Homogeneous Regions of Precipitation Trends Across the Amazon River Basin, Determined From the Global Precipitation Climatology Centre - GPCC

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Article

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HOMOGENEOUS REGIONS OF PRECIPITATION TRENDS ACROSS THE AMAZON RIVER BASIN, DETERMINED FROM THE GLOBAL PRECIPITATION CLIMATOLOGY CENTRE - GPCC

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Abstract: Spatiotemporal patterns of precipitation are influenced by complex interactions between climate and land cover changes, such as deforestation, fires and droughts. The Amazon River Basin has local and global impacts in regard to the hydrological cycle; therefore, it is fundamental to understand how precipitation patterns and intensity are changing. The aim of this study was to analyze precipitation trends and form homogeneous regions of precipitation trends in the Amazon River Basin using data from the meteorological satellite Global Precipitation Climatology Centre (GPCC), applying nonparametric methods (Mann-Kendall, Spearman and Sen's slope) and fuzzy C-means to identify specific regions that are undergoing changes in hydrological patterns. The results show changes in the behavior of rainfall over time and in the intensity of the events. The statistics applied to form clusters resulted in 6 well-divided homogeneous groups, each with unique characteristics. Specifically, the central-southern areas of the basin showed negative precipitation trends (-1.17 mm/year) forming a homogeneous region (RH 1), while in the northern region, there was an increasing trend in precipitation (2.73 mm/year). In general, over the 37 years studied, the wet areas have tended to become wetter and the dry areas drier. Other homogeneous regions had their own results and unique characteristics, which are in agreement with other studies, such as those in Porto Velho, Rondônia, where this area had a diagonal pattern of precipitation decrease.

Keywords: Mann-Kendall; Sen’s slope; Precipitation Indices; Amazon River Basin; Precipitation Variations.

1. INTRODUCTION

The Amazon River basin, located in South America, contains approximately 60% of the world's tropical forests, according to a study by Arvor et al. (2017), which play a vital role in regulating climate circulation patterns, which in turn contribute to local and global biodiversity and sustain ecosystems (Haghtalab et al. 2020).

The current ecosystems have suffered several impacts, especially in the last three decades, due to increased human activities in the region, examples being the development of infrastructure, inadequate extraction of natural resources, advance of deforestation, vegetation suppression, replacement of forests for pastures, expansion of the agricultural sector, among others (Costa and Pires 2010; Davidson et al. 2012).

Impacts such as these alter land use patterns causing pressures on soils and riverbeds, consequently the climate and the hydrological water cycle (Longobardi et al. 2016). In addition, they affect land surface characteristics such as reflectance index and roughness (Albedo), which directly alter surface energy and water flows (Haghtalab et al. 2020).

Actions such as reductions in surface roughness due to the extraction of vegetation cover unbalance the regional hydroclimate, causing thermal changes. In contrast, the preservation of forests helps maintain the climate and soil in the region (Walker et al 2009; Khanna et al 2017).

Although much debated, the effects of vegetation cover removal on climate circulation patterns are also affected by climatic phenomena such as the El Niño-Southern Oscillation (ENOS) and the Pacific Decadal Oscillation (PDO), as discussed by Marengo and Espinoza 2016.

ENOS events have been recurrent in recent years, aggravating droughts and intensifying floods (Laurance et al. 2002). Thus, one of the influences that precipitation has suffered in recent years may be related to changes in sea surface temperatures, the occurrence of ENOS events, atmospheric circulation phenomena such as SACZ and ITCZ, and the removal of vegetation cover (Marengo and Espinoza 2016; Khanna et al. 2017).

In this way, quantifying changes in the variability of precipitation in the Amazon River basin region becomes essential to analyse the effects produced by such anomalies, since precipitation is non-uniform and if studied at smaller scales, the influence of other factors can be perceived, resulting in greater spatial and temporal variability (Laurance et al. 2002; Funatsu et al 2012).

In 2004, Marengo (2004) published a scientific study about precipitation trends in the Brazilian Amazon, using meteorological stations. According to the research data, there was a strong negative trend in precipitation, based on the historical series from 1929 to 1998. However, Satyamurty et al. (2010), using multidecadal station datasets, found only weak rainfall trends, a fact that further makes studies of trends in the region an important factor in understanding rainfall behaviour.

As science advances, studies in the region have also advanced. Debortoli et al. (2015) detected more negative than positive rainfall trends in deforested regions in Amazonia during the transition months between the wettest and wettest seasons. According to the study, the relationship between deforestation and rainfall resulted in a reduction of approximately 88% in the rainfall records of the pluviographs. However, Almeida et al. (2017) found no trends between the period 1973 to 2013 for the same area, with the same data source. However, it is known that in the Amazon region, the recorded data often present measurement problems, failures in their records and/or absences, a fact that some studies have addressed the use of meteorological satellite data.

According to Paca et al. (2020), the increased use of remote sensing products and global precipitation datasets are suitable for hydrological studies, especially in remote, unmeasured and data-deficient areas. For this reason, Salviano et al. (2016) used monthly precipitation data from the Climatic Research Unit (CRU), and analysed the trends in Brazil, and found some changes in rainfall behaviour.

