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doi:10.1016/j.atmosenv.2011.12.019.



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1 **RAIN PATTERN ANALYSIS AND FORECAST MODEL BASED ON GPS**
2 **ESTIMATED ATMOSPHERIC WATER VAPOR CONTENT**

3

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18

19 **RAIN PATTERN ANALYSIS AND FORECAST MODEL BASED ON GPS**
20 **ESTIMATED ATMOSPHERIC WATER VAPOR CONTENT**

21

22 **ABSTRACT**

23 Rain is one of the fundamental processes of the hydrologic cycle as it can be the source
24 of wealth or natural hazards. This experiment focuses in the relationship between rain
25 occurrence and atmospheric pressure (P_{atm}) and atmospheric water vapor content
26 (PW), GPS estimated. The available nine years time series of each variable were
27 analyzed. It allowed to state the existence of three rain patterns and monthly differences
28 in the P_{atm} -PW combinations. In spite of rain episodes take place only for some of the
29 P_{atm} -PW combinations, only these variables are unable to explain the rain occurrences
30 because of not always they take place. This because a forecast sliding windows model
31 with neural network was developed, to capture nonlinear relations that can not to be
32 fully reflected by the lineal probabilistic ones based on the observed rains, P_{atm} and
33 PW series. This model stated a good correlation between the observed rains and the
34 forecast, with a positive impact of the PW but negative of P_{atm} . This model was able to
35 predict the rain precipitation with a reasonable precision and reliable accuracy up to a
36 56 hours horizon.

37

38 **KEYWORDS**

39 GPS, water vapor, rain, forecast model, meteorology.

40

41

42 **1. INTRODUCTION**

43 From an environmental and a human point of view, rain is one of the fundamental
44 processes of the hydrologic cycle. Rain is the water source of the natural vegetation and
45 crops. It is also the origin of the majority of the domestic consumption water as well as
46 in the industry, services, etc. Finally, it is possible to mention to rain like origin of
47 natural hazards, both by the large periods of water absence and by the occurrence of
48 torrential phenomena. In the Mediterranean climate zones this situation is especially
49 evident: these zones are usually water needy, with little and irregular precipitations and
50 with more or less frequent torrential episodes. These phenomena cause damages in
51 environment and provoke great economic and human losses. For this reason, it is
52 fundamental to advance in the knowledge of rain as a natural process, key for the
53 management of this valuable resource and for the forecast of risks associated to extreme
54 events. One of the key variables in the precipitation occurrence is the atmospheric water
55 vapor content. Several studies have established the existence of large water vapor
56 contents in the atmosphere previous to the intense precipitation occurrence in the
57 Mediterranean area (Champollion et al., 2004; Cucurull et al., 2004; Brenot et al.,
58 2006). Nevertheless aspects as the time between the atmospheric water vapor peak and
59 the occurrence of rain or its intensity, they are not already satisfactorily stated, partly
60 had to the complexity of the process and partly to the difficulty to determine the
61 atmospheric water vapor content. GPS during this last decade became an instrument of
62 great interest in meteorology. This is due to its proved effectiveness for the estimation
63 of the water vapor content of the atmosphere, comparable in exactitude to the classic
64 instruments in meteorology as radiosondes (RS) and the water vapor radiometers,
65 without their limitations (Haase et al., 2003; Champollion et al., 2004; Vedel et al.,
66 2004; Jade et al., 2005; Jin et al., 2007). Nowadays there are a great amount of GPS

67 reference stations, which allows collecting atmospheric water vapor data, in all those
68 zones in which this infrastructure exists. Where the series available are sufficiently long
69 it is possible in addition the analysis of temporary patterns, long term trends, etc.
70 (Gradanarsky et al., 2002; Jade et al., 2005; Jin et al., 2007).

71 This article shows an experimental analysis that establishes the relation between the
72 variations of the water vapor content and the atmospheric pressure, with rains observed
73 during the period 2002-2010 in the city of Pamplona, located in the north of Spain.
74 Three patterns of precipitation occurrence have been observed and a model of rain
75 forecasting, based on the time analysis of the atmospheric GPS water vapor content, has
76 been developed.

77

78 **2. MATERIALS AND METHODS**

79 *2.1. Location and local climatology*

80 The selected location for this experiment is the city of Pamplona, in the north part of
81 Spain (see figure 1), located at 440 meter above sea level.

82

83 **FIGURE 1**

84

85 From the climatic point of view, this city is located in a transition zone between the
86 Atlantic climate and the Mediterranean one. During the winter period, several Atlantic
87 disturbances from polar front, coinciding when the Azores anticyclone moves away,
88 cause precipitation in a water or snow way. The appearance of winter anticyclones
89 cause dry and cold days. During summer time temperature has a strong rise caused by
90 the daytime warming and the weakly and the moving away of the draught stream due to
91 the Azores anticyclone situated in a northern position. The high temperatures and the

92 lack of rain during summer are only modified for the appearance of cold air at high
93 altitude causing isolated storms which are the only precipitations of this period. The
94 transition between winter and summer takes place gradually, with alternation of raining
95 days caused by the Atlantic influence and with dry days caused by dorsal anticyclones
96 (Gobierno de Navarra, 2001). Table 1 shows the more significant climatic parameters of
97 Pamplona.

