
Un análisis geográfico

de la información disponible sobre
la precipitación media mensual para
los Andes venezolanos

A geographical analysis on the mean
monthly precipitation information
available of the Venezuelan Andes

Paolo Ramoni-Perazzi

Universidad de Los Andes, Facultad de Ingeniería,
Centro de Simulación y Modelos, Facultad de
Ciencias, Laboratorio de Zoología Aplicada.
rpaolo@ula.ve

Magdiel Ablan-Bortone

Universidad de Los Andes, Facultad de Ingeniería,
Centro de Simulación y Modelos, Mérida, Venezuela.
mablan@ula.ve

Dirk R. Thielen

Instituto Venezolano de Investigaciones Científicas,
Centro de Ecología, Laboratorio de Productividad
y Desarrollo Vegetal, Miranda, Venezuela
dirkthielen@gmail.com

Resumen

Evaluamos la aptitud de la información pluviométrica disponible para los Andes venezolanos en relación a: (1) precisión de las coordenadas geográficas de los metadatos; distribución sobre (2) el plano *lat-lon* y (3) gradiente de elevación; (4) reportes de precipitación dudosos; (5) autocorrelación espacial; y (6) correlación entre precipitación y elevación. Evaluamos 342 estaciones pluviométricas, 314 de ellas proveyeron información para al menos un mes por 10 años o más entre 1950 y 2000. De éstas, 27 requirieron corrección de sus coordenadas geográficas. Parte de las estaciones estuvieron distribuidas aleatoriamente sobre el plano *lat-lon* y parte estuvieron ligeramente agrupadas en el estado Táchira y valles longitudinales. El gradiente de elevación estuvo adecuadamente representado, excepto las cotas extremas. No encontramos valores de precipitación dudosos. Concluimos que la cantidad, calidad y distribución espacial de los datos de precipitación media mensual disponible para el área de estudio excede los requerimientos mínimos para interpolaciones espaciales.

Palabras clave: estaciones pluviométricas; distribución espacial; calidad de los datos; precipitación media mensual; Andes de Venezuela.

Abstract

We assessed the appropriateness of pluviometric information available of the Venezuelan Andes, in relation to: (1) precision of geographic coordinates in metadata; distribution pattern on (2) lat-long plane and (3) elevation range; (4) dubious precipitation reports; (5) spatial autocorrelation; and (6) correlation between elevation and mean monthly precipitation. We evaluated 342 weather stations, out of which 314 provided information for at least one month during 10 or more years between 1950 and 2000. Corrections of their geographic coordinates were required by 27 of them. Part of the weather stations were randomly distributed on lat-long plane and the rest were slightly clustered in Táchira State and along longitudinal valleys. Elevation gradient was adequately represented, except for the extreme heights. Besides, we found no dubious precipitation values. We concluded that the amount, quality and spatial distribution of mean monthly precipitation data available for the study area exceed the minimal requirements for spatial interpolations.

Key words: weather stations; spatial distribution; data quality; mean monthly precipitation; Venezuelan Andes.

1. Introduction

The knowledge of the precipitation patterns is fundamental to planning, risk evaluation, and decision making. Moreover, this information is valuable to generate other climatic variables (for example, Hijmans *et al.*, 2005), widely used to estimate the relationships among localities occurrence for given species and their environmental characteristics (Franklin, 2009), knowledge used in biogeography, conservation biology, and ecology (Elith & Leathwick, 2009; Elith *et al.*, 2011). However, the knowledge about precipitation patterns of mountainous areas is usually absent or incomplete, given the complex topography, degree of geographic dispersion of the pluviometric information (Prudhomme & Reed, 1999), and biases due to the position of the pluviometric stations within the landscape: usually in the valleys easy to access but with lower precipitation, if compared to the surrounding more elevated lands (Johansson & Chen, 2003).

Probably in no other region the knowledge of the geographic distribution of precipitation is more obviously needed and, indeed, indispensable than in the Tropical Andes, where, in addition to the aforementioned disadvantages, one of the world's highest biodiversity (Olson & Dinerstein, 1998; Myers *et al.*, 2000; Brummitt & Lughadha, 2003) meets one of the world's highest levels of threat (Cincotta *et al.*, 2000). On this regard, Venezuelan Andes stand out by the overlap between a great biodiversity (Huber & Oliveira Miranda, 2010), an accelerated human population growth (Pulido, 2014), and a complex relief with the concomitant precipitation patterns diversity (Vivas, 1992; Rodríguez & Defives, 1996; Silva León, 2010; Jiménez & Oliver,

2005). Indeed, while external slopes (both Llanos' and Maracaibo's Lake) tend to be more wet, with precipitation being positively correlated to the elevation until an inversion point wherefrom this correlation becomes inverse, the internal valleys are more complex with spotted drier areas due to rain shadows (Vivas, 1992).

Moreover, Venezuelan Andes act like an orographic barrier between two precipitation regimes (Monasterio & Reyes, 1980; Rodríguez & Defives, 1996). On the one hand, the Llanos slope shows the unimodal precipitation pattern typical of the Northern portion of South America as described by Hastenrath (1984), while the Maracaibo's Lake slope shows the bimodal precipitation pattern typical of the Caribbean region as described Taylor & Alfaro (2005).

The geographic distribution of precipitation can be quantified from point samples, represented by the weather stations, and then estimate for non-sampled areas applying methods of spatial interpolation (Burrough & McDonnell, in order to ensure reliable results).

However, information provided by meteorological stations can contain mistakes and gaps generated during transcription, transmission and codification processes (Meek & Hatfield, 1994). For such a reason, a quality control is required as a first step to detect erroneous values (Štěpánek *et al.*, 2009), paying attention to both the quality of the associated metadata (geographic coordinates, elevation, etc.) and the quality of the reported values (for example, precipitation), which have shown some error level in other latitudes (Peterson *et al.*, 1998).

