

# Site location study for a high-mountain millimeter observatory in the Colombian Andes I: In situ data

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December 2016

**Abstract.** This document describes the preparation of an article using L<sup>A</sup>T<sub>E</sub>X 2<sub>ε</sub> and `iopart.cls` (the IOP Publishing L<sup>A</sup>T<sub>E</sub>X 2<sub>ε</sub> preprint class file). This class file is designed to help authors produce preprints in a form suitable for submission to any of the journals listed in table ?? on the next page. You are not obliged to use this class file—we accept submissions using all common L<sup>A</sup>T<sub>E</sub>X class and style files. The `iopart.cls` class file is supplied merely as a convenience for those authors who find it useful. This document gives both general advice that applies whatever class file you use, and specific advice that applies if you choose to use `iopart.cls`.

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*Keywords:* Water Vapor, Atmospheric Effects, Site Testing, Radio Astronomy, Satellite Communication,

Submitted to: *PASP*

## 1. Introduction

The development of astronomical instrumentation technology in the 0.2-2 THz range has been rapidly growing in recent years. Also, interest in THz technology, specially applied to satellite telecommunications has also grown due to the saturation of the “classical radio window” in telecommunications (Hosako et al. 2007), and atmospheric models for absorption of THz photons (Rosenkranz 1998, Slocum et al. 2013) and artifact removal models (Withayachumnankul et al. 2008) have been developed recently due to this interest. Near-equatorial countries face a challenge in using this frequency band for astronomical observations and telecommunications using terabit satellite links (Suen 2016) due to the presence of a tropical belt of dense water vapor which efficiently absorbs THz radiation (Seidel et al. 2008). In the Northern Andes, previous studies of astronomical site testing in the visible range have shown that high nighttime humidity conditions make this region suitable only for educational observatories (Pinzón et al. 2015). However, considering that millimeter/sub-millimeter observations need not be done during the night, unusually dry, clear-daytime-sky, high altitude regions in the Northern Andes could be suitable candidates for a world-class millimeter-wave observatory.

Astronomical observations in the millimeter and sub-millimeter wavelength range require that atmospheric effects affecting absorption at these wavelengths are kept to a minimum (Chamberlin & Grossman 2012, Radford & Peterson 2016, Cortés et al. 2016). The main factor contributing to the atmospheric opacity is water vapor, which very efficiently absorbs light in the THz range (Pardo, Cernicharo & Serabyn 2001, Pardo, Serabyn & Cernicharo 2001, Kuhn et al. 2002) due to a continuum absorption spectrum formed by collisionally broadened absorption lines of water vapor in this frequency range (Clough et al. 1989, Pickett et al. 1998, Turner et al. 2009). In order to characterize a site according to its atmospheric transparency to THz radiation, it is necessary to retrieve the precipitable water vapor profile either via remote sensing techniques such as microwave radiometry (Peter & Kämpfer 1992, Paine et al. 2000, Battistelli et al. 2012), satellite measurements (Aumann et al. 2003, Jones et al. 2012, Suen et al. 2014, Wentz & Meissner 2016), radiosonde humidity measurements (Liljegren et al. 2001, Luini & Riva 2016) or indirectly via models of in situ climatological measurements (Lew & Uscka-Kowalkowska 2016) or GPS-delay studies (Niell et al. 2001, Wang et al. 2007).

Most of the precipitable water vapor that can potentially affect the path of a THz photon hoping to get through the atmosphere actually exists in the troposphere. The lower the elevation of a potential site, the longer the path becomes for that photon, increasing its chances of being absorbed by a water vapor molecule (Liebe 1989, Clough et al. 1989, Slocum et al. 2013). For this reason, the quality of a site is determined by the atmospheric water vapor column above the potential site (Smith et al. 2001, Cimini et al. 2007, He et al. 2012, Bustos et al. 2014). This water vapor column is usually

expressed as the amount of precipitable water vapor, given in mm.

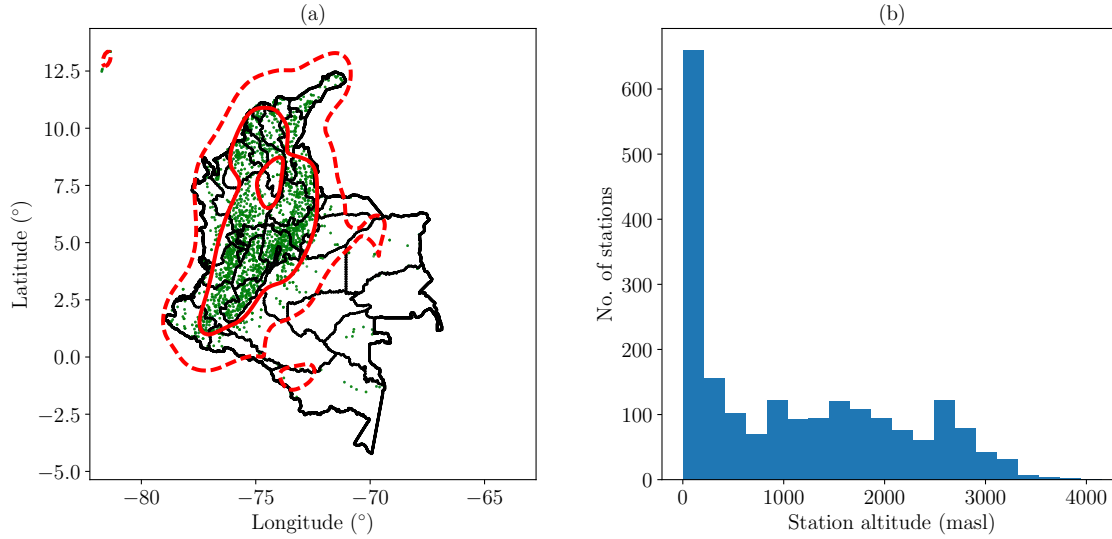
The water vapor column above a potential site can change rapidly (during the course of the day) or it can change seasonally (Cadeddu et al. 2013, Caumont et al. 2016). This is why medium-to-long term monitoring of the atmosphere above a site is required before building an expensive mm/sub-mm wave radio telescope. However, even in best-case scenarios, earth-based telescopes will always be limited by atmospheric absorption of light specially at THz frequencies, where windows of observations are few and in some cases, narrow (Archibald et al. 2002, Denny et al. 2013).

Although radiometer measurements are desirable for directly measuring the atmospheric water vapor column, their development and/or deployment can be complex and expensive (Pazmany 2007, Peng et al. 2009). For this reason we screened historic climate data for evidence of local long-term clear sky, low humidity conditions as proxies for a locally low precipitable water vapor column. By low-dimensionally embedding the data, we are able to reduce the dimensionality of multi-annual monthly data from  $N_{\text{dim}} = 12$  to  $N_{\text{dim}} \leq 3$ . Thus, we can correlate unusually dry regions regardless of their geographical location. Given that the climatological variables were sparsely measured by weather stations across Colombia, we evaluated the aptness of a given location using a Bayesian probability-derived quality index. Finally, we geographically clustered our candidate locations in order to identify regions of interest. We compared our regions of interest with regions with unusually low precipitable water vapor in low-resolution water vapor satellite maps (Suen 2016) and find a possibly significant geographical correlation. In an upcoming paper we will analyze satellite data in order to retrieve high-resolution seasonal precipitable water vapor maps for our regions of interest.

This paper is organized as follows.

## 2. The Dataset

The meteorological data used in this study were gathered over 30 years (1981-2010) in 2046 weather stations monitored by the Instituto de Hidrología, Meteorología y Estudios Ambientales (IDEAM) in Colombia (Figure 1). The variables that we considered relevant to our work were: Precipitation (mm/mo), Rain Days (d/mo), Relative Humidity (%), and Sunshine Duration (h/d). These variables are reported as multi-annual monthly data, i.e. each variable is reported monthly from January to December averaged over the 30 year range. For precipitation, each monthly datum corresponds to the cumulative monthly value. For rain days, each monthly datum corresponds to the number of rain days for that month. For relative humidity, each monthly datum corresponds to the average daily value averaged over each month. For sunshine duration, each monthly datum corresponds to the daily value averaged over each month. All stations reported precipitation values, although only 2002 reported rain days, 445 reported



**Figure 1.** Distribution of weather stations in the dataset. (a)  $1\sigma$  (solid) and  $2\sigma$  (dashed) contours of a gaussian kernel density estimation of the geographical distribution of weather stations (small green points) from the IDEAM 1981-2010 database. The estimation was done using the Python `scipy.stats.gaussian_kde` function. (b) Altitude histogram for all stations in the dataset.

