir region to the city of Sidi Ifni. This led us to subdivide this area into two sub-regions: region 3_1 and region 3_2. We recalculated the coefficients of the RQ model for each sub-region, resulting in improved accuracy and a significant reduction in the gap between observations and the RQ model.

This subdivision is geographically justified by the influence of the High Atlas range, which plays a crucial role in distinguishing between the precipitation regimes of sub-regions 3_1 and 3_2.

Table 1: Quantiles and Coefficients of the RQ Model by Region

Region	Region 1	Region 2	Region 3_1	Region 3_2	Region 4	Region 5
Tau	0,6	0,7	0,6	0,6	0,4	0,9
ERA5	1,14	0,98	0,88	0,69	-0,06	1,23
GPM	0,21	0,23	0,17	0,02	0,90	-1,20
TRMM	0,42	0,69	0,12	0,71	0,74	0,84
PERSIANN	0,06	0,77	0,21	0,39	0,48	2,13

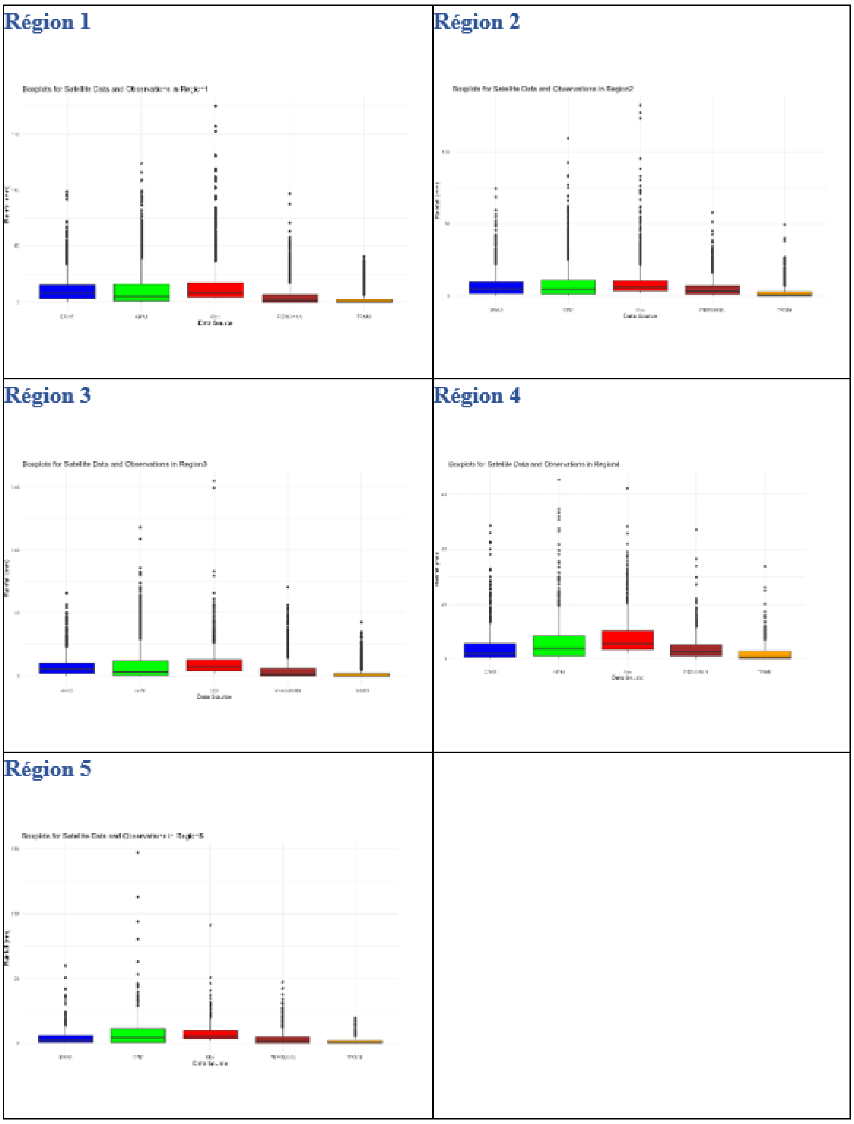
Results of LR Model

The linear regression model was developed to demonstrate that this model does not yield good results in reproducing extreme precipitation events. The results obtained for each region are given in Table N°2.