Silva et al. (2018) also used reanalysis data. For the present study, the data used were from the Tropical Precipitation Measurement Mission (TRMM), from 1998 to 2015. According to the authors' results, 92.3% of the Brazilian Amazon had no rainfall trends during the historical series, while 4.2% had significant negative trends ($p \leq 0.05$) and 3.5% had positive trends.

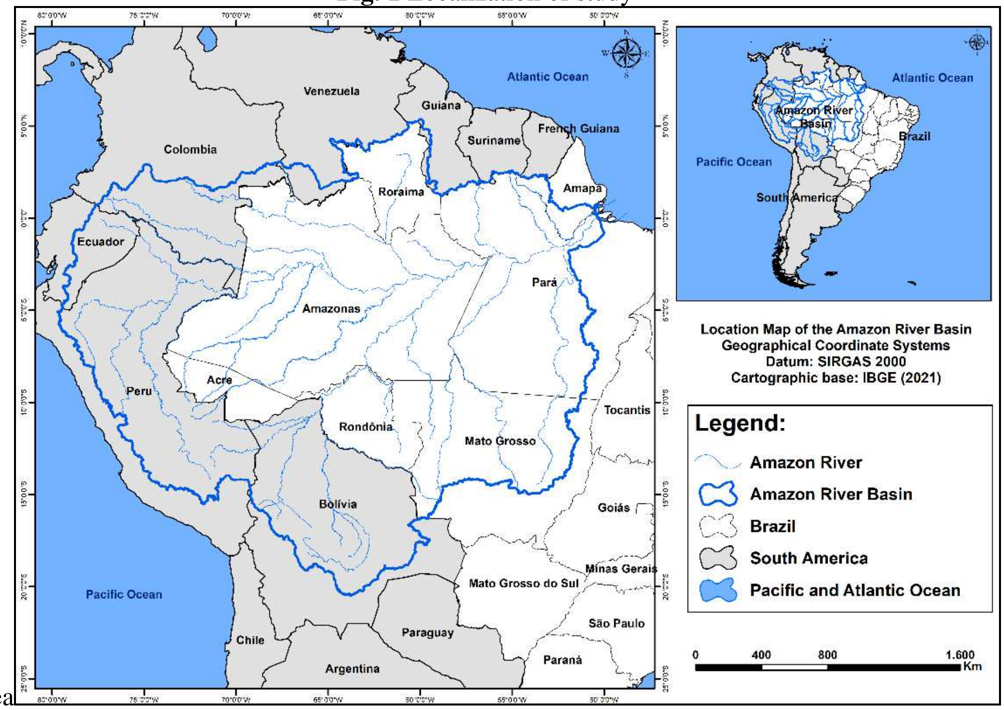
Thus, the objective of this study was to analyze rainfall trends for the Amazon River Basin, using the non-parametric methods of Mann-Kendal, Spearman and Sen's Slope, with the aim of identifying and forming homogeneous groups of rainfall trends, through the Fuzzy C-Means technique, using meteorological satellite data provided by the Global Precipitation Climatology Centre (GPCC), for the period 1982 to 2021, with a focus on identifying specific regions that are undergoing changes in hydrological patterns and that can serve as potential aids in studies about the knowledge of the area and its impacts on the regional hydrological cycle.

2. MATERIALS AND METHODS

2.1. Area of study

The present study was developed for the Amazon River Basin (HBRA), in South America (Fig. 1), which has a territorial extension of approximately 7,050,000 km². The HBRA is composed of 7 Brazilian Federative Units, namely: Acre, Amazonas, Rondônia, Roraima, Amapá, Pará and Mato Grosso, and part in other South American countries, such as Bolivia, Peru, Ecuador, Colombia, Venezuela, Republic of Guyana, Suriname and French Guyana.

Fig. 1 Localization of study área



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The Amazon Basin is considered the most productive basin in South America, with the Amazon River as its main river, contributing approximately 15% of the average global runoff, and having two large tributaries, the Negro and Solimões Rivers (Campos 2004; Silva 2013). Characteristic with high rainfall volumes, it has a high correlation with ENOS events (Filizola 1999; Marengo et al 2011).

Tomassela et al. (2013), highlight that the eastern portion of the BiH is influenced by the Intertropical Convergence Zone (ITCZ) and the western portion by the South Atlantic Convergence Zone (SACZ), being characterized by an equatorial type climate, with intense precipitation throughout the year and an average temperature between 24°C and 36°C.