**Table 1.** Types of stations classified according to its measured variables.

Type	Precip.	Rain Days	Relative Humidity	Sunshine Duration	No. of Stations
$T_1$	Y	N	N	N	29
$T_2$	Y	Y	N	N	1563
$T_3$	Y	N	Y	N	1
$T_4$	Y	Y	Y	N	117
$T_5$	Y	N	N	Y	1
$T_6$	Y	Y	N	Y	8
$T_7$	Y	N	Y	Y	13
$T_8$	Y	Y	Y	Y	314

relative humidity, and 336 reported sunshine duration. This means that not all stations registered all the meteorological variables relevant to this work. Thus, we classify stations according to which variables they measured (Table 1).

### 3. Low-Dimensional Embedding of Climatological Data

Our goal is to classify and group together stations that show a similar climatological behavior for each variable, regardless of the station's location, elevation or type. Since

climate data track multi-annual seasonal variations, we can correlate weather patterns of regions which are not obviously related climatologically but might show a similar behavior, e.g. dry weather patterns in Guajira (a desert region in the north of Colombia) with similar dry conditions present at high-mountain sites in the Andes.

We classified stations using a low-dimensional embedding of the data (Shaw & Jebara 2009) for each variable. This ensures that a classification algorithm can uncover features in the data even when the data are projected across a number of dimensions that is lower than the native dimensionality of the data (which in this case is monthly, i.e.  $N_{\text{dim}} = 12$ ). This involves applying a dimensionality reduction algorithm followed by a clustering algorithm. Given that we wish to make a grouping of stations showing similar climatological patterns without making too many assumptions on the data, we decided to use unsupervised learning techniques. In our case, we chose Principal Component Analysis (PCA) covering 95% of the variance followed by a Gaussian Mixture Model selected by a low/locally minimum Bayesian Information Criterion (BIC).

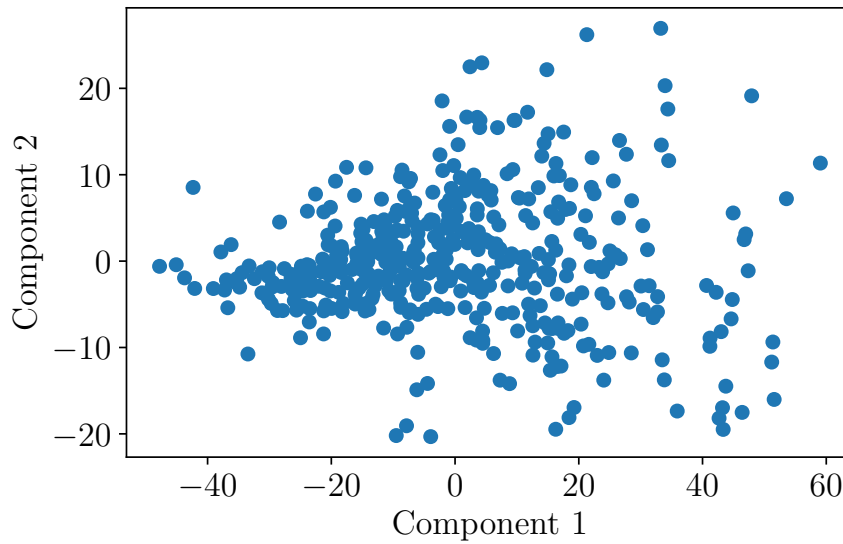
### *3.1. Principal Component Analysis*

We were able to reduce the dimensionality of the data for each variable from  $N_{\text{dim}} = 12$  to  $N_{\text{dim}}^{\text{PCA}} \leq 3$ , while ensuring that at least 95% of the variance of the data is explained by the least amount of components. For precipitation, rain days and sunshine duration,  $N_{\text{dim}}^{\text{PCA}}(95\%) = 3$  and for relative humidity  $N_{\text{dim}}^{\text{PCA}}(95\%) = 2$ . To do this we used the Python `sklearn.decomposition.PCA` module (Pedregosa et al. 2011). Figure 2 shows the relative humidity data projected across 2 principal components explaining 95% of the variance, thus preserving most of the original structure of the data.

### *3.2. Gaussian Mixture Models*

After projecting the data along the components found by the PCA algorithm, we clustered the dimensionally-reduced data using a Gaussian Mixture Model, which uses an Expectation-Maximization algorithm to find a Maximum Likelihood model composed of a number  $N_{\text{G-C}}$  of Gaussian distributions, each of which represents a cluster in the data (Reynolds 2009). Depending on the restrictions put on the covariance of each Gaussian distribution across the data space, the number of free parameters can go from  $N_{\text{G-C}}(N_{\text{dim}} + 1)$  (spherical covariance) to  $N_{\text{G-C}}(3N_{\text{dim}} + 1)$  (full covariance). Since the number of components and covariance restriction is given by the user and not *a posteriori* by the algorithm, we need to make sure that the Gaussian components do not over-fit the data, e.g. a model which yields one cluster per datum should be disallowed.

In order to achieve this, we compare the Bayesian Information Criterion (Schwarz 1978) for a grid of Gaussian clusters ( $N_{\text{G-C}} < 20$ ) and covariance restriction methods for each variable (Figure 3). To do this we used the Python `sklearn.mixture.GMM` module (Pedregosa et al. 2011). We selected the models which produced the lowest BIC



**Figure 2.** Relative humidity data projected across 2 principal components. The dimensionality of the data has been reduced from 12 to 2 while covering 95% of the variance of the data.

**Table 2.** Climate clusters according to a lowest BIC-based selection of Gaussian Mixture Models. See Figure 3.

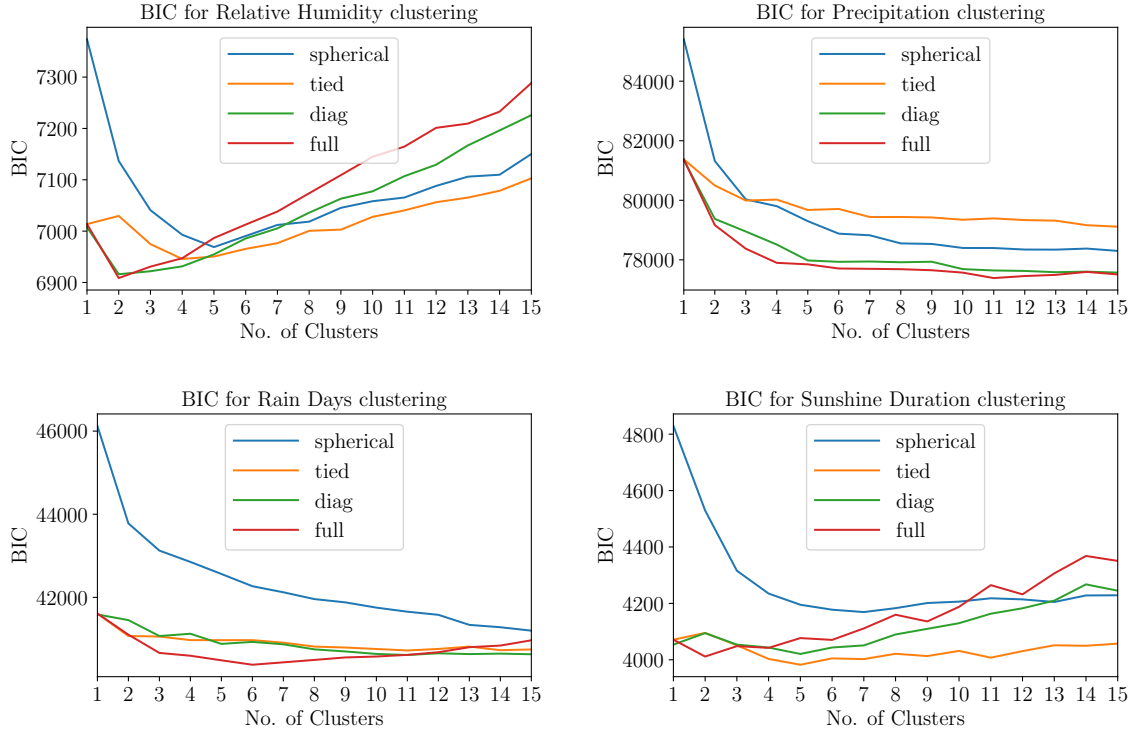
Variable	Symbol	Lowest BIC No. of Clusters	Lowest BIC Cov. Method	Preferred Clusters
Precipitation	$P$	11	Full	2,3,7,11
Rain Days	$D$	6	Full	1,4,6
Relative Humidity	$H$	2	Full	2
Sunshine Duration	$S$	5	Tied	1,4,5

value, and plotted the GMM-classified, PCA-projected climate data in Figure 4.