Table 2: Coefficients of the RL Model by Region

Region	Region 1	Region 2	Region 3_1	Region 3_2	Region 4	Region 5
ERA5	0,97	0,85	0,88	0,85	0,12	0,12
GPM	0,27	0,20	0,46	-0,04	0,93	0,46
TRMM	0,20	0,88	0,23	0,91	0,61	0,24
PERSIANN	0,02	0,08	0,07	0,40	0,57	0,80

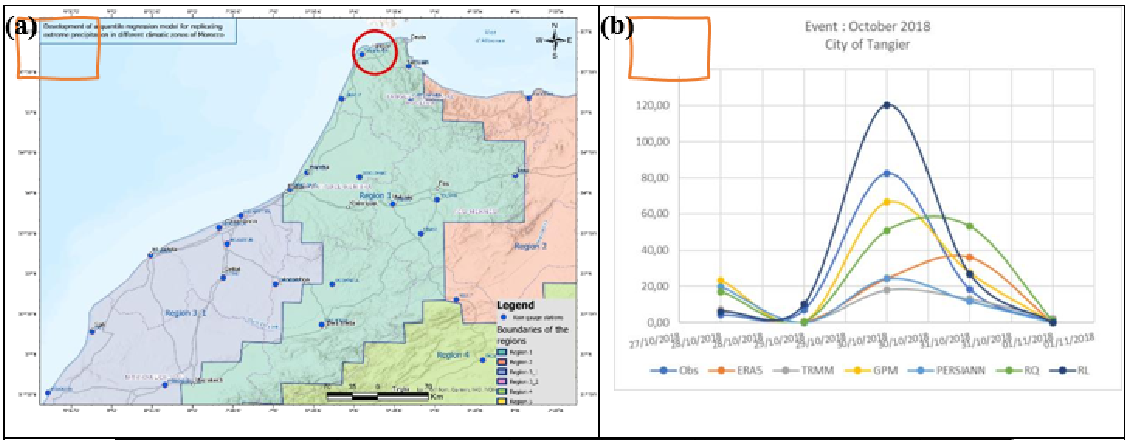
Table 3: Boxplot of Rainfall > 2mm in the Five Regions



Validation of the developed model

We validated the performance of our developed RQ model through different approaches. First, we performed validation using extreme events recorded at the stations that were used to construct the model. Second, we used extreme events recorded at stations managed by the DGM that were not used in constructing the RQ model. Finally, we conducted a final validation using extreme events observed at stations outside the DGM network, specifically at stations managed by the DRPE.

Another validation of the RQ model was carried out by testing the model's performance on events that occurred outside the [2000-2018] timeframe, specifically the events of January 2021 at the El Maleh dam station, located about 25 km upstream from the city of Mohammadia.



(c)

Date	Obs	ERA5	TRMM	GPM	PERSIANN	RQ	RL
28/10/2018	4,20	7,07	7,07	23,40	19,78	17,12	6,13
29/10/2018	7,00	0,30	0,00	0,25	0,00	0,40	10,21
30/10/2018	82,50	24,49	17,84	66,70	24,29	50,92	120,38
31/10/2018	18,40	36,16	13,03	27,56	11,73	53,27	26,85
01/11/2018	0,00	0,10	2,07	0,00	0,00	0,98	0,00
Cumul evnement	112,10	68,12	40,01	117,91	55,80	122,69	163,57
Différence/sol		39%	64%	-5%	50%	-9%	-46%

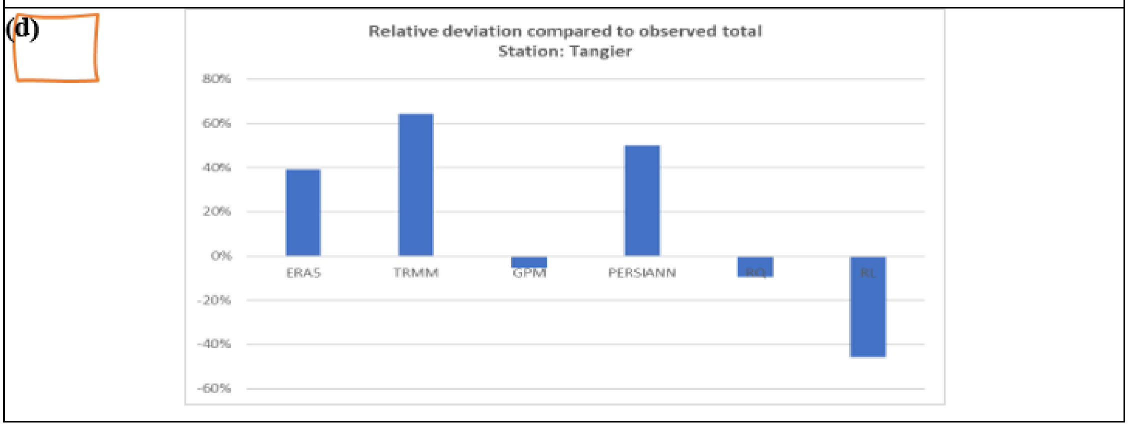
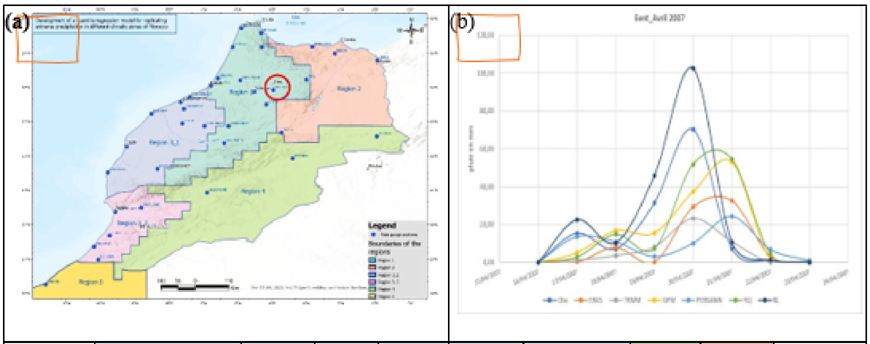