98

99 TABLE 1

100

101 *2.2. Meteorological data.*

102 As it has been stated in 2.1, the precipitation occurrences in Pamplona are related to
103 changes in the Atmospheric Pressure (P_{atm}), so both atmospheric variables were
104 considered. RS atmospheric water vapor content data, expressed as Precipitable Water
105 (PW), were considered as reference values. The nearest RS sites are Santander and
106 Zaragoza cities, placed at 190 and 143 km respectively from Pamplona. All the
107 meteorological data were supplied for the Spanish Meteorology Agency (AEMET).
108 Precipitation and P_{atm} were available with an hourly frequency meanwhile RS PW data
109 are registered with an 12 hours interval (0000 UTC, 1200 UTC).

110 For the development of this experiment the following sets of data were available: (I) RS
111 PW data for the period 2001-2010 at Santander, (II) 2006-2010 RS PW values at
112 Zaragoza and (III) Hourly precipitation and atmospheric pressure data for the period
113 2001-2010 at Pamplona.

114

115

116 *2.3. GPS atmospheric water vapor content determination*

117 The effect of the troposphere causes a delay in the propagation of microwave signals
118 that, in mid latitudes, results in a displacement in the zenith direction of about 2.4 m
119 (Boehm et al., 2005). Total tropospheric delay is the sum of two components: first one
120 is the hydrostatic component caused by the atmosphere dry gases, named Zenital
121 Hydrostatic Delay (ZHD). This component is very steady and contributes with more
122 than 90% of the total tropospheric effect. It is directly proportional to the ground
123 atmospheric pressure and it can be determined with accuracy better than 1% using the
124 Saastimoinen model (Saastamoinen, 1972). The second component is the wet one
125 known as Zenital Wet Delay (ZWD). It is caused mainly by the atmospheric water
126 vapor content and to a lesser extent to the liquid water in the atmosphere. It is
127 responsible for most of the variations on the ZTD values and because of the
128 heterogeneity of the water vapor content in the atmosphere it isn't possible its
129 modelation with the required accuracy (Haase et al., 2003).

130

131 $ZTD = ZHD + ZWD$ [1]

132

133 The relation between Precipitable Water (PW) and ZWD is given by the formula

134

135 $PW = \Pi \cdot ZWD$ [2]

136

137 where PW is the atmospheric water vapor content expressed as Precipitable Water in
138 millimeters of water column and Π is an empirical term that is dependent on the average
139 temperature of the atmospheric cross section (Haase et al., 2003; Champollion et al.,
140 2004).

141 The GPS data used to monitor the PW content were 24-hour rinex files with a sampling
142 rate of 30 s from the GPS reference stations available in Pamplona, located 500 m far
143 from the meteorological station meteorological and Santander and Zaragoza GPS sites.
144 Data were processed using the Gamit v-10.40 program (Herring et al., 2006). Gamit
145 parameterizes the ZTD as a stochastic variation of the Saastimoinen model with
146 piecewise linear interpolation in between the solution epochs. The variation is
147 constrained to a Gauss-Markov process with an a priori power density. We used three
148 12-hour slicing window in each day to get hourly PW values, removing the first and the
149 last values from each slicing window to avoid the edge effect of the Gauss-Markov
150 process (Jin et al., 2007). The computation strategy was the usual in this kind of
151 calculations, and it is shown in table 2 (Champollion et al., 2004; Cucurull et al., 2004;
152 Brenot et al., 2006; Jin et al., 2007).

153

154

TABLE 2

155

156 3. RESULTS

157 3.1. GPS and radiosounding PW analysis

158 To verify the calculation's strategy goodness, RS PW registered series and the GPS PW
159 estimated values were analyzed. In the case of Santander, the available series was 2001-
160 2010 instead for Zaragoza it was 2006-2010.

161 Figure 2 shows the correlation between the GPS and the RS PW values, where $R^2=0.83$
162 for Santander and $R^2=0.81$ for Zaragoza were obtained.

163

164 FIGURE 2

165

166 These results evidence the goodness of the GPS used calculation strategy and the
167 capacity of the GPS as atmospheric water vapor content estimator.

168

169 *3.2. Rain, PW and atmospheric pressure relationship*

170 As previously shown in 2.1, atmospherically speaking, unstable periods in Pamplona
171 are associated to low pressures which make easy the coming in of the cool fronts from
172 the north, causing precipitations. For this reason a study during the rains phenomena of
173 the P_{atm} and the water vapor content was carried out with the available data series.
174 Three different patterns of these variables were established in this study during the rains
175 phenomena. Figure 3 shows some examples of each type of the precipitation observed
176 patterns.