From the climatological clusters in Figures 5-?? we selected clusters that indicate a dry, sunny climate. Table 2 shows the selected number of clusters and covariance method for each variable along with our preferred clusters. From here on, if a station appears in one of our preferred clusters, we will say that it satisfies our criterion for that specific variable.

#### 4. Discussion

We wish to identify all stations for whom all four criteria (humidity, precipitation, rain days, sunshine duration) for identifying a region as having a stable sunny, dry climate

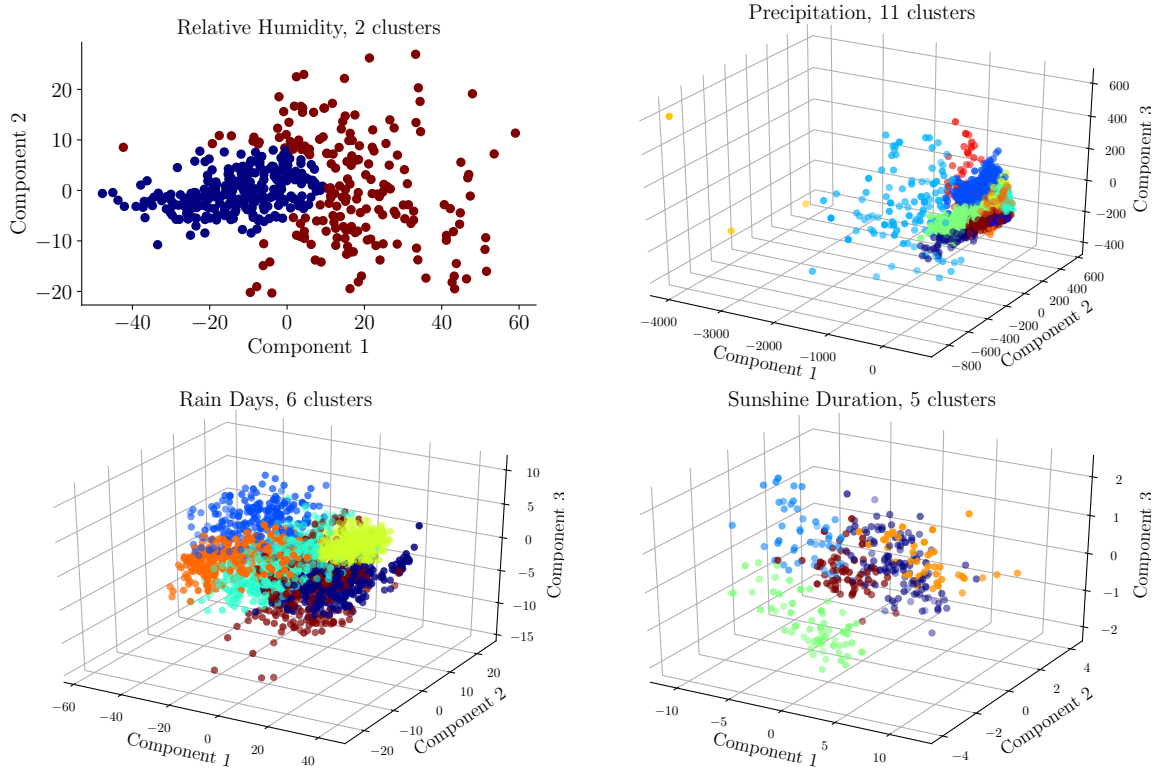


**Figure 3.** Bayesian Information Criterion (BIC) results for Gaussian Mixture Models using a different number of clusters and using different covariance restriction methods applied on each measured variable dataset.

can be met. However, since only a few stations measured all variables, it is not straightforward to accept or reject stations based on their satisfying a criterion, i.e. belonging to one of our preferred clusters. This requires setting up a measure of quality for individual stations depending on their location and the variables they measured. We will describe the selection process and probabilistic analysis that allows us to quantify a station's capability for indicating regions with an unusually dry, sunny climate.

We start by creating a shortlist of stations that meet criteria for (and only for) the variables they measured. This means that if a station has precipitation and humidity data, it should belong to a humidity and precipitation cluster listed in Table 2 or else it is rejected. 665 stations across Colombia showed such behavior. However, since we are interested in high-mountain regions, we included a criterion for elevation limiting our list to 119 stations located above 2000 masl. This shortlist was further reduced by requiring that the total average plus  $1\sigma$  for precipitation, rain days, and relative humidity is less than 4.3 mm/d, 17 d/mo, and 81% respectively, and for sunshine duration, more than 4 h/d for any given station. This left us with 83 weather stations.

However, we want to give a measure of the quality of the station vis-a-vis our



**Figure 4.** Lowest BIC Gaussian Mixture Model clustering of reduced dimensionality climate data. Colors indicate the results of the clustering classification.

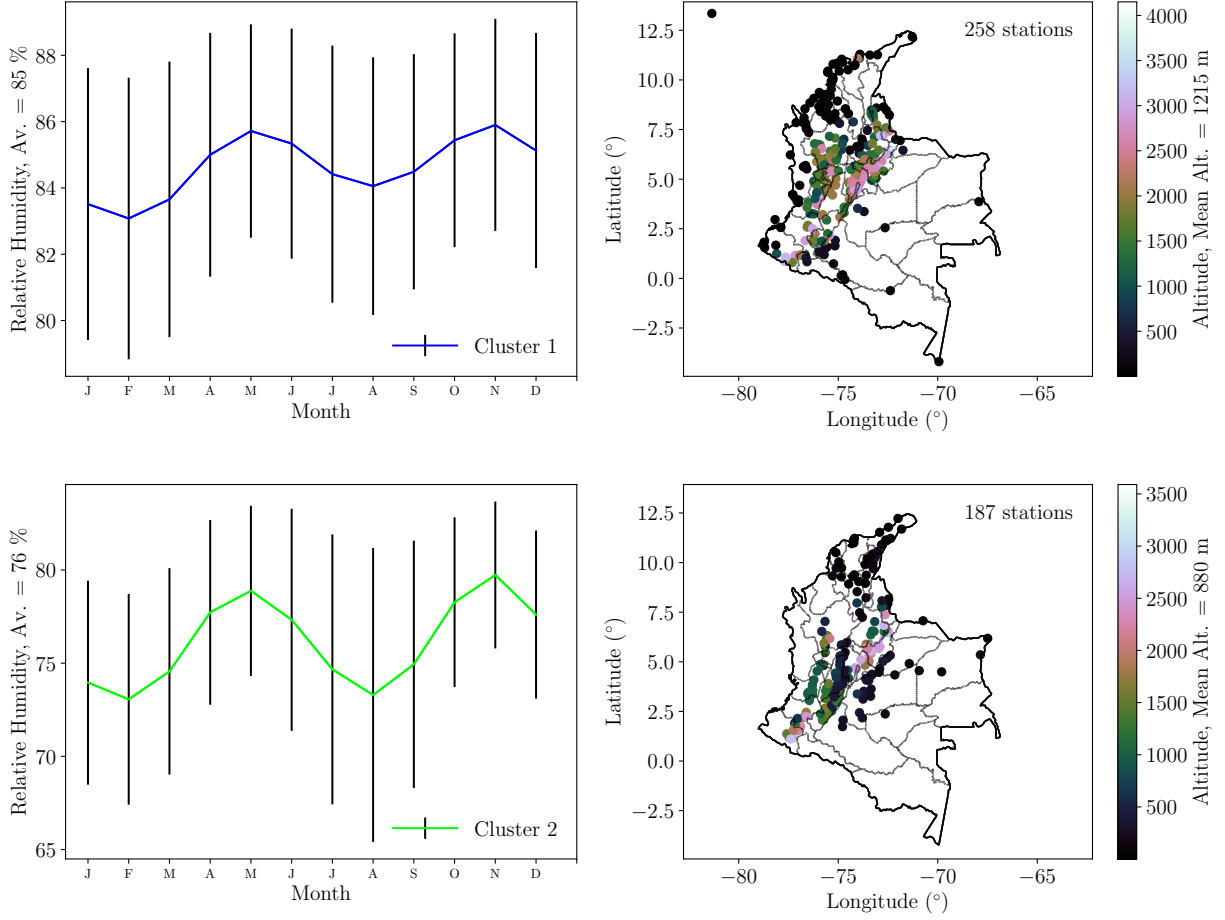
criteria, i.e. a station that meets less than all four criteria should still be considered in our analysis, but it cannot be given the same importance as a station that meets all four criteria. In order to account for this, and controlling for the fact that stations are not distributed evenly in elevation (Figure 1b), we propose a quality measure based on a probabilistic analysis of the data.