Figure 2: (a) Location of the Tangier station, (b) Observed Rainfall, Rainfall Calculated by different Satellites, Rainfall Calculated by the RQ Model and RL Model, (c) Model, (d) Difference Compared to the Observed Cumulative Rainfall.

Station: City of Fez The difference between the observed cumulative rainfall and the rainfall calculated by the RQ model for the events used for validation varies between -3%, as shown in Figure 2 (c) for the April 2007 event in the city of Fez, Figure 2 (a), and -9% for the station.

(a) (b)



(c)

Date	Obs	ERA5	TRMM	GPM	PERSIANN	RQ	RL
16/04/2007	0,00	0,04	0,00	0,00	0,00	0,05	0,00
17/04/2007	15,40	0,34	1,27	5,11	13,58	2,79	22,47
18/04/2007	7,10	7,99	3,59	16,79	10,74	14,80	10,36
19/04/2007	31,40	0,22	8,18	15,66	3,09	7,16	45,82
20/04/2007	70,30	29,36	23,30	37,38	10,14	51,79	102,58
21/04/2007	7,20	32,67	10,98	53,13	24,28	54,53	10,51
22/04/2007	0,80	3,28	0,00	1,23	6,70	4,40	1,17
23/04/2007	0,00	0,19	0,00	0,34	1,07	0,35	0,00
Cumul evnement	**132,20**	**74,09**	**47,34**	**129,63**	**69,60**	**135,86**	**192,90**
Différence/sol		**44%**	**64%**	**2%**	**47%**	**-3%**	**-46%**

(d)

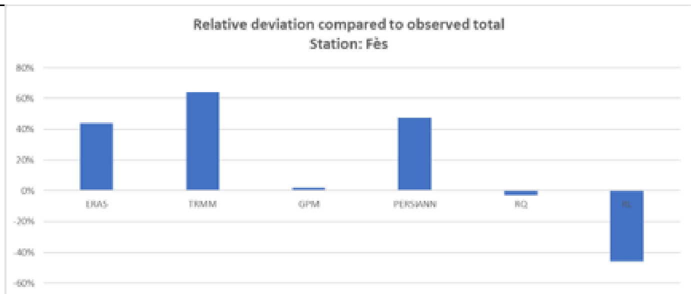
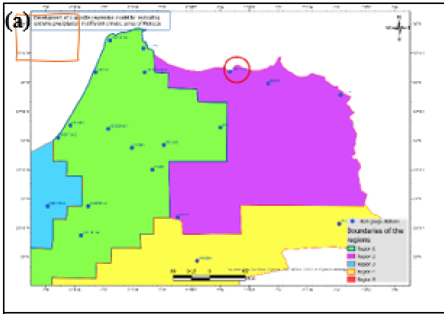


Figure 3: (a) Location of the Fez Station, (b) Observed Rainfall, Rainfall Calculated by different Satellites, Rainfall Calculated by the RQ Model and RL Model, (c) Model, (d) Difference Compared to the Observed Cumulative Rainfall.