On the other hand, a key question is whether the sampling (weather stations) lo-

calities are distributed uniformly, randomly or clustered throughout the study area. The importance of this information lies on the uniformity assumptions on which many geostatistical analysis are based (Webster & Oliver, 2007).

In this paper, we assessed in detail the appropriateness of the pluviometric information available for the Venezuelan Andes area, in relation to **1)** the precision of the geographic coordinates provided with the weather stations metadata; **2)** horizontal distribution pattern on the *lat-lon* plane; **3)** vertical distribution pattern along the elevation range; and **4)** the existence of dubious precipitation reports. We also explored the spatial autocorrelation and correlation with elevation of the mean monthly precipitation in the study area.

2. Materials and Methods

2.1. Study area

Venezuelan Andes are a prolongation of the Andean mountain range of some 400 km in length and some 100 km at the widest point, which extends from Táchira State NW to Lara State, including portions of Apure, Mérida, Barinas, Trujillo and Portuguesa States. It is the result of the oblique collision between the continental Maracaibo block of the Caribbean Plate and the South American Plate, which created two mountain ranges delimited longitudinally by the Boconó fault (Bermúdez *et al.*, 2011). Táchira depression divides the Venezuelan Andes transversally into two portions: **a)** «Macizo del Tamá» to the SW, shared with Colombia, and **b)** «Cordillera de Mérida», separated from «Serranía de San Luis» and «Cordillera de La Costa» by the Lara depression.

We used the digital elevation model (hereafter DEM) from the corrected Shuttle Radar Topography Mission (SRTM), version 4 (Jarvis *et al.*, 2008), with a resolution of three arc-seconds. Particularly, we used the «srtm_22_10.asc», «srtm_22_11.asc», «srtm_23_10.asc» and «srtm_23_11» files, from which we selected the area corresponding to the Venezuelan Andes using Quantum GIS, version 1.8.0 (Quantum GIS Development Team, 2013). We plot the mean elevation values by row and by column in order to explore the existence of spatial trends in this respect along both altitude and longitude.

2.2. The geographic distribution of weather stations

We evaluated 341 weather stations, located in the Venezuelan Andes or in the surrounding piedmonts, 340 under the care of the Instituto Nacional de Meteorología e Hidrología (INAMEH), and one of the Universidad de Los Andes. We also included information published by Redaud *et al.* (1991) about a weather station in a relevant location: the upper portion of Nuestra Señora river valley. For each weather station, we counted on the following information: **a)** the metadata, consisting at least of station code, name, geographic coordinates and elevation, and **b)** monthly precipitation, measured at least for 10 years between 1950 and 2000, both years inclusive.

We used R language version 3.1.2 (R Development Core Team, 2014) for analysis and computing because its advantages in the analysis of spatially oriented data (Bivand *et al.*, 2008). All analysis were carried out at Centro de Simulación y Modelos, Facultad de Ingeniería, Universidad de Los

Andes. Additional information can be accessed at <http://webdelprofesor.ula.ve/ciencias/rpaulo/prpInvestigacionBioclimaPP.html>

We checked the geographic location of the weather stations contrasting the locality indicated in the metadata against information provided in freeware resources such as GoogleEarth, version 7.1.2.2041 (Google Inc., 2014), VenRut®, version 13.07 (GPSYV, 2013), as well as scientific articles and some few field prospectations. We corrected the reported geographic coordinates and elevations when **1)** the consulted sources reported a locality whose location raised overall doubts, or **2)** the provided geographic coordinates located them in an obviously unlikely area (too far from reference point, on groundwater bodies, ravines, etc.) in which case we adopted the geographic coordinates of the homonymous town.

We assessed whether the sampling localities (weather stations) were distributed uniformly, randomly or clustered on the lat-lon plane in the study area through the nearest neighbor distances analysis (Dixon, 2002). Therefore, we graphically evaluated the compatibility of the sampling pattern with respect to the Complete Spatial Randomness (CSR), which assumes that there are no particular regions in the study area where events are more likely to occur and that the occurrence of one event does not modify the probability of occurrence of another one in the vicinity, comparing the empiric against the expected function (Bivand *et al.*, 2008). Thus, we compared the observed distribution of the nearest neighbor distances, $\hat{G}(r)$, against the theoretical cumulative distribution function (cdf), also calculating the value α of the critical level through a Monte Carlo simulation (Dixon, 2002; Diggle, 2003).

Furthermore, we calculated the aggregation index of the nearest neighbor following Clark & Evans (1954): a raw measurement of the clustering, randomness or uniformity degree of a given point pattern, consisting of the relationship between the mean distance observed among nearest neighbors and the expected Poisson distribution for a point pattern of the same intensity.

We also explored spatial point pattern density non-parametrically through kernel smoothing (Bivand *et al.*, 2008), a method that estimates an unobservable underlying probability density function through an algorithm that disperses the mass of the empirical distribution function over a regular grid, using the fast Fourier transform to convolve this approximation with a discretized version of the kernel, and then uses linear approximation to evaluate the density at the specified points.

To assess the adequacy of the weather stations disposition from the elevation point of view, we compared the distribution function of the elevation of the localities where the weather stations were located against the distribution function of the elevation of the DEM, using a non-parametric Kolmogorov-Smirnov test (Zar, 1999).

2.3. Mean monthly precipitation values

Besides the habitual calculation of basic statistics for mean monthly precipitation (mean, median, standard deviation, variation coefficient, skewness and kurtosis), we explored the existence of dubious values through histograms, box-and-whiskers plots, as well as bubble plots of the mean monthly precipitation.

2.4. Precipitation and geographic distribution

We calculated the Moran's I coefficients (Gittleman & Kot, 1990) for each month using both the corrected sampling (weather stations) localities and their respective mean monthly precipitation values. Finally, we also assessed the degree of correlation between mean monthly precipitation and elevation.