#### 4.1. Bayesian probabilistic analysis

We quantify the quality of a given site using the probability for the hypothesis that a station which appears in our shortlist meets all four criteria, given that it is located at a given elevation. We can write down this probability in terms of the following events:

- $C$  is the event that a given station meets all four criteria, i.e. belongs to our preferred clusters for the four variables relevant to this study.
  - $C$  is actually the conjunction of all four of the  $P, D, H, S$  events “The station belongs to a preferred cluster for variable  $X$ ”, i.e.  $C = P \cap R \cap H \cap S$ .
- $A$  is the event that a given station appears in our shortlist.
- $T_i$  is the event that a given station is of type  $T_i$  (See Table 1).



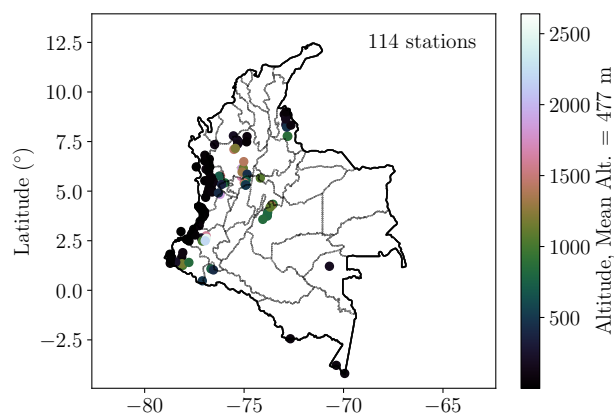
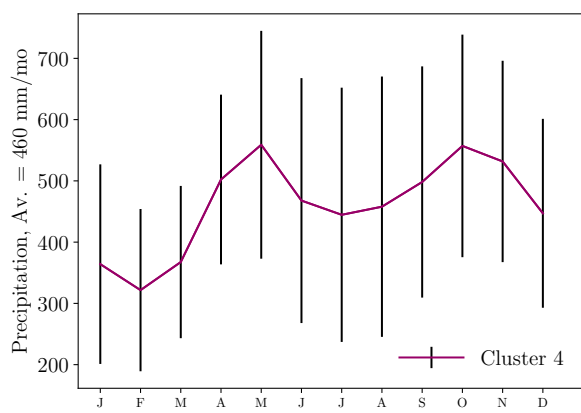
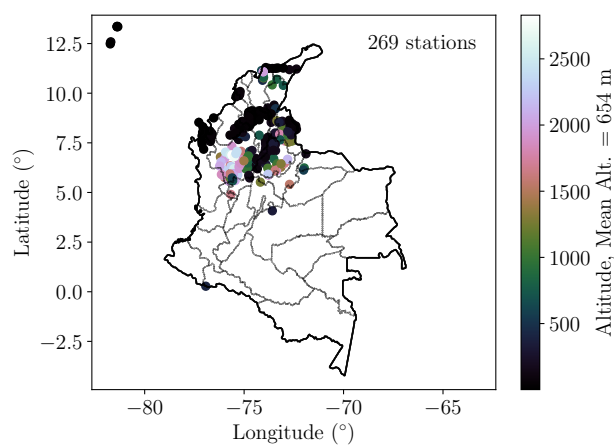
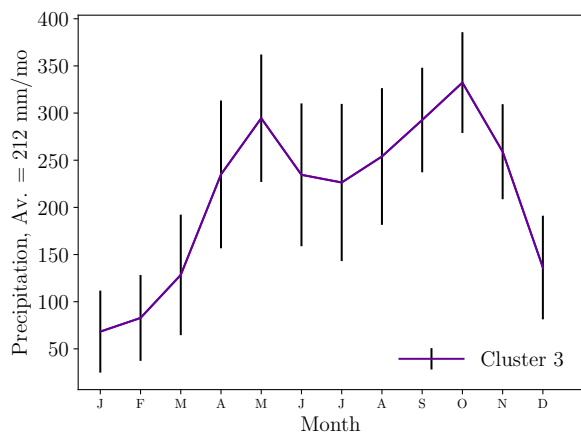
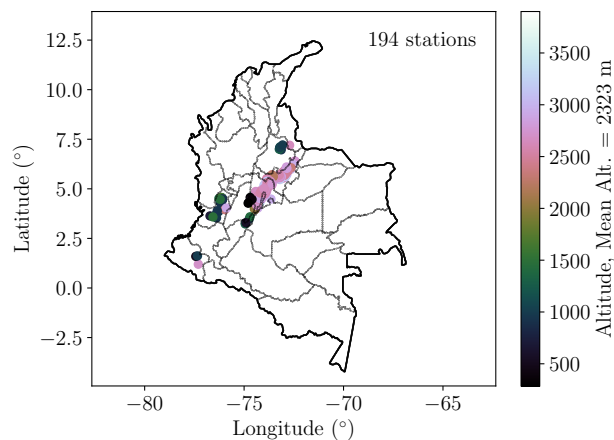
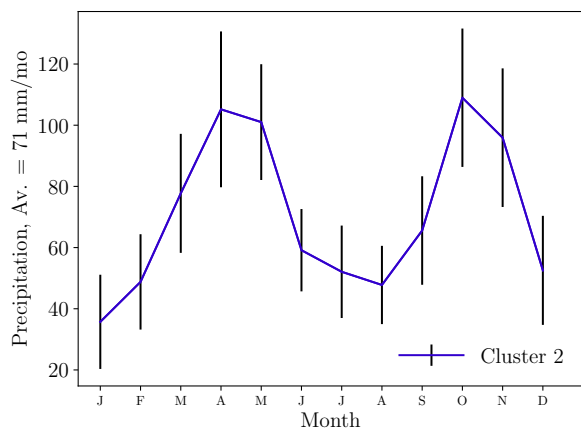
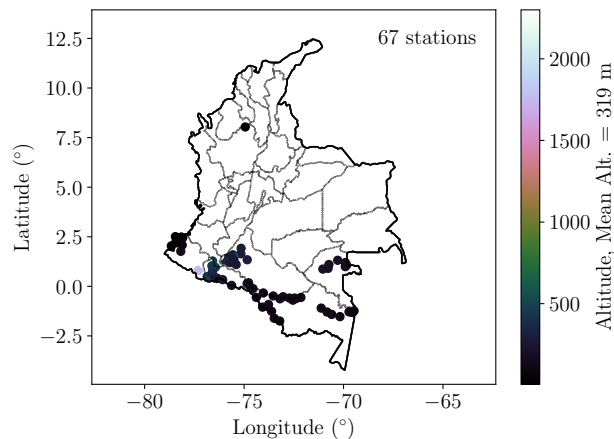
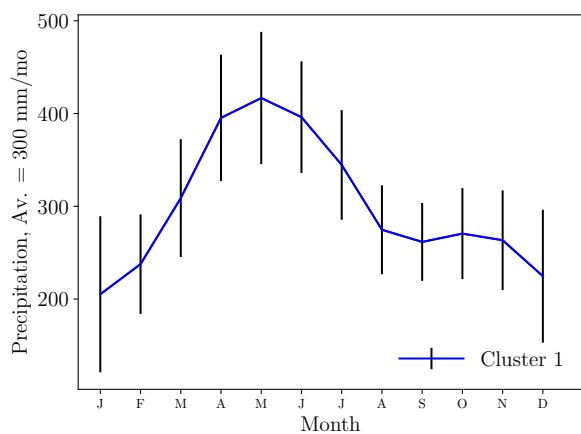


**Figure 5.** Climate clusters as predicted by the lowest-BIC Gaussian Mixture Model for relative humidity. Left column: Average monthly relative humidity and standard deviation (error bars) for each climate cluster. Right column: Geographical location and altitude of weather stations in each relative humidity cluster.