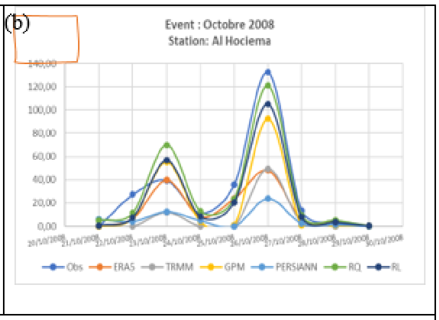
Validation of RQ Model in Region 2

The validation of our RQ model for region 2 was conducted using the event of October 2008, which occurred from October 21 to October 29, recorded at the Al Hoceima station, as shown in Figure 4 (a). The recorded cumulative rainfall was 263.20 mm. In general, all satellite products significantly underestimated this event, as shown in Figure 4 (c). The RL model performed better than all the satellite products, but not as well as the RQ model, which estimated a cumulative rainfall of 258.78 mm, a difference of 2%.

(a)



(b)



(c)

Date	Obs	ERA5	TRMM	GPM	PERSIANN	RQ	RL
21/10/2008	0,00	0,29	0,00	0,00	6,10	4,97	0,73
22/10/2008	27,20	6,86	0,07	7,13	4,14	11,59	7,69
23/10/2008	39,50	39,66	11,93	55,47	12,62	69,51	56,58
24/10/2008	11,30	8,26	0,00	4,22	4,82	12,77	8,28
25/10/2008	35,80	23,84	0,07	1,19	0,00	23,67	20,62
26/10/2008	132,50	48,22	49,40	92,55	23,93	120,84	105,20
27/10/2008	13,70	5,86	2,80	0,78	2,38	9,66	7,79
28/10/2008	3,20	3,96	0,00	0,77	1,48	5,19	3,65
29/10/2008	0,00	0,61	0,00	0,00	0,00	0,60	0,52
Cumul Ey	**263,20**	**137,56**	**64,27**	**162,11**	**55,46**	**258,78**	**211,07**
Diff par rapport Obs		**48%**	**76%**	**38%**	**79%**	**2%**	**20%**

(d)

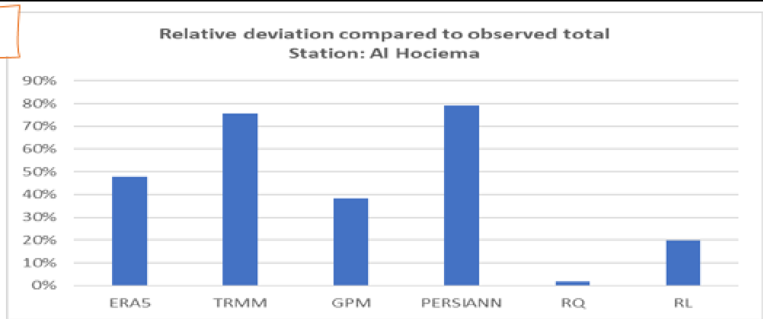


Figure 4: (a) Location of the Al Hoceima Station, (b) Observed Rainfall, Rainfall Calculated by Different Satellites, Rainfall Calculated by the RQ Model and RL Model, (c) Model, (d) Difference Compared to the Observed Cumulative Rainfall.

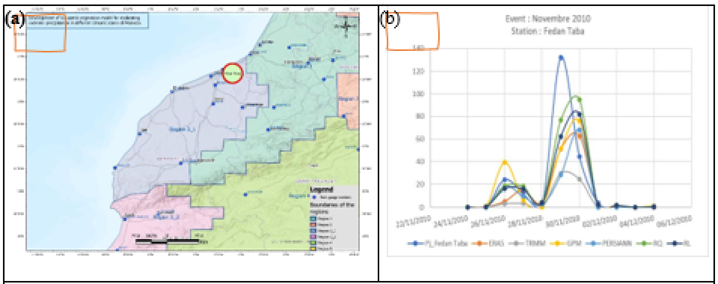
Validation of RQ Model in Region 3

Region 3_1

Fdan Taba Station: The observed event in November 2010 at Fedan Taba station, which is a station not used in constructing our RQ model, as shown in Figure 5 (a), lasted for 6 days from 26/11/2010 to 01/12/2010, resulting in a cumulative rainfall of 219.6 mm.

The use of our developed RQ model accurately reproduced this event with a precision of 1%, estimating a cumulative rainfall of 218.04 mm for the same period. In contrast, all other satellite products underestimated this event, as depicted in Figure 5 (c).