3. Results

3.1. Study area

The resulting DEM consisted of a grid of 4,081 rows by 4,077 columns, that is, 16,638,237 pixels from which 7,860,219 (47%, a surface of 66,529 km²) effectively contained elevation information and the others consisted of surrounding lowlands excluded from further analysis (codified as -9999). The plot of mean elevation values by row and by column indicates appreciable geographic trends neither in altitude nor in longitude (Figure 1).

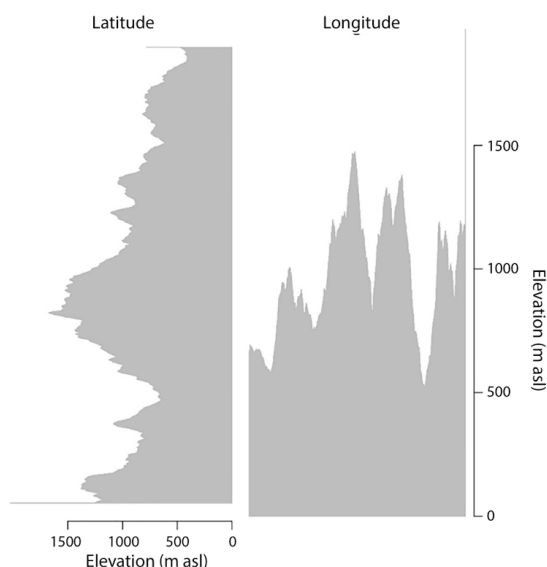


Figure 1 Mean elevation values of the study area according to the DEM used in this research for both rows (latitude) and columns (longitude)

3.2. The geographic distribution of weather stations

Of the 342 weather stations in the study area, 314 provided mean monthly precipitation data for at least one month for 10 or more years between 1950 and 2000, both years inclusive (Chart 1). The larger number of weather stations were located in Táchira (total 88/useable 81), followed by Mérida (76/71), Trujillo (67/61), Lara (62/60), Barinas (26/21), Portuguesa (19/17), Zulia (three/two), and finally Apure (one/one). We detected that at least 27 (8.6 %) of these 314 weather stations required some correction with regards of the geographic coordinates provided by their metadata. The mean distance of these 27 corrections was of 12.9 km, within a range from 0.5 km (Station serial 3138 «Chacantá») to 109.2 km (Station serial 3027, «Páramo La Culata», whose original geographic coordinates provided in the metadata located it in the Barinas' Llanos).

Nearestneighbor distances among weather stations range from 0.28 km to 30.14 km, median 4.18 km and third quartile 8.39 km. The comparison between the empiric distribution of the nearest neighbor distances, $\hat{G}_{obs}(r)$, and the theoretical cumulative distribution function, $\bar{G}(r)$, indicated that a portion of the weather stations were distributed randomly, while the remnant ones were slightly clustered so long as part of the empiric distribution lied above the mean, including the critic rank, suggesting an excess of short distances among nearest neighbors (Figure 2). This observation was reinforced by the aggregation index of the nearest neighbor (Clark & Evans, 1954), whose calculated value was 0.88. It is noteworthy that when this index lies above one indicates uniformity; one indicates ran-

Chart 1 Weather stations in the studied area whose geographic coordinates were corrected. Code, weather station serial; ID, Name of the weather station according to metadata; Lat_{orig} and Long_{orig}, original latitude and longitude according to metadata; Lat_{corr} and Long_{corr}, corrected latitude and longitude; Δ(km), distance in kilometers between original and corrected distance. Dir(°), direction in degrees from original coordinates toward the corrected ones

Code	ID	Lat _{orig}	Long _{orig}	Lat _{corr}	Long _{corr}	Δ(km)	Dir(°)
	Barinas						
3186	Pedraza-La Vieja	7.934167	-71.052778	7.917170	-71.060040	2.08	202
	Lara						
1222	El Zancudo	9.783333	-69.538889	9.778730	-69.550670	1.42	244
1272	Banco de Baragua	10.146944	-69.591944	10.157730	-69.675240	9.21	277
1278	El Cují	10.166667	-69.316667	10.146970	-69.311350	2.18	169
2201	Curarigua	9.999167	-69.918611	9.979470	-69.938510	3.28	227
2251	Humocaro Alto-vivero	9.625556	-69.988056	9.607060	-69.987900	2.02	180
	Mérida						
3027	Páramo La Culata	8.746667	-70.070833	8.749240	-71.060940	109.21	227
3023	El Molino	8.204167	-71.550000	8.198180	-71.552150	0.71	212
3024	Valle Grande	8.716667	-71.083333	8.673170	-71.102590	5.23	203
3035	El Vigía	8.607500	-71.629722	8.633190	-71.650110	3.66	320
3047	Mérida-Aeropuerto	8.600000	-71.183333	8.583611	-71.160833	3.15	126
3052	Mesa Bolívar	8.478333	-71.584722	8.475180	-71.597000	1.41	257
3067	Tovar-Alcaldía	8.341944	-71.750000	8.330040	-71.753700	1.40	197
3072	Mucubají	8.802778	-70.822778	8.798800	-70.825980	0.57	216
3080	El Morro	8.451389	-71.184444	8.443333	-71.187460	0.97	200
3134	Canaguá	8.135556	-71.440278	8.125000	-71.460278	2.51	241
3138	Chacantá	8.175556	-71.433333	8.180833	-71.434722	0.47	342
3199	Mucujepe	8.648056	-71.568889	8.662170	-71.587250	2.49	303
8056	San Pedro-Chiguará	8.506944	-71.575000	8.506111	-71.548889	2.91	92
8057	Tostós	8.426667	-71.339444	8.375560	-71.289410	7.95	135
	Táchira						
4030	Punta Piedras	7.613056	-71.506667	7.641389	-71.490567	3.61	29
4051	Las Delicias	7.566667	-72.433333	7.565278	-72.445556	1.45	281
4085	Uribante-Sitio de Presa	7.754167	-71.964444	7.906389	-71.747664	29.38	54
4086	Las Bocas de Caparo	7.683333	-72.433333	7.771111	-71.460556	107.95	83
4087	Potosí	7.633333	-71.950000	7.936986	-71.722328	42.20	36
4092	La Hormiga	7.823333	-71.813889	7.814880	-71.820330	0.88	231
	Trujillo						
7151	Monte Carmelo	9.195833	-70.814722	9.204722	-70.812897	1.04	10