177

178 FIGURE 3

179

180 TYPE 1

181 This type of rains takes place mainly in autumn and spring, during P_{atm} decreasing
182 phases associated to the coming in of fronts. The rains begin when P_{atm} values are
183 under 970 MBar. The mean rain intensities take values around 1.5 mm/h. The end of
184 this type of rains coincides with a P_{atm} relative minimum of around 960 Mbar. The
185 usual duration of these kinds of rains is around 20-40 hours. During this period the
186 atmospheric water vapor content remains stable with light variations mainly caused by
187 the coming in of wet air from the Atlantic Ocean.

188

189

190 TYPE II

191 The second type of rains takes place mainly during the winter months. PW values are
192 lower than in the case of type I rains because of winter period is cooler than type I
193 months. In this case rains coinciding with a P_{atm} increasing, beginning the rain around
194 950 Mbar, maintaining this situation until more or less 965 Mbar. The mean rain
195 intensities also reach values around 1.5 mm/h and the duration of this kind of rains is
196 also around 20-40 hours. During this time PW increases from values lower than 5 mm
197 up to 10-15 mm because of the coming in of wet air from the sea, as in the case of type
198 I.

199

200 TYPE III

201 The third type of rains appears coinciding with a minimum relative value of P_{atm} and a
202 maximum relative of PW. This type of rains occurs in any time and provokes rains with
203 duration up to 10 hours and with larger intensities than in the types I and II, with values
204 between 1.7 and 3.4 mm/h. Whereas in rains type I PW did not vary more than 5 mm
205 and in type II showed an increase between 5-10 mm, in type III the precipitation had
206 associated a PW decrease below 15 mm because the loss of humidity in the atmosphere
207 during the rain it is not compensated with an entrance of humidity from the sea
208 associated to the entrance of a new front.

209

210 The representativity of these types of precipitation patterns was analyzed with a joint
211 representation of P_{atm} , PW and hourly rain data series as it is showed in figure 4.

212

213 FIGURE 4

214

215 Figure 4 shows the characteristic triangular shape of the yearly PW-Patm data. Low PW
216 values can be observed for all range of Patm, but maximum PW values are only
217 observed with Patm around 965 Mbar. Between the whole set of data it can be observed
218 that the PW-Patm records of the each month are distributed predominately in specific
219 zones of the graph, being only some of these combinations which register rain. That
220 way, the corresponding data from December and January are concentrated in the left
221 zone of the graph. February, March, April and May show more dispersion in their
222 register with a gradual movement to mean Patm and largest PW values zone, which are
223 clearly observed during the month of July, August and September. Since October the
224 dispersion of the data is going up and they start to move to the left zone of the graph as
225 winter is arriving. At the same time, the precipitation data are concentrated in specific
226 zones of PW and Patm combinations for each month. This situation is especially clear
227 for the months of June, July and August where rain episodes, over all the more intenses,
228 are located in determinate zones. In this time of the year precipitations correspond to
229 type III. Types II and III, take place mainly during spring and autumn months, have
230 smaller intensities and show a strong dispersion across the Patm-PW combinations. The
231 concentration of the rains in the Patm-PW graph has been characterized by the circles
232 that, with a minimum section, include 50 % of the total amount of rain for each month.
233 Graphical representation of these circles is showed in figure 4 and numerical data are
234 showed in table 3.

235

236 TABLE 3

237

238 This table shows the Patm-PW coordinates of the circles's centers, their radius and the
239 observed probability of rain for the circles' area. The changes of the position of the

240 circles's centers along the year agree with the observed rain pattern. The smaller radius
241 of the circles takes place in the summer months, demonstrating a bigger concentration
242 of the summer rains in specific Patm-PW combinations. The biggest radius are those
243 corresponding to spring and autumn months, that also agree with the rains' dispersion
244 observed for these epochs. Finally, the rain probability of the occurrence of rain in the
245 circles takes values from 3.3% for September to 33.2% for December. These values are
246 small, demonstrating that, although rains show a relationship with Patm and PW and
247 their occurrence is few probable except for their specific values, these variables are not
248 able to explain by themselves the occurrence of rain episodes.

249

250 **4. TIME SERIES BASED RAIN FORECAST MODEL**

251 As it was stated in the previous section, Patm and PW combinations were not able to
252 explain completely the occurrence or not of rain events. This because, and having nine
253 data years, rain time series and its relationship with the considered variables were
254 analyzed. The choosed method was sliding windows with neural network to capture
255 nonlinear relations that can not to be fully reflected by the lineal probabilistic ones
256 (Johnson and Padilla, 2004; Daza, 2008; Mellit, 2008; Parisi, 2008; Roldao, 2008).

257 In this study, a 24 hours sliding window was analyzed. For each window, a neural net
258 classifier runs in order to predict the next window. This neural net operator learned a
259 model by means of a feed-forward neural network trained by a backpropagation
260 algorithm (multi-layer perceptron). The used activation function was the usual sigmoid
261 function. The values ranges of the attributes were scaled to -1 and +1 by this operator in
262 order to normalize the neural inputs. With this classifier method, as shown in the figure
263 5, it is possible to follow the object series (precipitation), and its prediction based in
264 Patm and PW series.