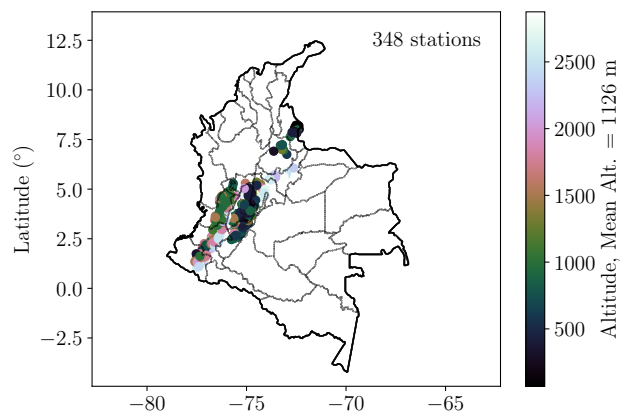
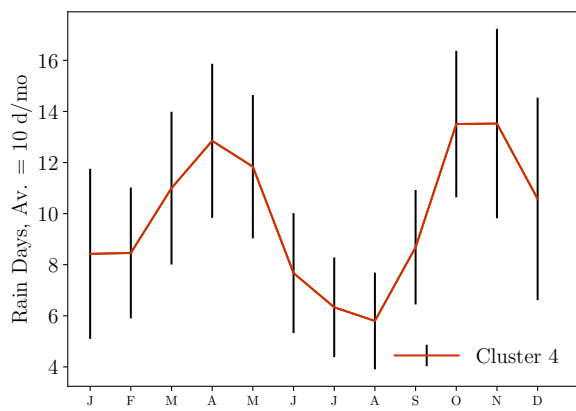
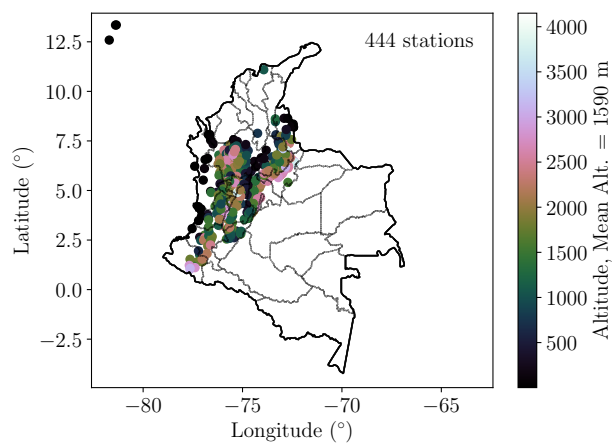
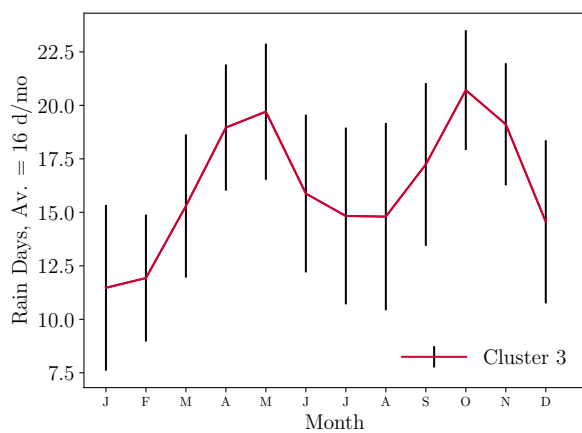
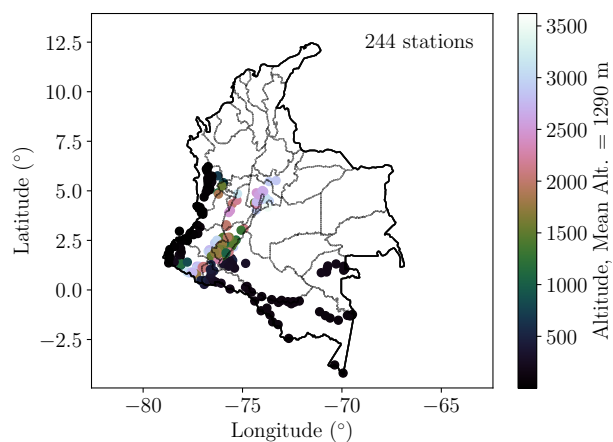
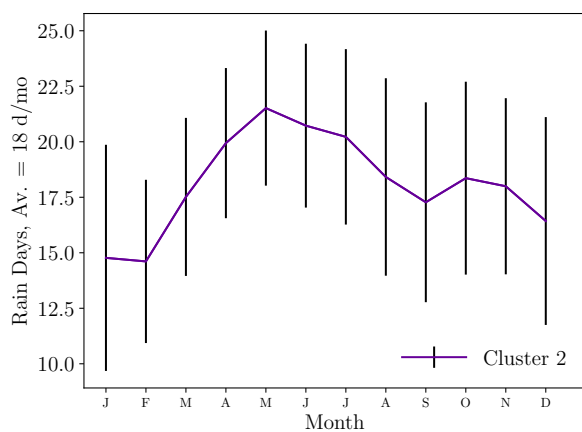
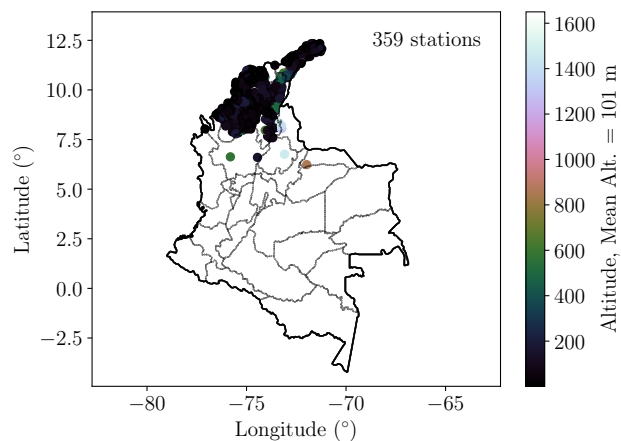
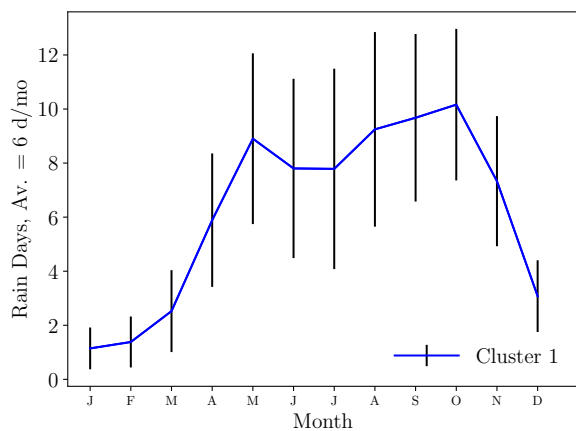
- For example, if  $M_X$  is the event “the station measured variable  $X$ ”, then the event  $T_7$  is equivalent to  $M_P \cap \neg M_R \cap M_H \cap M_S$
- $h$  is the event that a given station is located at an elevation  $h$ .