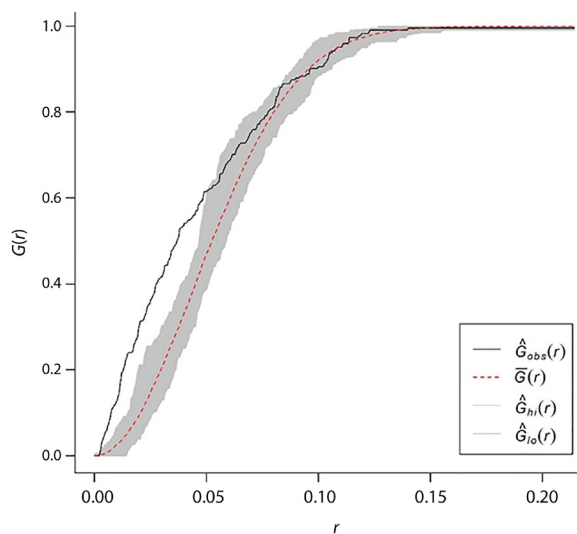


Figure 2 Comparison between the observed distances among nearest neighbors, $\hat{G}_{obs}(r)$, and the theoretical cumulative distribution function, $\hat{G}(r)$, with a confidence rank established using Monte Carlo simulations ($\hat{G}_{io}(r) - \hat{G}_{hi}(r)$)

domness and below one indicates clustering of the point pattern.

The spatial density distribution of weather stations measured through kernel smoothing (Bivand *et al.*, 2008) demonstrated the dependency of local estimates of density on band amplitudes: narrow amplitudes yielded more extreme values, while wide amplitudes reduced the interquartile

Chart 2 Basic statistics of kernel smoothing density estimates of weather stations spatial distribution using four different bandwidth

	0.25	0.50	0.75	1.00
Minimum	28.99	51.22	63.34	69.04
1st quartile	60.14	68.88	71.57	73.48
Median	79.86	79.80	77.77	76.69
Mean	81.42	79.87	78.42	77.72
3rd quartile	99.01	89.47	85.01	81.64
Maximum	184.82	118.17	97.09	91.41

ranges (Chart 2). Furthermore, this dependency also was observed in figure 2, where low sigma values highlighted a greater density (clustering) of weather stations in Táchira State as well as along the longitudinal valleys.

When comparing graphically the distribution function of the elevation values of our DEM against the distribution function of the weather stations elevations (Figure 3), our results suggested that the study area was adequately represented throughout the elevation range, except for the most extreme heights. Such observation was corroborated by the two-sample Kolmogorov-Smirnov test ($D = 0.28$; $p = 0.281$).

3.3. Mean monthly precipitation values

Mean monthly precipitation throughout the year showed a drier period among December-March, being wettest the rest of the year (Figure 4). The greatest variability observed in the June-August quarter reflected the diffe-

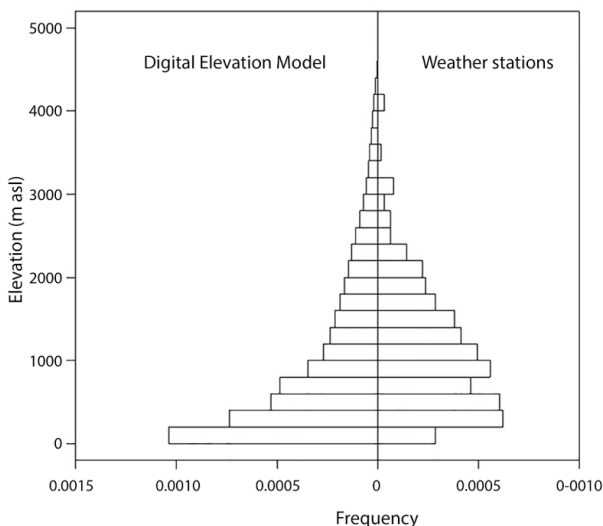


Figure 3 Comparison of the elevation distributions of both the pixels in DEM (right) and the location of weather stations (left) in the study area

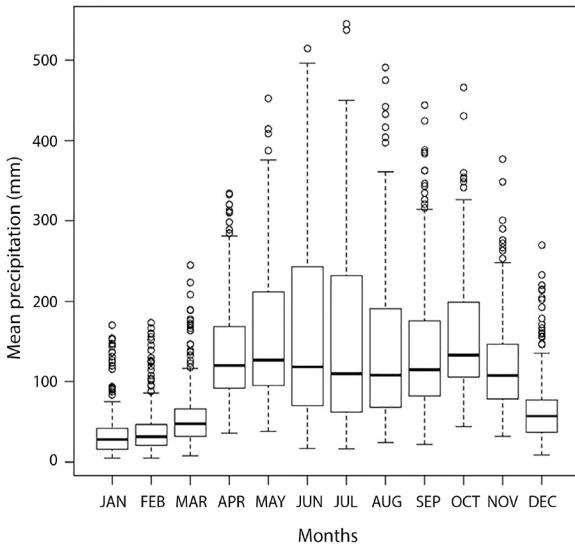


Figure 4 Variation of the mean monthly precipitation in the study area throughout the year

rences between the unimodal precipitation regime of Llanos slope and the bimodal pattern of the Maracaibo’s Lake slope with its characteristic short dry season around August. On the other hand, **Figure 4** also suggested the absence of aberrant mean monthly precipitation values, which could represent erroneous measures, suggestion shared by the histograms in **Figure 5** which additionally highlighted that mean monthly precipitation is positively skewed for all months.