(a) (b)



(c)

Date	Pj Fedan Taba	ERA5	TRMM	GPM	PERSIANN	RQ	RL
24/11/2010	0	0,04	0,00	0,52	0,00	0,17	0,14
25/11/2010	0	0,40	0,00	0,71	0,00	0,54	0,47
26/11/2010	24	5,17	3,27	39,31	18,50	18,34	16,11
27/11/2010	12,1	15,28	3,36	6,51	9,84	17,99	15,75
28/11/2010	2,5	4,40	0,50	0,21	2,68	4,49	4,05
29/11/2010	132,1	51,17	29,59	51,60	28,36	76,88	62,43
30/11/2010	44,5	62,82	24,32	75,96	68,13	94,87	81,94
01/12/2010	3,9	2,79	0,00	0,00	0,00	2,49	2,21
02/12/2010	0,5	1,77	0,00	0,77	0,00	1,78	1,56
03/12/2010	0	0,03	0,00	0,00	0,00	0,03	0,03
04/12/2010	0	0,00	0,13	1,25	0,62	0,45	0,39
Cumul_Event	**219,6**	**143,88**	**61,17**	**176,84**	**128,12**	**218,04**	**185,09**
Différence/cumul_Event		**34%**	**72%**	**19%**	**42%**	**1%**	**16%**

(d)

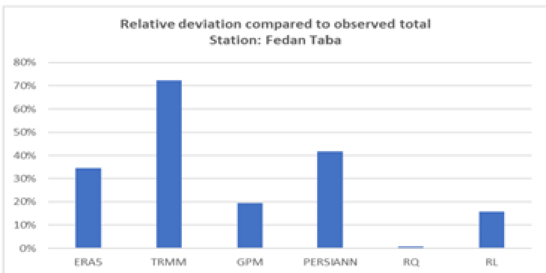
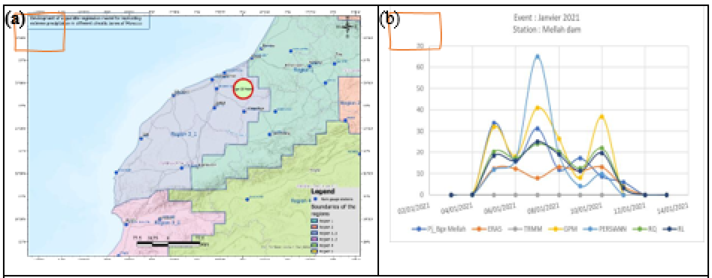


Figure 5: (a) Location of the Fdan Taba Station, (b) Observed Rainfall, Rainfall Calculated by Different Satellites, Rainfall Calculated by the RQ Model and RL Model, (c) Model, (d) Difference Compared to the Observed Cumulative Rainfall.

El Maleh dam

We also utilized the most recent floods in January 2021, occurring in the Casablanca-Mohammedia regions, to apply our model to a real case that was not part of the data used for constructing the RQ model, which spans from January 1, 2000, to December 31, 2018. A cumulative rainfall of 123.9 mm (Figure No. 5) was recorded at the Mellah dam station from January 3, 2021, to January 11, 2021, located approximately 25 km upstream of the city of Mohammedia. For the same period, our RQ model allowed us to calculate a cumulative rainfall of 119.9 mm, resulting in a difference of 3%, which is very promising.

(a) (b)



(c)

Date	Pj_Mellah dam	ERA5	TRMM	GPM	PERSIANN	RQ	RL
03/01/2021	0	0,01	0,00	0,00	0,00	0,01	0,01
04/01/2021	0	0,00	0,00	0,21	0,00	0,06	0,05
05/01/2021	33,7	12,22	0,00	31,97	11,81	20,37	18,33
06/01/2021	15,5	12,17	0,00	17,99	16,38	17,14	16,03
07/01/2021	31,3	7,79	0,00	40,92	64,88	24,06	25,12
08/01/2021	11,8	12,97	0,00	26,55	19,35	20,38	18,96
09/01/2021	17,1	11,15	0,00	7,98	4,03	12,40	11,14
10/01/2021	8,6	12,91	0,00	36,73	9,75	22,01	19,56
11/01/2021	5,9	3,90	0,00	0,07	0,00	3,49	3,10
12/01/2021	0	0,00	0,00	0,00	0,00	0,00	0,00
13/01/2021	0	0,00	0,00	0,00	0,00	0,00	0,00
Cumul_Event	**123,9**	**73,12**	**0,00**	**162,43**	**126,19**	**119,93**	**112,30**
Différence/cumul_Event		**41%**	**100%**	**-31%**	**-2%**	**3%**	**9%**

(d)

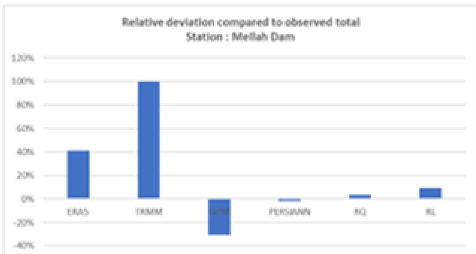
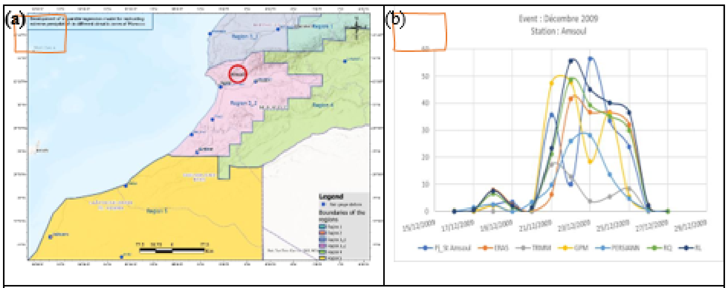