Thus, the probability that a station  $j = (0, 1, \dots, N_{\text{stations}})$  of type  $T_i$ , meets all four criteria ( $C$ ) and appears in our shortlist ( $A$ ) given that it is located at an elevation  $h$ , can be written as  $P_j = P(C \cap A \cap T_i | h)$ . We cannot calculate exactly this probability, as it depends on unknown unknowns, i.e. whether a station that did not measure a given variable in reality belongs to one of our preferred climatological clusters for that variable. Thus we will use Bayes’ theorem to help estimate this probability using simpler conditional probabilities. First we control for the inhomogeneous distribution

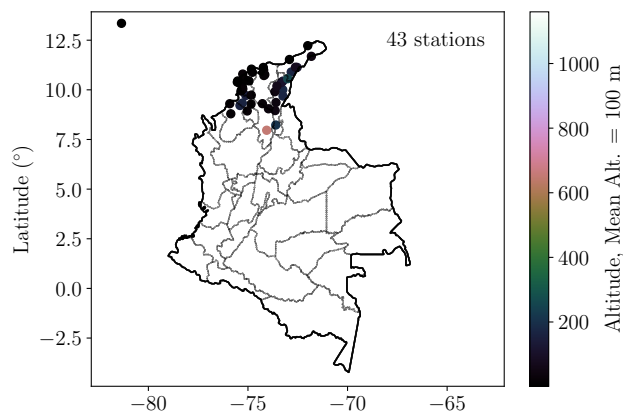
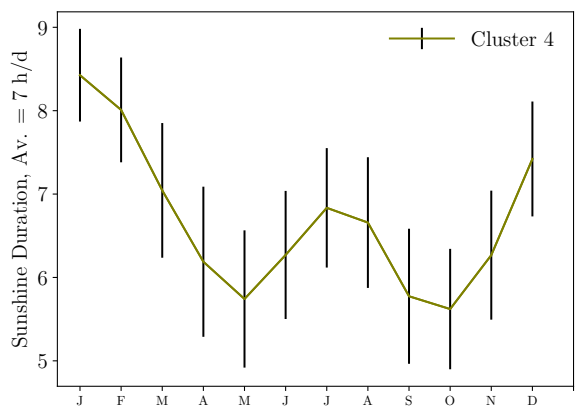
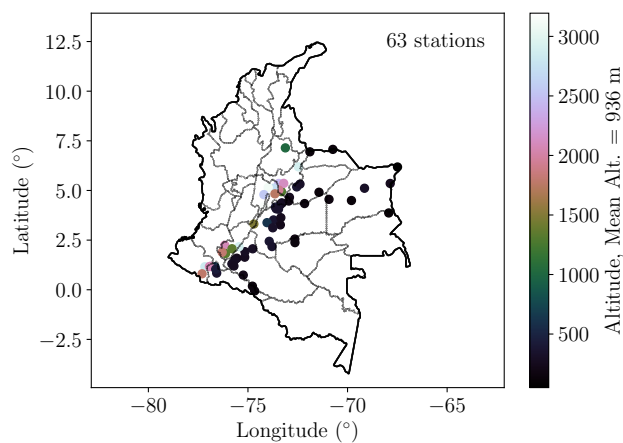
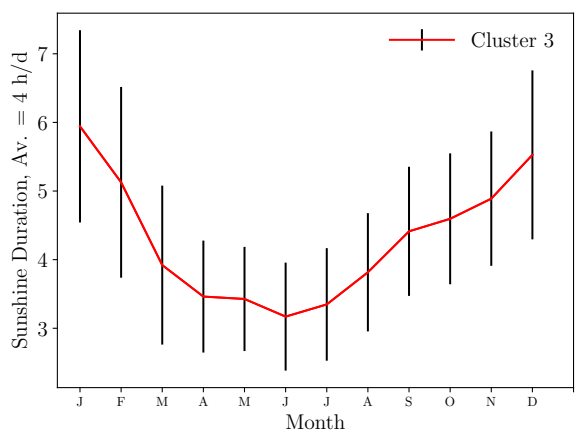
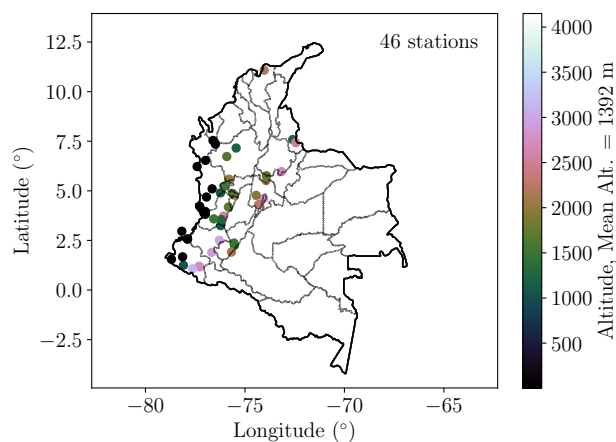
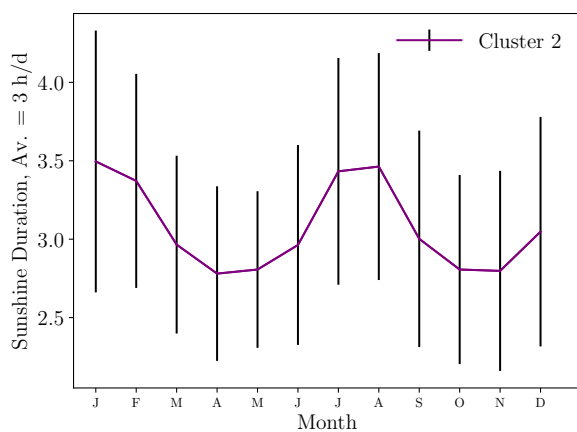
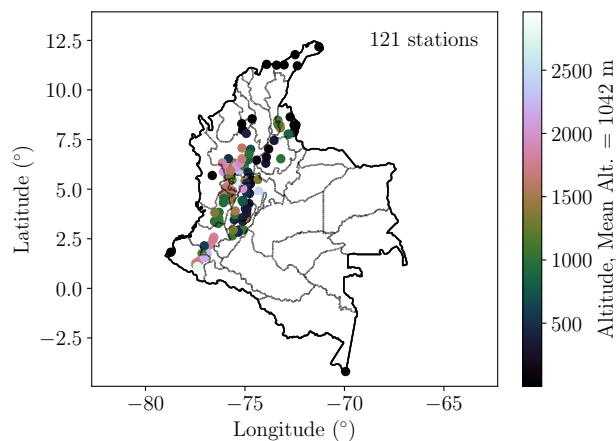
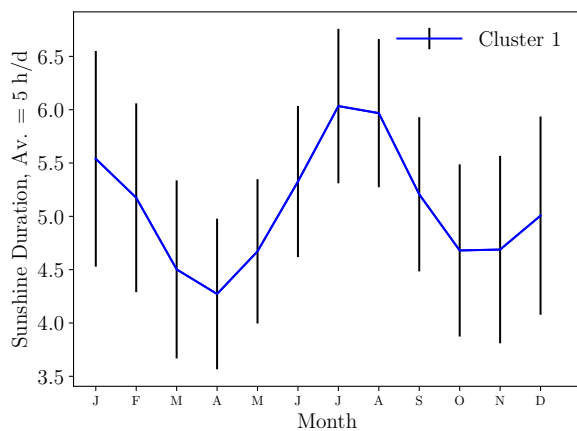
# *Site Location Study for a Millimeter Observatory in the Colombian Andes I: In Situ 10*



# *Site Location Study for a Millimeter Observatory in the Colombian Andes I: In Situ* 11



# *Site Location Study for a Millimeter Observatory in the Colombian Andes I: In Situ* 12



of elevations  $P(h)$ ,

$$P(C \cap A \cap T_i | h) = \frac{P(C \cap A \cap T_i \cap h)}{P(h)} . \quad (1)$$

The joint probability of all events  $C \cap A \cap T_i \cap h$  can be rewritten as,

$$P(C \cap A \cap T_i | h) = \frac{P(h | C \cap A \cap T_i)}{P(h)} P(C \cap A \cap T_i) . \quad (2)$$

If a station satisfies all four criteria,  $P(C \cap A \cap T_i) = 1$ . This probability can be expressed in terms of simpler conditional probabilities,

$$P(C \cap A \cap T_i | h) = \frac{P(h | C \cap A \cap T_i)}{P(h)} P(C | A \cap T_i) P(A | T_i) P(T_i) . \quad (3)$$