Furthermore, the presence of dubious values was also discarded by the bubble plots (**Figure 6**), which additionally demonstrated a displacement throughout the year

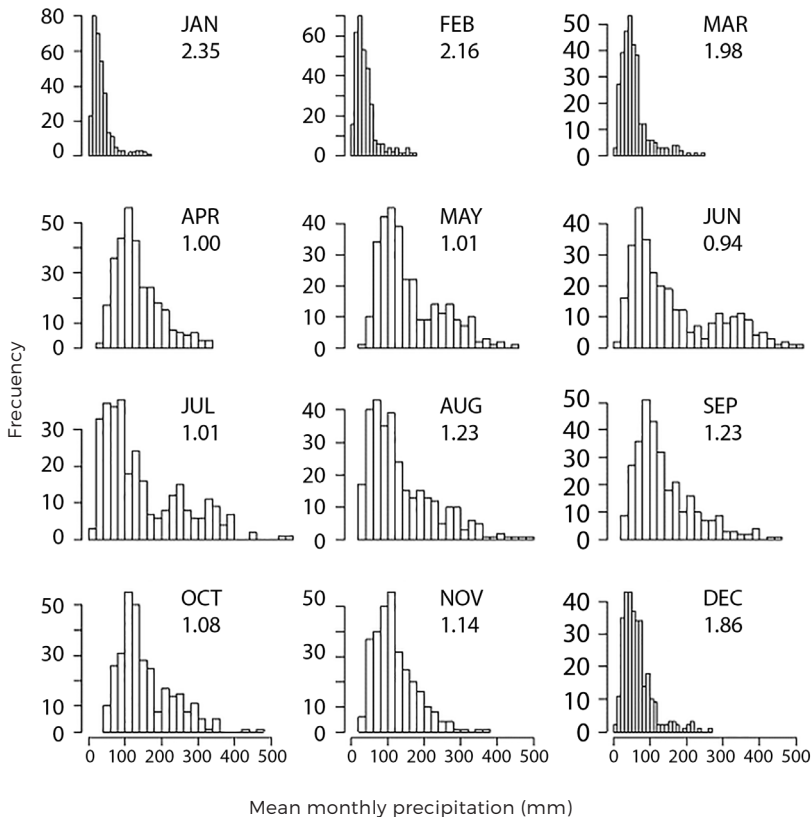


Figure 5 Histograms and skewness corresponding to the mean precipitation for each month

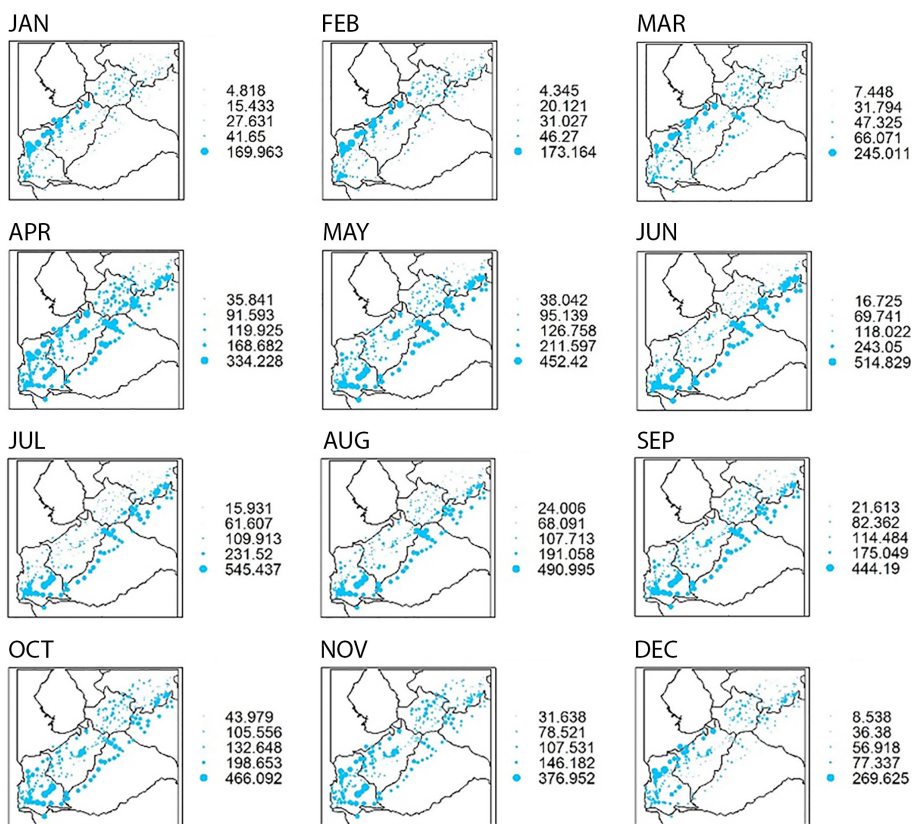


Figure 6 Bubble plots of the mean precipitation for each weather station for each month

of the mean monthly precipitation relative maxima: these are concentrated on the Maracaibo's Lake slope at Táchira and Mérida in January, moving gradually toward the Llanos slope during the subsequent months, where they are concentrated by June to August, returning gradually back to Maracaibo's Lake slope by December.