Figure 6: (a) Location of El Malleh Dam Station, (b) Observed Rainfall, Rainfall Calculated by different Satellites, Rainfall by RQ Model and RL Model, (c) Model, (d) Difference Compared to the Observed Cumulative Rainfall.

Region 3_2

Amsoul Station

The Amsoul station, managed by DRPE, was not used in the construction of the Quantile Regression (RQ) model. We selected the December 2009 event, with a cumulative rainfall of 165 mm. Except for ERA5 and GPM, which show respective deviations of 0% and 3%, other satellite products significantly underestimate the cumulative rainfall of the event. The RQ model shows a deviation of -13% compared to ground data, while the Linear Regression (RL) model exhibits a deviation of -30%.



(c)

Date	Pj St Amsoul	ERA5	TRMM	GPM	PERSIANN	RQ	RL
16/12/2009	0	0,03	0,00	0,13	0,00	0,02	0,02
17/12/2009	0	0,00	0,00	0,15	1,30	0,51	0,51
18/12/2009	2,4	7,89	0,00	1,98	2,44	6,47	7,61
19/12/2009	3,4	2,32	0,00	0,12	0,00	1,62	1,97
20/12/2009	0	0,01	0,00	0,98	3,32	1,32	1,30
21/12/2009	35,7	6,22	17,30	47,39	9,81	21,17	23,20
22/12/2009	10,1	41,57	12,69	47,90	25,88	48,74	55,46
23/12/2009	56,3	36,59	3,71	18,38	28,04	39,28	45,01
24/12/2009	33,4	36,66	5,40	36,19	13,54	35,16	40,15
25/12/2009	23,7	31,95	8,40	5,42	4,64	30,01	36,46
26/12/2009	0	2,21	0,00	0,60	0,56	1,76	2,08
27/12/2009	0	0,00	0,00	0,07	0,00	0,00	0,00
Cumul_Ev	**165,00**	**165,45**	**47,50**	**159,33**	**89,52**	**186,06**	**213,77**
Diff par rapport Obs		**0%**	**71%**	**3%**	**46%**	**-13%**	**-30%**

(d)

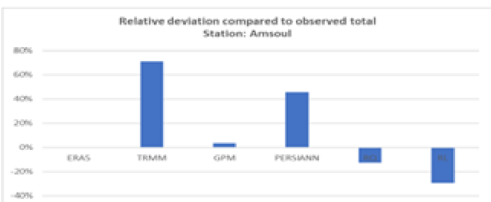


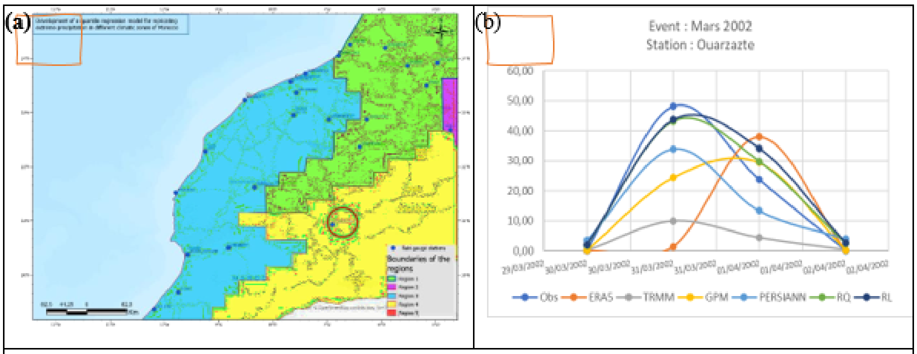
Figure 7: (a) Location of the Amsoul station, (b) Observed Rainfall, Rainfall Calculated by different Satellites, Rainfall by RQ Model and RL Model, (c) Model, (d) Difference Compared to the Observed Cumulative Rainfall.