265

266 FIGURE 5

267

268 Visually, it is clear a correlation between the trends of the observed rain and the
269 prediction model, but not in the absolute amount of the picks. So, it was studied the
270 direct correlation between the real and predict series, and the no-lineal impact of the
271 Patm, and PW values with the rain precipitation. For a 10 hours horizon window, the
272 correlation model between observed rain and its prediction showed the following
273 results: with both Patm and PW $R^2 = 0.686$, without Patm and with PW $R^2 = 0.764$ and
274 with Patm and without PW $R^2 = 0,568$. (see figure 6)

275

276 FIGURE 6

277

278 This shows, from a mathematical point of view, a negative impact of Patm in the
279 prediction developed model. The model is a time series of a linear component (temporal
280 sequence) and other non linear more or less pronounced (relation between PW and the
281 precipitation), and it makes sense the use of neural network techniques in order to
282 capture nonlinear relations that have not been fully reflected by order methods.

283 Checking different scenarios of accuracy, the best fits correlation trends without the
284 Patm attribute were studied for different horizon windows. Horizon window is the data
285 series that we want to predict, so, in a larger window, there will be more data to
286 discover, and the accuracy will be worst.

287 With this premise, there are takings trends correlations with different horizons,
288 specifically, 10 hours, 24, 48 and 56, and on the whole case, with all attributes (year,
289 moth, hour, PW and rain precipitations), except Patm.

290

291 FIGURE 7

292

293 Results of the correlation between the target series and the prediction ones are in figure
294 7. In the worst cases, with the biggest horizon window (56 hours), the correlation R^2
295 between the forecast rain precipitation and the real precipitation is greater than 0.563,
296 and than the regression coefficient, $B_0 = 0.9$, which is statistically significant. It means
297 that the rain trend can be estimated from its corresponding temporal behaviour and the
298 no-linear relationship between the others attributes, PW, principally. So we can predict
299 when it will be a strong variation in the temporal series and take account when will be a
300 peak in the time series, in order to predict the strength of that variation, not in absolute
301 terms, but the pulse power.

302

303 **5. CONCLUSIONS**

304 Across this experiment, the relationship between rain and GPS estimated water vapor
305 content has been analyzed for the nine years available data series in Pamplona (North of
306 Spain). The analysis of the Pamplona's Patm-PW-Rain series agreed with the fact that
307 from a meteorological point of view, the occurrence of rain events in the study area is
308 usually linked to atmospheric low pressures and water vapor entries, caused by Atlantic
309 disturbances. Thus, three precipitation occurrence patterns were stated, associated to the
310 different Patm-PW behavior across the year's epochs. The plot of the Patm-PW and
311 rains combinations for each month showed differences between the different seasons
312 across the year. Winter and summer months demonstrated to have quite clear
313 characteristic Patm-PW patterns, meanwhile during the spring and autumn months,
314 Patm-PW patterns are gradually changing from winter to summer or vice versa. Not in

315 all the possible Patm-PW combinations, rains take place. Mainly on winter and summer
316 months rains appear at specific Patm-PW combinations. During spring and autumn
317 months Patm-PW and rain patterns evidence the winter-summer transitions with not so
318 clear Patm-PW-rain pattern. In spite of the three Patm-PW rain patterns observed and
319 the monthly Patm-PW patterns, Patm and PW combinations were unable to explain by
320 themselves the rain episodes occurrence because of, although rains only take place on
321 determined Patm-PW combinations, not always at those combinations rains take place.
322 To analyze the Patm-PW-rains relationship, a time series forecast model based on the
323 observed rains, Patm and PW series was developed. This model stated a good
324 correlation between the observed rains and the forecast, with a positive impact of the
325 PW but negative of Patm. This unexpected result could have its origin in the yearly
326 variability of the Patm-PW combinations' values when rains take place. The model
327 based on the PW values, the temporal behaviour of the rain occurrences, and the
328 temporal information (year, month, day), was able to predict the rain precipitation with
329 a reasonable precision and reliable accuracy up to a 56 hours horizon.

330

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390

391

392

393

TABLE 1. Pamplona climatic station location and climatic parameters used in this study. (Gobierno de Navarra, 2001).

Latitude (UTM)	4736171
Longitude (UTM)	611323
Elevation	440
Annual Average Precipitation (mm)	701.3
Average Temperature (degrees)	12.6
Maximum Continental Index (Gorzinsky)	18.9
Köppen Index	Cfb
Gausson Index	Sb
Potential evapotranspiration (PET), Thornthwaite Index	707.0
Agroclimate classification by Papadakis.	Wet Mediterranean (ME)

TABLE 2. Defining parameters of the computation strategy.