3.4. Precipitation and geographic distribution

According to Moran's *I* coefficients (Gittleman & Kot, 1990), the mean monthly precipitation values were spatially autocorrelated in the study area ($p < 0.0001$ for all cases; **Chart 3**), averaging 0.183 within a range between 0.147 (March) and 0.206 (June). On

Chart 3 Observed Moran's *I* coefficients of spatial autocorrelation of the mean monthly precipitation data of the 314 weather stations. The expected coefficients were -0.003, Standard Deviations were 0.012, and $p < 0.0001$ in all cases

Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
0.18	0.15	0.14	0.16	0.18	0.20	0.20	0.19	0.19	0.18	0.20	0.19
6	1	7	2	0	6	4	8	3	5	1	4

the other hand, mean monthly precipitation and elevation were correlated for any month (Figure 7).

4. Discussion

Although a greater number of weather stations would always be desirable, our analysis indicated that the amount and geographic distribution of the weather stations providing relevant information can be considered adequate, for example, to be used to generate reliable mean monthly precipitation interpolations. This is a surprising finding given that the climatological network was not set *ad hoc* to accomplish such target.

Effectively, Burrough & McDonnell (1998) suggested that at least 50 to 100 samples are required to yield a stable variogram, while Webster & Oliver (1992) indicated that 100 samples are the minimal amount needed as to generate reliable estimations, although in the case of a normally distributed isotropic variable 150 samples are enough and 225 samples are reliable. Therefore, the amount of samples, that is, the 314 weather stations with relevant information on mean monthly precipitation available in the study area exceeds by far the minimal requirements to generate reliable interpolations.

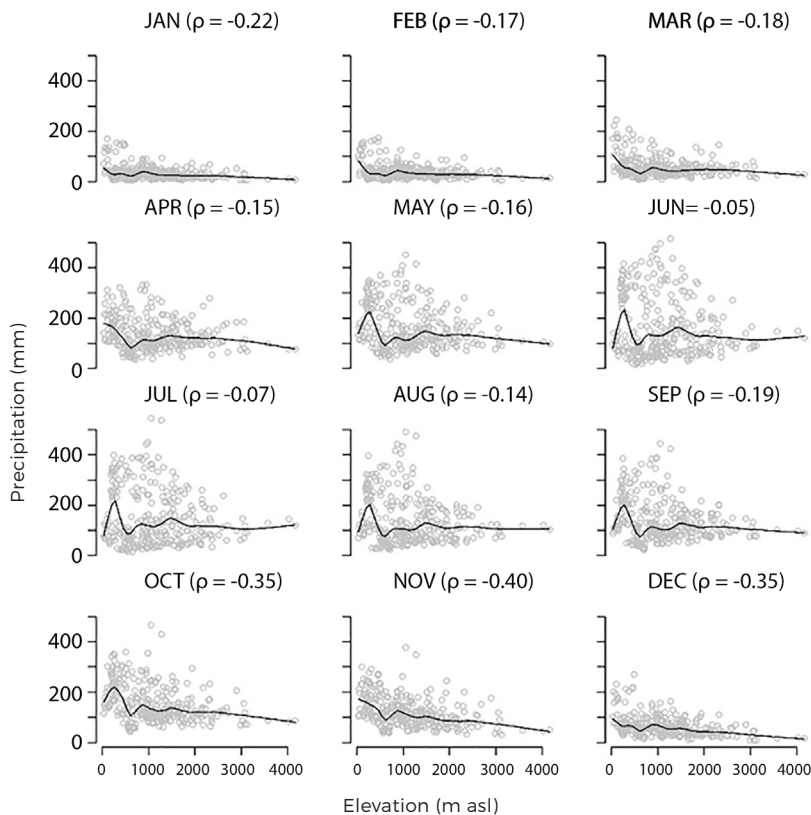


Figure 7 Spearman correlation between mean monthly precipitation and elevation, contrast highlighted through a loess curve

On the other hand, although Englund *et al.* (1992) indicated that the spatial distribution pattern of samples (random, stratified or regular) has a worthless effect on the performance of some spatial interpolation techniques such as the ordinary kriging, others have indicated the opposite (Li & Heap, 2014), because variograms are sensible to sample clustering degree when, for example, there is heteroscedasticity or a relationship among the local mean and the data variance (Goovaerts, 1997). Thus, an intensive sampling or great proportion of clustered samples are convenient in the case of data with variogram with short range, while variograms with wide range require few samples distributed more uniformly (Marchant & Lark, 2006).

Moreover, Li & Heap (2011) indicated that an irregular sampling pattern, or samples spatially distributed accordingly to the degree of variability of the primary variable in a given region, would be preferable than a uniform sampling pattern. Otherwise, samples could be excessively dispersed as to identify the correlation and result in a pure nugget (Webster & Oliver, 2007), reducing the precision of the predictions (Gotway *et al.*, 1996), because a wider space among samples implies less information in the resulting maps (Li & Heap, 2014). Thus, a spatial sampling pattern excessively dispersed can yield interpolated surfaces much more variable in those areas with high density of samples than in areas where such density is low, resulting in structures which are nothing but artifacts due to the configuration of data (Li & Heap, 2014).

In such a sense, the weather stations evaluated in the present study were located following an adequate pattern which was

almost random, with a slight tendency to clustering specially in the Táchira State as well as along the longitudinal valleys where the dynamics of winds and other phenomena may result in deep differences within short distances with regards of precipitation characteristics.

The distribution of the weather stations along the elevation gradient also indicated an adequate sampling pattern. In fact, only lowest and highest heights were underrepresented, but the first constituted the surrounding lowlands with more homogeneous precipitation characteristics, while the last occupied a very small portion of the study area.

Mountains influence regional climates modifying the precipitation patterns: intercepted wind trades are forced to ascend, cool down, saturate (given that cold air holds a lower humidity than warm one) and precipitating most of their humidity on windward slopes, to descend thereafter throughout the leeward slopes as a cold and dry air mass that picks up the humidity in the environment (Vivas 1992). This situation explains why there was correlation between elevation and mean monthly precipitation for any month in the study area.