Validation of RQ Model in Region 4

Ouarzazte Station

To validate the quantile regression (RQ) model in region 4, we selected the March 2002 event recorded at the Ouarzazate station, as illustrated in Figure 8(a). This event, lasting two days, accumulated 71.90 mm of precipitation. By analyzing the satellite product totals, we observe that all satellite products detected the event with varying discrepancies compared to ground-based measurements, ranging from 80% for TRMM to 24% for PERSIANN. The RQ model manages to minimize the discrepancy to -7% compared to ground data, while the linear regression (RL) model reduces the discrepancy to -15%.

(a) (b)



(c)

Date	Obs	ERA5	TRMM	GPM	PERSIANN	RQ	RL
30/03/2002	0,00	0,00	0,00	0,11	3,49	1,76	2,06
31/03/2002	48,20	1,40	9,96	24,37	33,88	43,18	43,70
01/04/2002	23,70	38,05	4,32	29,41	13,33	29,77	34,20
02/04/2002	0,00	0,10	0,26	0,25	3,95	2,31	2,66
Cumul_Ev	71,90	39,55	14,55	54,15	54,65	77,02	82,62
Diff par rapport Obs		**45%**	**80%**	**25%**	**24%**	-7%	**-15%**

(d)

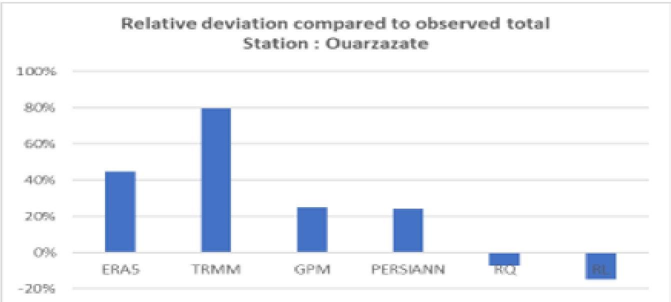


Figure 8: (a) Location of the Ouarzazate station, (b) Observed Rainfall, Rainfall Calculated by different Satellite Products, Rainfall from the RQ Model and the RL Model, (c) Model, (d) Discrepancy Compared to Observed Total.

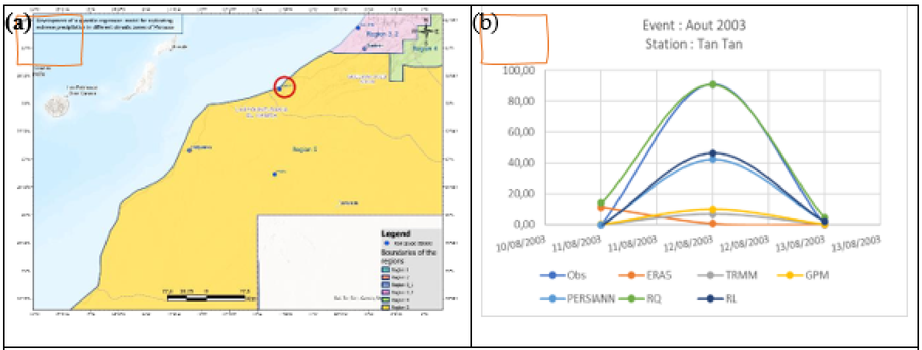
Validation of RQ Model in Region 5

Region 5 is characterized by an arid climate with rare precipitation. Therefore, we used rainfall events exceeding 10 mm to build our RQ model, as opposed to the 20 mm threshold used for other regions. This decision aims to retain more data, as our preliminary data analysis showed that extreme events in this region are rare and do not exceed 50 mm. The validation of the RQ model yielded satisfactory results. In this region, only stations managed by the DGM are available.

Tan Tan Station

For the August 2003 event recorded at the Tan Tan station, as shown in Figure 9(a), we observe that ERA5 did not detect this event, as illustrated in Figure 9(a) and (b). TRMM and GPM detected the event but with very low totals (TRMM = 6.84 mm and GPM = 10.19 mm) compared to the ground-measured total of 91.10 mm, as shown in Figure 9(c). In contrast, PERSIANN estimated a total of 44.35 mm. Using our quantile regression (RQ) model, the total reached 109.47 mm, with a 20% overestimation compared to the ground data. This total is higher than all satellite products and the linear regression, which provided a total of 47.78 mm, resulting in a 48% underestimation compared to the ground data.