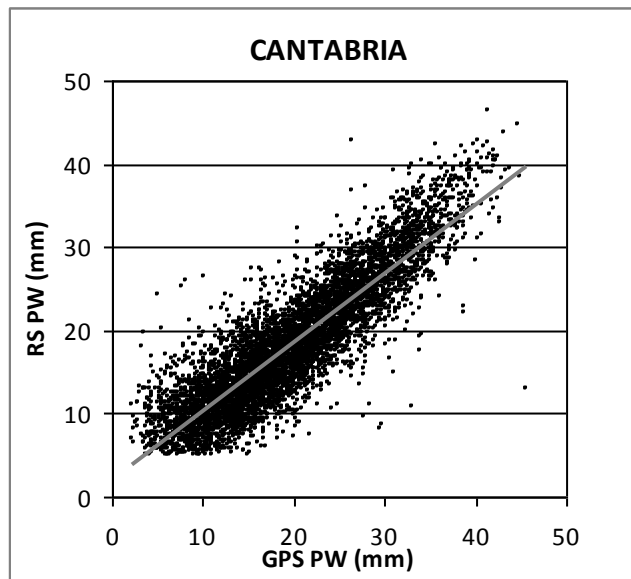
GPS observable	LC
ZTD interval	1 hour
Gauss-Markov process	Constraints 0.5 m Power density $2\text{cm}/\text{hour}^{1/2}$ Correlation time 100 hours
Ephemeris	IGS Final
Earth Orientation Parameters	USNO
Reference Frame	ITRF 2000
Cutoff angle	10°
Sampling rate	30 s
Mapping functions	Global Mapping Functions
Coordinates constraints	Loose
Variation Model of the antenna phase center.	Absolute antenna phase centers

TABLE 3. Numerical parameters of the circles containing 50% of the monthly rains.

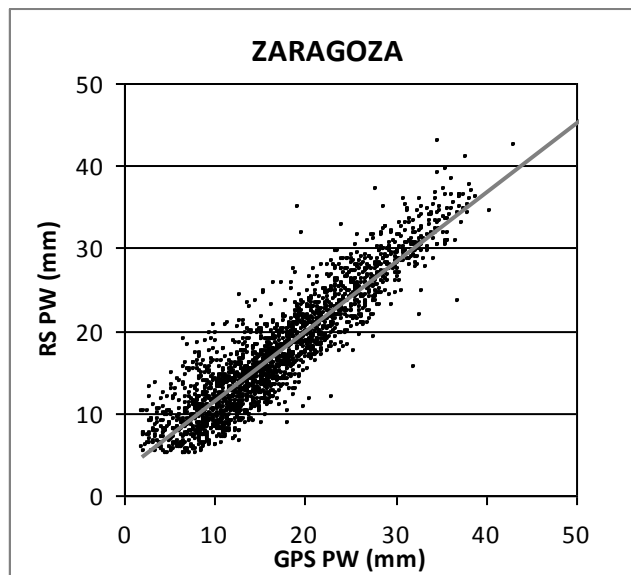
Month	Center		Radius	Rain Probability
	X (Pw)	Y (Patm)		
January	10.0	956.9	7.959	23.8
February	8.9	954.2	9.250	21.2
March	12.7	959.0	7.897	19.9
April	15.8	955.6	6.960	11.1
May	20.3	957.5	6.021	13.1
June	28.2	959.3	5.395	12.1
July	34.8	961.8	5.719	7.9
August	29.4	960.8	6.834	4.8
September	29.7	956.9	5.909	3.3
October	21.1	955.3	8.192	13.1
November	13.6	956.6	6.140	11.2
December	11.7	954.9	8.605	27.1



FIGURE 1. Location of the city of Pamplona, Santander and Zaragoza.



a)



b)

FIGURE 2. Comparison of Radiosounding and GPS PW values during the available period. a) Santander 2001-2010 and b) Zaragoza 2006-2010