The World Meteorological Organization (2012) standards indicate that for regional models, observational data must have a resolution of at least 10 km, and must be representative of significant portions of the region of interest. Considering the nearly random distribution of the weather stations throughout the study area, with three quarters of them being separated 8.39 km or less from its nearest neighbors, and distributed along most the elevation gradient, the data on precipitation available in the study area fulfilled such standards.

Finally, Guerra *et al.* (2009) defined the climatic information available for Venezuela as ‘scarce and little reliable’ both at temporal and spatial scales, especially in the case of the Andean region, as a result of an insufficient climatologic network, short recording series and problems with the information gathering. Our results contradicted, at least partially, such asseverations for the period 1950-2000, although available data suggests that most of the weather stations under INAMEH responsibility stopped to generate information thereafter.

5. Acknowledgements

We are deeply indebted to Professors Herbert Hoeger, Mayerlin Uzcátegui, Giorgio Tonella, Kay Tucci and Francisco Hidrobo for providing computing facilities. Doctors Luis Fernando Chaves Sanabria, María Angelina Pacheco and Julia Chacón Labella provided us with fundamental literature. This article is dedicated to the memory of Professor-Herbert Hoeger (1959-2015). This research was funded by the Consejo de Desarrollo Científico, Humanístico, Tecnológico y de las Artes, CDCHTA of Universidad de Los Andes, Project code C-1911-14-01-B.

6. References quoted

- BERMÚDEZ, M. A.; VAN DER BEEK, P. & M. BERNET. 2011. «Asynchronous Miocene-Pliocene exhumation of the central Venezuelan Andes». *Geology*, 39(2): 139-142.
- BIVAND, R. S.; PEBESMA, E. J. & V. GÓMEZ-RUBIO. 2008. *Applied Spatial Data Analysis with R*. Springer, New York, USA.
- BRUMMITT, N. & E. N. LUGHADHA. 2003. «Biodiversity: Where’s hot and where’s not». *Conservation Biology*, 17(5): 1.442-1.448.
- BURROUGH, P. A. & R. A. MCDONNELL. 1998. *Principles of geographical information systems*. Oxford University Press, Oxford.
- CINCOTTA, R. P.; WISNEWSKI, J. & R. ENGELMAN. 2000. «Human population in the biodiversity hotspots». *Nature*, 404(6781): 990-992.
- CLARK, P. J. & F. C. EVANS. 1954. «Distance to nearest neighbour as a measure of spatial relationships in populations». *Ecology*, 35(4): 445-453.
- DIGGLE, P. J. 2003. *Statistical analysis of spatial point patterns*. Arnold, London, UK.
- DIXON, P. M. 2002. «Nearest neighbour methods». In: A. H. EL-SHAARAWI & W. W. PIEGORSCH (eds.). *Encyclopedia of environmetrics*. pp. 1.370-1.383 John Wiley & Sons, New York, USA.
- ELITH, J. & J. R. LEATHWICK. 2009. «Species distribution models: ecological explanation and prediction across space and time». *Annual Review of Ecology, Evolution and Systematics*, 40: 677-697.
- ELITH, J.; PHILLIPS, S. J.; HASTIE, T.; DUDÍK, M.; CHEE, Y. E. & C. J. YATES. 2011. «A statistical explanation of MaxEnt for ecologists». *Diversity and Distributions*, 17(1): 43-57.

- ENGLUND, E.; WEBER, D. & N. LEVIANT. 1992. «The effects of sampling design parameters on block selection». *Mathematical Geology*, 24(3): 329-343.
- FRANKLIN, J. 2009. *Mapping species distributions: spatial inference and prediction*. Cambridge University Press. Cambridge.
- GITTLEMAN, J. L. & M. KOT. 1990. «Adaptation: statistics and a null model for estimating phylogenetic effects». *Systematic Zoology*, 39(3): 227-241.
- GOOGLE INC. 2014. *Google Earth (version 7.1.2.2041)*. Available at: <http://www.google.com/earth/download/ge/agree.html> 20 July 2013.
- GOOVAERTS, P. 1997. *Geostatistics for natural resources evaluation*. Oxford University Press. New York, USA.
- GOTWAY, C. A.; FERGUSON, R. B.; HERGERT, G. W. & T. A. PETERSON. 1996. «Comparison of kriging and inverse-distance methods for mapping soil parameters». *Soil Science Society of America Journal*, 60(4): 1.237-1.247.
- GUERRA, F.; GÓMEZ, H.; GONZÁLEZ, J. & Z. ZAMBRANO. 2009. «Modelización de la distribución de la precipitación para el estado Táchira utilizando SIG's y geoestadística». *Geoenseñanza*, 14(2): 293-318.
- GPSYV. 2013. *VENRUT. Mapas de Venezuela para GPS ruteables (version 13.07)*. Available at: <http://www.gpsyv.net> 25 July 2013.
- HASTENRATH, S. 1984. «Interannual variability and annual cycle: mechanisms of circulation and climate in the tropical Atlantic sector». *Monthly Weather Review*, 112(6): 1.097-1.106.
- HIJMANS, R. J.; CAMERON, S. E.; PARRA, P. J.; JONES, P. G. & A. JARVIS. 2005. «Very high resolution interpolated climate surfaces for global land areas». *International Journal of Climatology*, 15: 1.965-1.978.
- HUBER, O. & M. A. OLIVEIRA MIRANDA. 2010. «Ambientes terrestres de Venezuela». In: J. P. RODRÍGUEZ, F. ROJAS SUÁREZ & D. G. HERNÁNDEZ (eds.). *Libro rojo de los ecosistemas terrestres de Venezuela*. Pro-vita, Compañías Shell in Venezuela and Lenovo Venezuela, Caracas, Venezuela.
- INSTITUTO NACIONAL DE METEOROLOGÍA E HIDROLOGÍA (INAMEH). Climatología, datos de precipitación mensual. Caracas, Venezuela..
- JARVIS, A.; REUTER, H. I.; NELSON, A. & E. GUEVARA. 2008. Hole-filled SRTM for the globe (version 4). Available from the CGIAR-CSI SRTM 90m Database: <http://srtm.csi.cgiar.org>. 15 July 2013.
- JIMÉNEZ, N. & J. E. OLIVER. 2005. «South America, Climate of». In: J. E. OLIVER (ed.). *Encyclopedia of World Climatology. Encyclopedia of Earth Sciences series*. pp. 673-678. Springer. Dordrecht.