Here  $P(h | C \cap A \cap T_i)$  is the distribution of elevations for a station type ( $T_i$ ) on our shortlist ( $C \cap A$ ),  $P(A | T_i)$  is the probability that a station of type  $T_i$  is in our shortlist,  $P(T_i)$  is the probability that a station type is  $T_i$ , and  $P(C | A \cap T_i)$  is the probability that a station meets all four criteria ( $C$ ) given that it is in our shortlist ( $A$ ) and is of type  $T_i$ . All of these probabilities except for the last one can be computed directly from the data. The probability  $P(C | A \cap T_i)$  has to be estimated indirectly, as we cannot presume to know under which conditions a station can satisfy all our criteria. We can rewrite this probability as,

$$P(C | A \cap T_i) = P(P \cap D \cap H \cap S | A \cap T_i) , \quad (4)$$

$$= \frac{P(P \cap D \cap H \cap S \cap A \cap T_i)}{P(A \cap T_i)} . \quad (5)$$

In order to estimate  $P(C | A \cap T_i)$  we assume that the probability of a station meeting our criteria for a given number of variables is independent of the station type. To illustrate this, let us assume that a given station is of type 1, so it only measured precipitation and rain days, i.e.,

$$T_1 = M_P \cap M_D \cap \neg M_H \cap \neg M_S . \quad (6)$$

If this station of type  $T_1$  is in our shortlist ( $A$ ), the  $P$  and  $D$  criteria are met. Thus,

$$P(P \cap D \cap H \cap S \cap A \cap T_1) = P(H \cap S | A \cap T_1) . \quad (7)$$

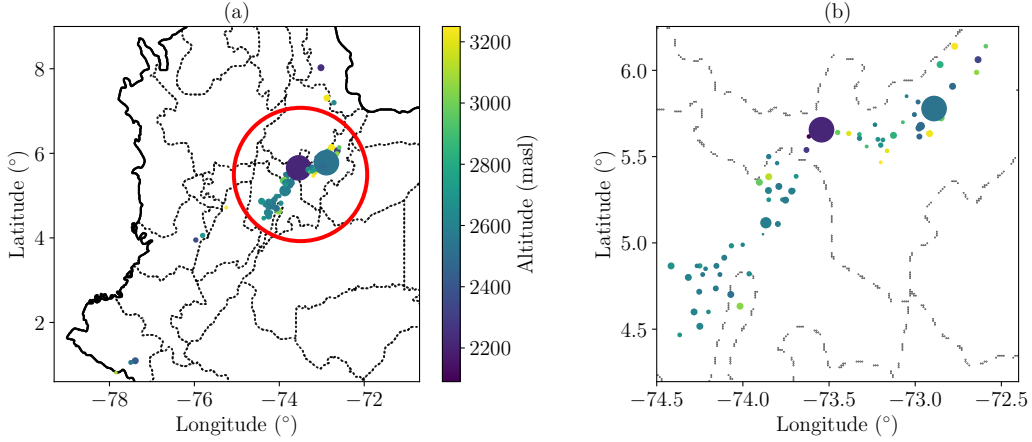
Substituting this into Eq. (5),

$$P(C | A \cap T_1) = \frac{P(H \cap S | A \cap T_1)}{P(A \cap T_1)} = P(H \cap S | A \cap T_1) \quad (8)$$

The last term in the previous expression is unknown, but we can approximate it assuming, as mentioned above, that it is independent of the station type. Therefore,

$$P(C | A \cap T_i) \simeq P(H \cap S) . \quad (9)$$

The probability on the right hand side of the previous equation can be directly computed from the data, as it only requires counting how many stations meet both  $H$  and  $S$  criteria. This procedure can be extended to all other station types.



**Figure 9.** Map of stations in our final shortlist. The highlighted region on (a) is seen in more detail in (b), which corresponds approximately to the Colombian *altiplano* region. Marker size is proportional to the probability  $P_j$ , where the largest size corresponds to  $Q_j = 10$ .

Since the probabilities for stations in our shortlist vary by orders of magnitude, for clarity's sake we decided to use a logarithmic quality index for a station in our shortlist. For  $j = (0, 1, \dots, N_{\text{stations}})$ ,

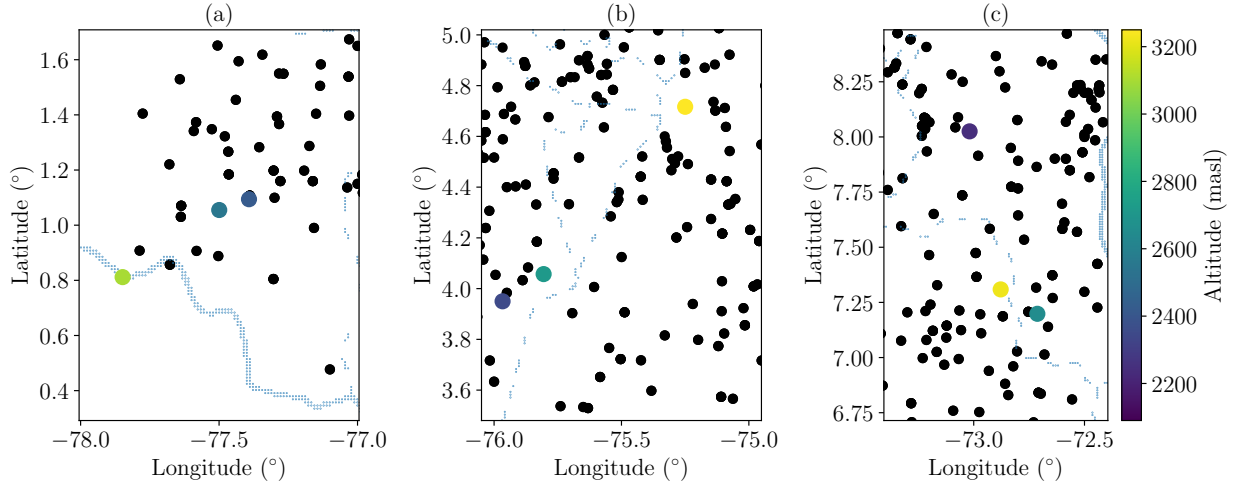
$$Q_j = 9 \frac{\log(P_j/P_{\min})}{\log(P_{\max}/P_{\min})} + 1. \quad (10)$$

Here  $P_{\min}$ ,  $P_{\max}$  are the lowest and highest values for the probabilities for the stations in the first shortlist of 665 stations that satisfy criteria for all measured variables. Thus, if  $P_j = P_{\max}$ ,  $Q_j = 10$ , and if  $P_j = P_{\min}$ ,  $Q_j = 1$ .

#### 4.2. Final selection

Given that many of our 83 candidate stations were lacking in relative humidity and sunshine duration data, we extrapolated using data from nearby stations (at less than 4 km away and at an elevation difference of less than 100 m). We made sure that in general, for stations less than 5 km away, the difference in relative humidity and sunshine duration data is less than 15%. The extrapolated data evidenced that 4 of the stations in the shortlist did not satisfy the relative humidity and sunshine duration criteria. The remaining 79 stations are mapped in Figure 9a.

We rejected 9 of the stations in Figure 9a, i.e. those located outside of the region located within the latitude, longitude range  $[(4.3, 6.2), (-72.4, -74.5)]$ . Even though they could be indicative of unusually dry, sunny regions, there are simply not enough stations nearby to say anything conclusively, as evidenced in Figure 10. Adding to this, the only variable they measured was precipitation ( $Q_j = 2.2$ ), which leads us to reject them from



**Figure 10.** Map of stations in our final shortlist but outside of the Colombian *altiplano* region highlighted in Figure 9. Marker size is proportional to the probability  $P_j$ , where the smallest size corresponds to  $Q_j = 2.2$ .