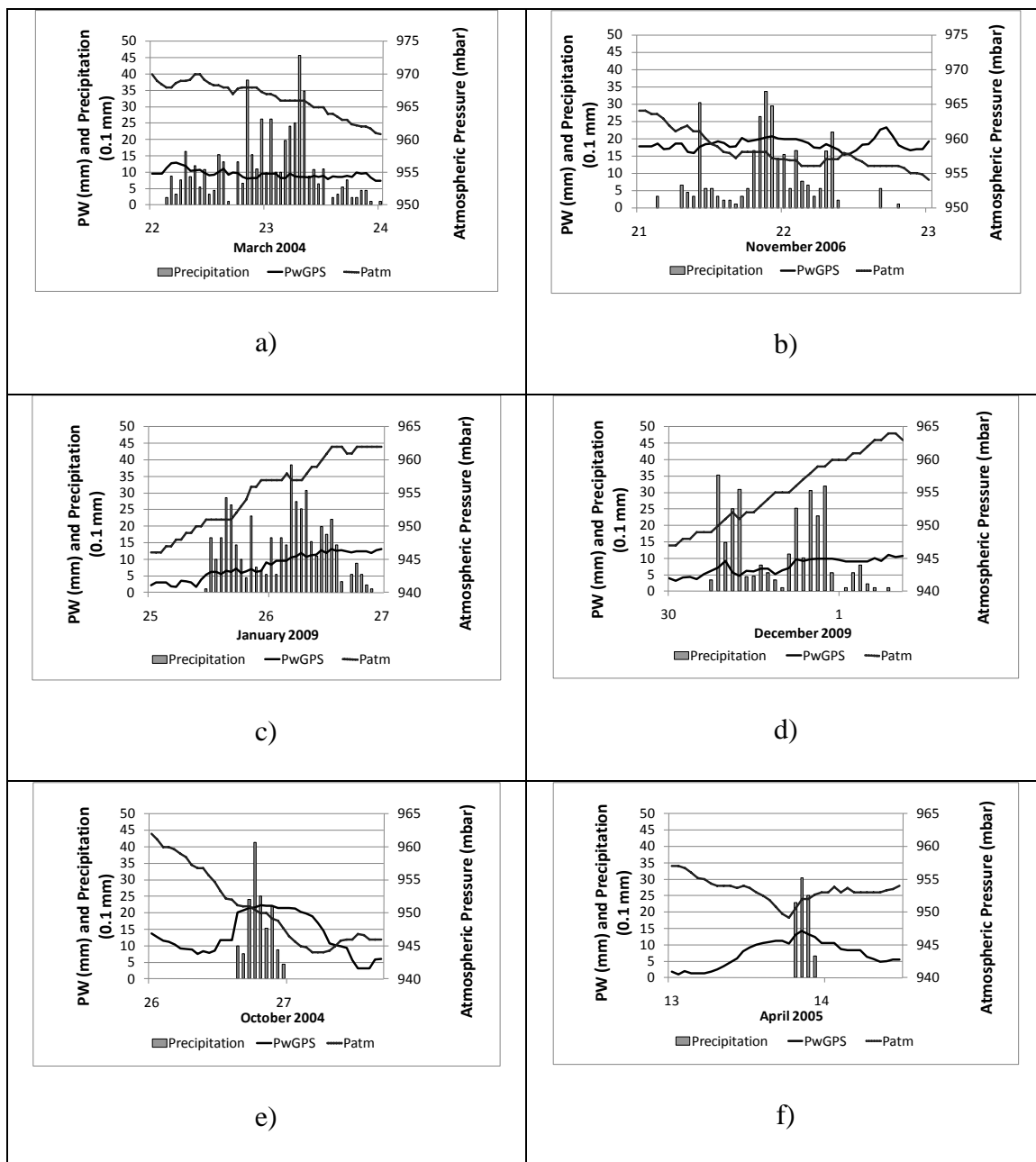


FIGURE 3. Different behavior of Patm-PW-Rain in Pamplona City. a) and b) Type I, c) and d) Type II, e) and f) Type III .