(a) (b)



(c)

Date	Obs	ERA 5	TRMM	GPM	PERSIANN	RQ	RL
11/08/2003	0,00	11,29	0,00	0,06	0,00	13,94	-0,80
12/08/2003	91,10	0,62	6,84	9,95	42,33	91,08	46,51
13/08/2003	0,00	0,00	0,00	0,17	2,02	4,44	2,02
Cumul_Ev	**91,10**	**11,91**	**6,84**	**10,19**	**44,35**	**109,47**	**47,74**
Diff par rapport Obs		**87%**	**92%**	**89%**	**51%**	**-20%**	**48%**

(d)

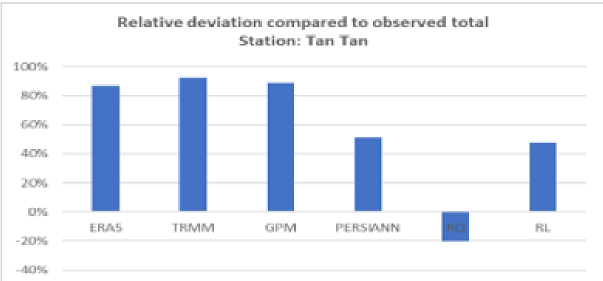


Figure 9: (a) Location of the Tan Tan station, (b) Observed Rainfall, Rainfall Calculated by different Satellite Products, Rainfall from the RQ Model and the RL Model, (c) Model, (d) Discrepancy Compared to Observed Total.

The validation of the RQ model developed for all climatic regions yielded highly satisfactory results. The developed model will enable researchers interested in hydrological modeling, natural disaster modeling, climate trends, etc., to generate reliable precipitation series, especially for extreme precipitation in various areas of the territory. Our main contribution, beyond the construction of an RQ model, is the addition of a sixth region, corresponding to the subdivision of region 3 into two sub-regions, region 3_1 and region 3_2, as illustrated in Figure 10.

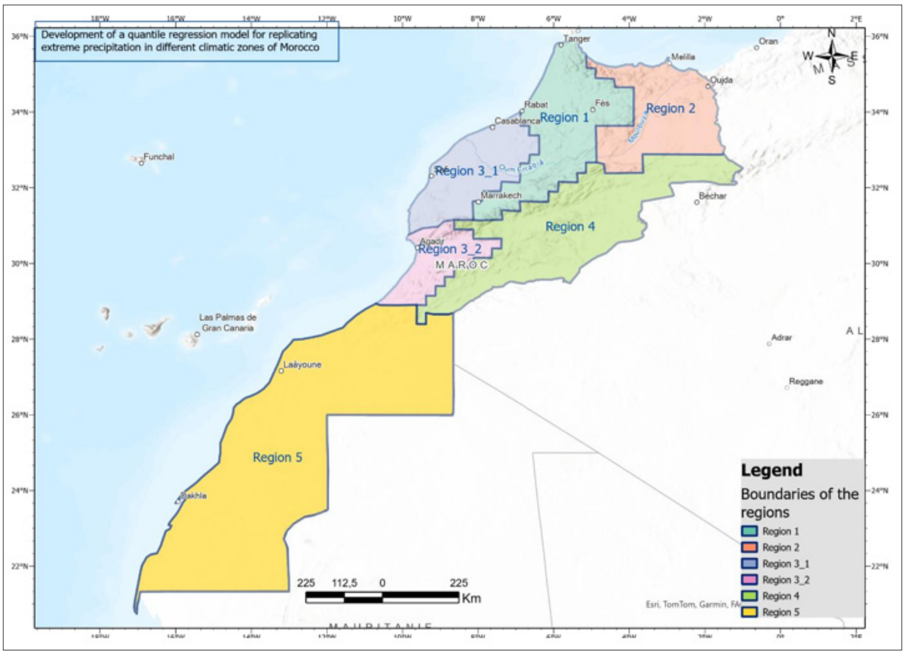


Figure 10: Final Division of Morocco into 6 Homogeneous Climatic Regions

Conclusion

Considering the climatic variability of Morocco and the research studies conducted in this context, we have subdivided the Moroccan territory into six homogeneous climatic regions, taking into account the climatic factors responsible for extreme events in each region.

Instead of using a single satellite product to reproduce extreme precipitation across all regions, as is often the case in traditional studies, our research has demonstrated that certain satellite products perform well in some regions but not in others. Therefore, we propose a model that integrates four satellite products, built based on the specific rainfall regime of each area.

This work has led to the subdivision of region 3 into two regions based on the analysis of the RQ model results. This subdivision is justified by the presence of the High Atlas Mountain range and the reduction of the discrepancy between the cumulative rainfall calculated by the RQ model and the observed cumulative rainfall.

The developed model provides highly satisfactory results compared to those of a linear regression model and the use of a single satellite product. The model's performance is particularly high in all regions except in region 5, where the discrepancy between the model's result and the observed rainfall is slightly higher than in other regions. This is due to false alarms from certain satellite products, given the very specific rainfall regime in this region.

To improve this work, further enhancements can be considered, including the integration of additional satellite products in the model's construction and the addition of data from other rain gauges from different organizations.

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