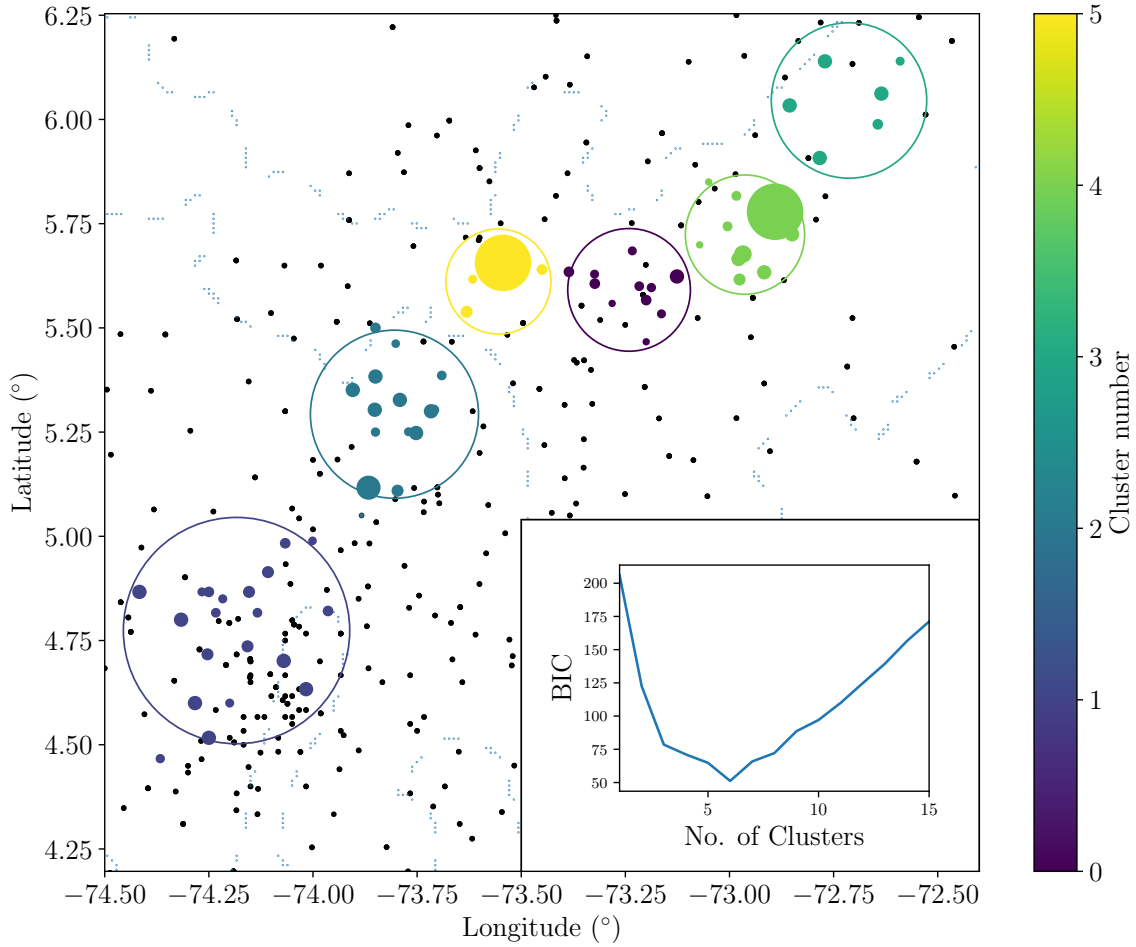
our shortlist.

The final 70 stations located in the Cundinamarca-Boyacá region of Colombia are shown in more detail in Figure 9b. This figure shows two candidate locations in the northern region (Boyacá department), where the quality index  $Q_j$  (proportional to the point size) indicates that all four criteria are satisfied. In order to see if those regions are geographically correlated, we grouped together these stations in a simplified manner using a lowest-BIC spherical covariance Gaussian Mixture Model on their coordinates 13.

## 5. Results

We selected clusters of climatologically similar stations across Colombia using an unsupervised learning low-dimensional embedding algorithm for each measured variable. From these clusters, 70 weather stations came up as potential candidates for identifying high-mountain regions (at an elevation greater than 2000 masl) with an unusually dry, sunny weather.

Figure 13 shows 6 candidate regions of interest, where weather stations indicating dry, sunny climate are regionally correlated. In order to visualize the extent of those regions we plotted the predicted variance regions for each cluster along with other (rejected) stations in our sample in Figure 13. It should be noted that the spherical variance GMM geographical clustering overestimates the extent of each region, and tells us nothing of their actual shape. We can now reject regions where the number of rejected



**Figure 11.** Geographical clustering results for a lowest-BIC spherical covariance Gaussian Mixture Model of the stations located inside the red circle in Figure 9b, indicating the predicted variance regions for each cluster (red circles), and plotted along rejected stations in our original dataset (black points). Marker size is proportional to the probability  $P_j$ , where the largest size corresponds to  $Q_j = 10$  and the smallest size corresponds to  $Q_j = 2.2$ . Embedded plot: BIC results for different number of clusters.

stations within the predicted variance regions is too similar to the number of stations in our shortlist in Figure 13. We discuss the suitability of each of these regions below, from South-West to North-East based on our Bayesian probabilistic quality index (Section 4.1).

### 5.1. La Sabana

The first cluster is located at (4.77°N, 74.18°W) and covers an radius of 15.3 km<sup>2</sup>. This is a region located to the west of Bogotá at an elevation above 2600 masl, with a large variety of microclimates. This explains the significant amount of stations from this region in our shortlist. However, Figure 13 shows that within this predicted variance



region there are more stations that do not satisfy our criteria than stations that do, and no single sub-region can be identified. This, compounded with the fact that most (70%) of these stations have a  $Q$  value lower than 5.6 due to the lack of humidity/sunshine data, implies that at the moment this is not a strong candidate region of interest.

### *5.2. Valle de Ubaté*

This cluster is located at (5.30°N, 73.80°W) and covers a radius of 11.4 km<sup>2</sup>. This region, located to the NNE of Bogotá is a hilly region along a valley at an elevation above 2600 masl. The ratio of number of stations that do not meet our criteria to the stations in this predicted variance region is low (0.3), and almost half of these stations (46%) have a  $Q_j$  value higher than 6. This indicates a potential candidate region, although more sunshine and humidity data are needed.

### *5.3. Villa de Leyva*

This cluster is located at (5.61°N, 73.55°W) and covers a radius of 7.11 km<sup>2</sup>. This region is located near the town of Villa de Leyva, and it is known for its dry weather. The ratio of stations not in our shortlist vs. the stations in this predicted variance region is not very low (0.4). However, Figure ?? seems to indicate that the actual region of interest is narrower than the predicted variance region, as the stations that do not satisfy our criteria are on the NNW and SSW fringes of said region. The presence of one very high- $Q_j$  station and the narrow GMM-predicted variance is indicative of this region being a strong candidate. However, its relatively low elevation (near 2200 masl) can signify the presence of too much atmospheric water vapor above the surface.

### *5.4. Cantón de Tunja*

This cluster is located at (5.59°N, 73.24°W) and covers a radius of 8.29 km<sup>2</sup>. The GMM-predicted variance region west of Tunja is located in the historic Tunja Canton, and even though the ratio of stations not in our shortlist to stations in this predicted region is low (0.31), there are simply not enough humidity and sunshine data to make any strong conclusion about this region. However, the high altitude of some of these stations is tantalizing, which is why we will keep this as a region of interest for our next paper.

### *5.5. Valle del Sol*

This cluster is located at (5.72°N, 72.96°W) and covers a radius of 8.06 km<sup>2</sup>. This is one of the most promising regions in our sample. Located in a wide, sunny valley (hence the name) at an elevation of 2600 masl, it is surrounded by mountains, and rains are not as common as elsewhere in the country. This region has the lowest ratio of not in our shortlist stations to stations in this predicted variance region (0.2), 40% of the stations have a  $Q_j$  value higher than 6, and one of the stations has a very high- $Q_j$  value. This

will be one of the regions of interest for our next paper, and we think that it warrants radiometer measurements to be carried out.

### 5.6. Pisba National Park

This cluster is located at (6.04°N, 72.71°W) and covers a radius of 10.52 km<sup>2</sup>. This is a *páramo* region, characterized by high-mountain tundra weather. The ratio of stations not in our shortlist to station in this predicted variance region is high (0.5), and it is unlikely that the mist allows for a low-atmospheric water vapor region to be located here, even if rain is sporadic. The lack of a high- $Q$  station means that more sunshine-humidity data are needed, but this is possibly not a region of interest.

One, to the NWW of Bogotá, another to the N of Bogotá, in the region known as Valle de Ubaté,

4000 masl might be interesting as well, but there are not enough stations.

Seasonality plots

## 6. Conclusions

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