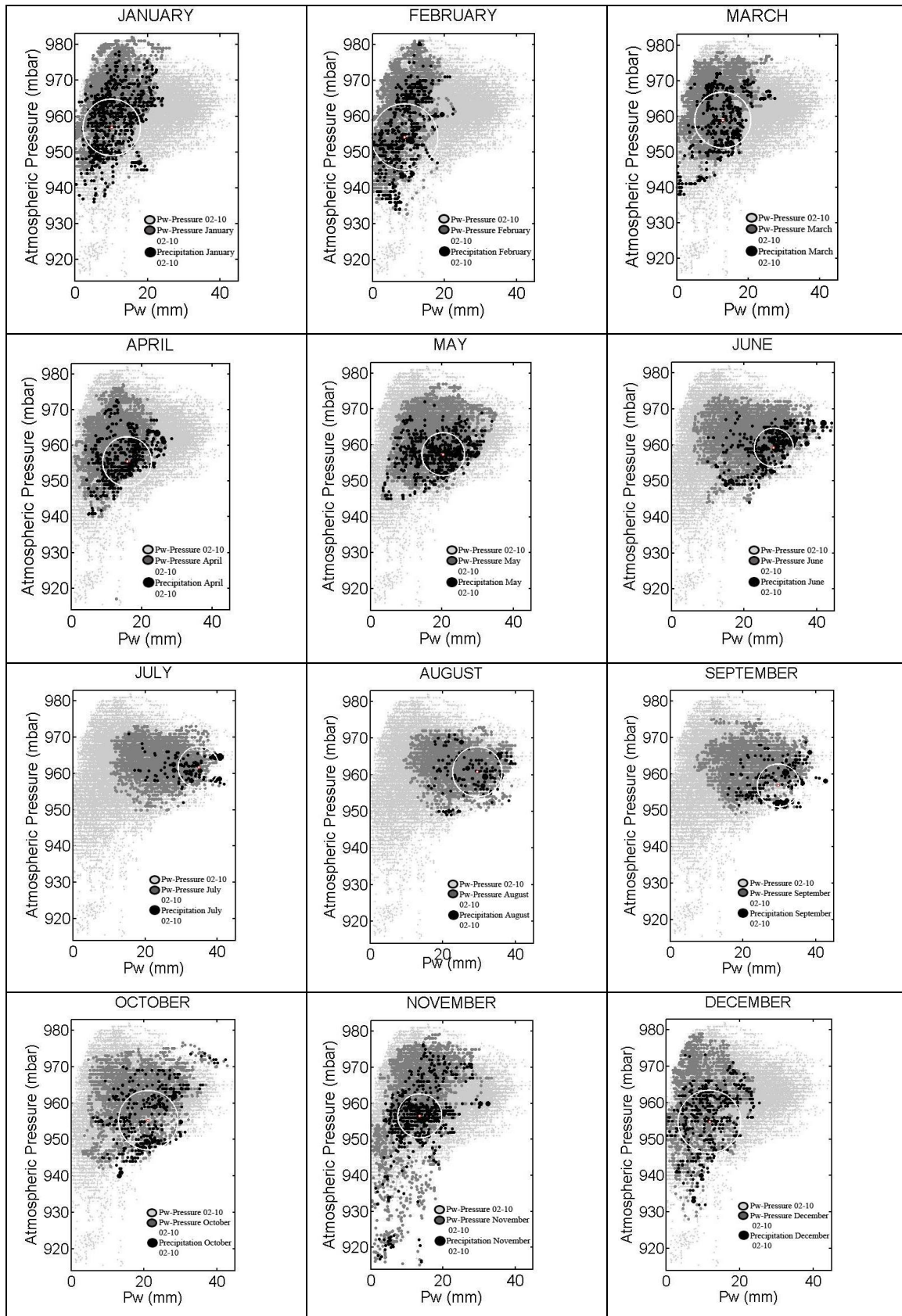
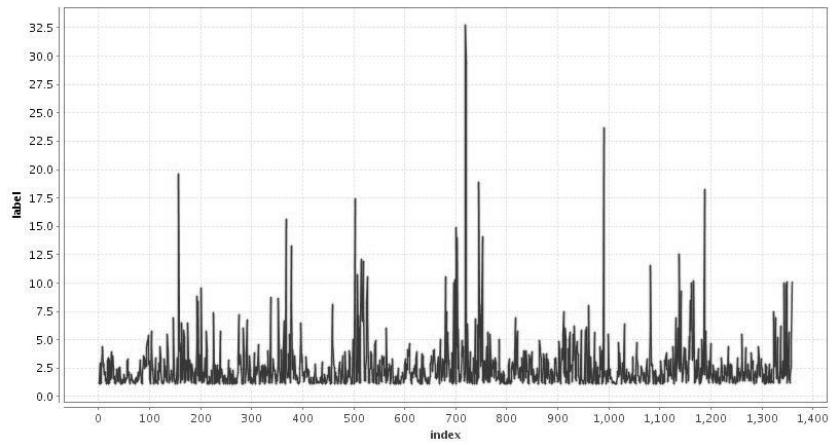


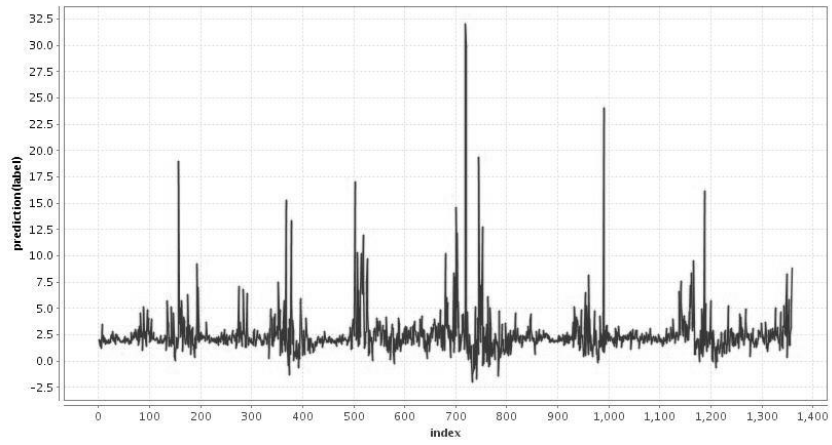
FIGURE 4. Hourly Patm-PW values distribution for the available serie (2001-2010).

Over the whole set of data the values of each month and the observed rains are showed.