- JOHANSSON, B. & D. CHEN. 2003. «The influence of wind and topography on precipitation distribution in Sweden: statistical analysis and modeling». *International Journal of Climatology*, 23(12): 1.523-1.535.
- LI, J. & A. D. HEAP. 2011. «A review of comparative studies of spatial interpolation methods in environmental sciences: performance and impact factors». *Ecological Informatics*, 6(3-4): 228-241.
- LI, J. & A. D. HEAP. 2014. «Spatial interpolation methods applied in the environmental sciences: A review». *Environmental Modelling & Software*, 53 (March): 173-189.
- MARCHANT, B. P. & R. M. LARK. 2006. «Adaptive sampling and reconnaissance surveys for geostatistical mapping of the soil». *European Journal of Soil Science*, 57(6): 831-845.
- MEEK D. W. & J. L. HATFIELD. 1994. «Data quality checking for single station meteorological database». *Agricultural and Forest Meteorology*, 69(1-2): 85-109.
- MONASTERIO, M. & S. REYES. 1980. «Diversidad ambiental y variación de la vegetación en los páramos de los Andes Venezolanos». In: M. MONASTERIO (ed.). *Estudios Ecológicos en los páramos andinos*. pp. 47-91. Editorial de la Universidad de Los Andes. Mérida, Venezuela.
- MYERS, N.; MITTERMEIER, R. A.; MITTERMEIER, C. G.; DA FONSECA, G. A. B. & J. KENT. 2000. «Biodiversity hotspots for conservation priorities». *Nature*, 403: 853-858.
- OLSON, D. M. & E. DINERSTEIN. 1998. «The global 200: a representation approach to conserving the Earth's most biologically valuable ecoregions». *Conservation Biology*, 12(3): 502-515.
- PETERSON T. C.; EASTERLING, D. R.; KARL, T. R.; GROISMAN, P.; NICHOLLS, N.; PLUMMER, N.; TOROK, S.; AUER, I.; BOEHM, R.; GULLETT, D.; VINCENT, L.; HEINO, R.; TUUOMENVIRTA, H.; MESTRE, O.; ALEXANDERSSON, H.; JONES, P. & D. PARKER. 1998. «Homogeneity adjustments of in situ atmospheric climate data: A review». *International Journal of Climatology*, 18(13): 1.493-1.517.
- PRUDHOMME, C. & D. W. REED. 1999. «Mapping extreme rainfall in a mountainous region using geostatistical techniques: a case study in Scotland». *International Journal of Climatology*, 19(12): 1.337-1.356.
- PULIDO, N. 2014. «Bordes urbanos metropolitanos en Venezuela ante nuevas leyes y proyectos inmobiliarios». *Cuadernos de Geografía*, 23(1): 15-38.

- QUANTUM GIS DEVELOPMENT TEAM. 2013. *Quantum GIS Geographic Information System*. Open Source Geospatial Foundation Project. Available at: <http://qgis.osgeo.org> 15 July 2013.
- R DEVELOPMENT CORE TEAM. 2014. *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. Vienna. Available at: <http://www.R-project.org> 12 May 2014
- REDAUD, L.; DE ROBERT, P.; MOTHES, M.; MAYTIN, C.; MATOS, F.; MONTILLA, M.; MONASTERIO, M. & I. GARAY. 1991. «Caracterización del sistema de producción agrícola de Los Nevados, Sierra Nevada de Mérida, Venezuela». In: J. SAN JOSÉ & J. CELECIA (eds.). *Enfoques de ecología humana aplicados a los sistemas agrícolas tradicionales del trópico americano*. pp. 153-198. CIET. Caracas, Venezuela.
- RODRÍGUEZ, N. & G. DEFIVES. 1996. «Zonas y patrones climáticos en la región andina». *Economía*, 11: 139-152.
- SILVA LEÓN, G. A. 2010. *Tipos y subtipos climáticos de Venezuela*. Escuela de Geografía, Universidad de Los Andes. Mérida-Venezuela. Trabajo de ascenso a la categoría de Titular. (Inédito).
- ŠTĚPÁNEK, P.; ZAHRADNÍČEK, P. & P. SKALÁK. 2009. «Data quality control and homogenization of air temperature and precipitation series in the area of the Czech Republic in the period 1961-2007». *Advances in Sciences and Research*, 3(1): 23-26.
- TAYLOR, M. A. & E. J. ALFARO. 2005. «Central America and the Caribbean, Climate of». In: J. E. OLIVER (ed.). *Encyclopedia of World Climatology. Encyclopedia of Earth Sciences Series*. pp. 183-188. Springer. Dordrecht.
- VIVAS, L. 1992. *Los Andes venezolanos*. Academia Nacional de la Historia. Caracas, Venezuela.
- WEBSTER, R. & M.A. OLIVER. 1992. «Sample adequately to estimate varigrams of soil properties». *Journal of Soil Science*, 43(1): 177-192.
- WEBSTER, R. & M. A. OLIVER. 2007. *Geostatistics for environmental Scientists*. John Wiley & Sons, Ltd. Chichester.
- WORLD METEOROLOGICAL ORGANIZATION. 2012. «Technical regulations. Basic documents». N° 2. Volume .1 *General meteorological standards and recommended practices*. WMO No. 49. Geneva, Switzerland.
- ZAR, J. H. 1999. *Biostatistical analysis*. Prentice Hall. New Jersey, USA.