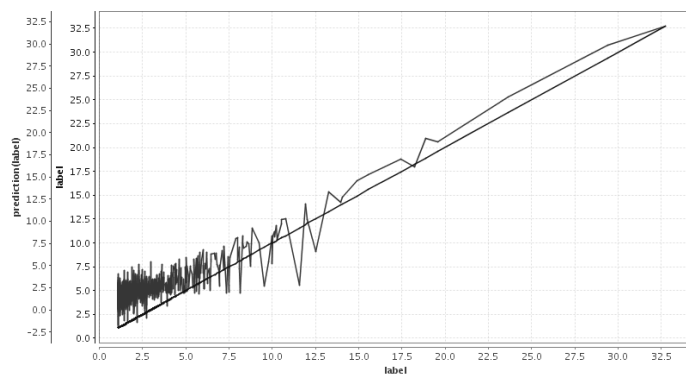
Circles represent the minimum area including the 50% of the monthly observed rains.



a)

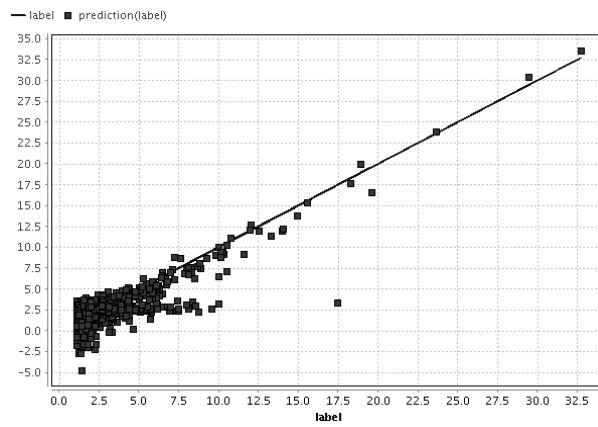


b)

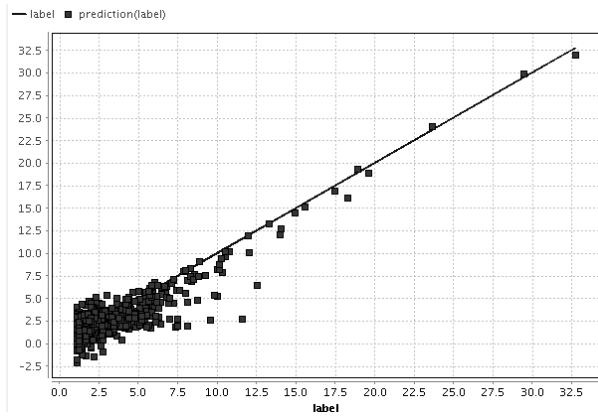


c)

FIGURE 5. Temporal trends and correlation between them.



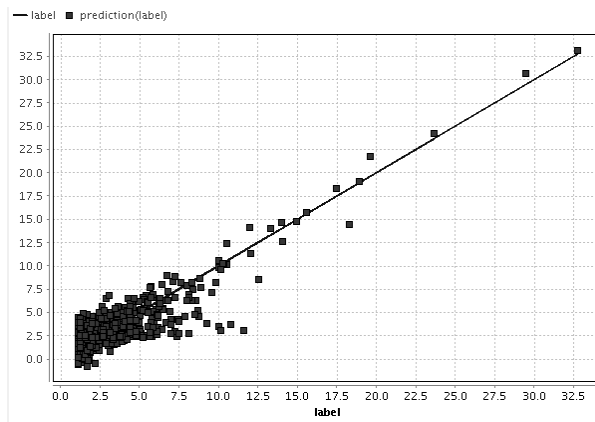
a)



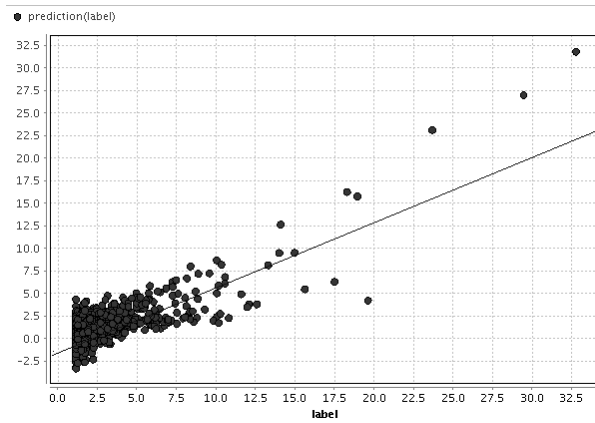
b)

c)

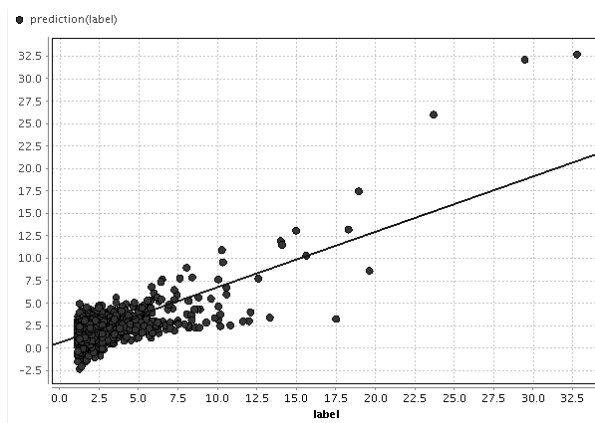
FIGURE 6. Trend series correlation, with Patm or without Patm.



a)



b)



c)

FIGURE 7. Correlations coefficients in different predict horizons.