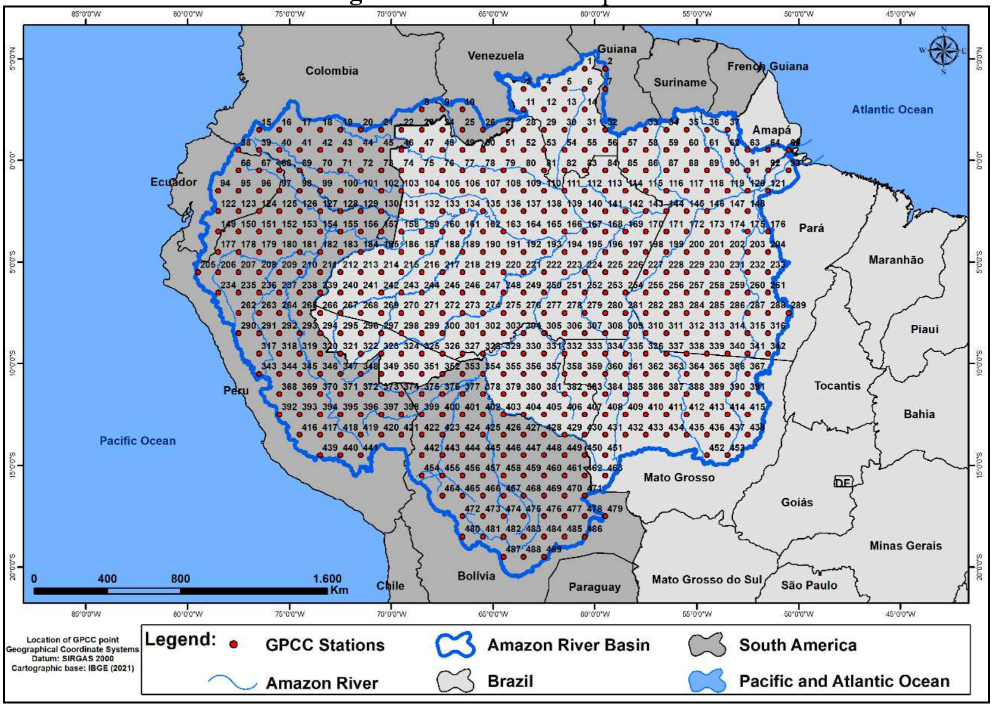
2.2. Data selection - Global Precipitation Climatology Centre (GPCC)

In this manuscript the GPCC satellite dataset was used. It is one of the most recent and accurate in precipitation estimation and production (Rustemeier et al. 2019).

Its data have been frequented in studies of global and regional climatology, and offers itself as an alternative of precipitation measurements, given that, especially in the Amazon, most stations are along the rivers, have faulty observations, some incorrect data, and unevenly distributed, do not obey some criteria established by the World Meteorological Organization (WMO 2008).

In this work, we used a grid of 0.5° x 0.5° latitude by longitude (Fig. 2), for a historical series of 39 years of precipitation data (1982 - 2021).

Fig. 2 Location of GPCC points



Source: Authors

Thus, it can be observed that there are 486 points in the study area. Where from them will begin the methodological procedures addressed here. Furthermore, satellite precipitation products have the advantages of (1) being uniform and continuous in space and time, (2) reporting values consistently, and (3) covering large areas at global or continental scale (Paca et al. 2020).

As addressed, the poor coverage within the study region (Delahaye; Kirstetter; Dubreiul 2015) and a new approach with a distinct data source from other studies, led to the use of this meteorological satellite in this study.

2.3. Nonparametric Methods

Nonparametric tests are so called because they are distribution-free statistics, not constrained by assumptions about population distribution; consequently, they can easily accommodate data that have a wide range of variation. Unlike parametric statistics, these distribution-free tests can be used with both quantitative and qualitative data (Scheff 2016).

In this sense, the nonparametric methods used in this work attempted to verify the occurrence of precipitation trends in the study area using the nonparametric tests of Mann-Kendall, Spearman and Sen's slope estimators.

Thus, tests such as Mann-Kendall, Spearman and Sen's slope are used to analyze the trends of various climatological variables to collaborate with the planning of water resources, as in a study conducted by Ishihara et al. (2014), Loureiro et al. (2015), Menezes and Fernandes (2016) and Asfaw et al. (2018).

These methods start from the principle of elaborating a hypothesis based on the probabilistic behavior of a series of one or more variables, defining a null hypothesis (H0) and another alternative hypothesis (Ha), such that the rejection of the null hypothesis depends on the type of test applied and the significance level (α) adopted (Loureiro et al. 2015).

Then, because they are two-tailed tests, to reject the null hypothesis (H0) and accept the alternative hypothesis (Ha), it is necessary that the absolute values of the methods are higher or lower than $Z\alpha/2$. Thus, this paper adopted a 95% confidence level and 5% significance level, i.e., $\alpha = 5\%$, $Z = \pm 1.96$ (Salviano et al. 2016).

For Pandey and Khare (2018), these methods did not require a normal distribution of data; with this, they become suitable for temporal trend analysis in climate and hydrological data series.

Therefore, the Mann-Kendall nonparametric test is a test used to identify changes in climate in time series studies, where the values must be independent and the probability distribution must always remain the same (Ely and Dubreuil 2017). Mann (1945) and Kendall (1975) defined the statistic of the method as the statistical variable S for a series of data (n) calculated from the sum of signs (sgn) of the difference, pairwise, of all values of the series (xi) in relation to the values that are forthcoming to them (xj), expressed in Equations 1 and 2:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn\,(xj - xi)$$

Equation (1)

$$sgn(xj - xi) = \begin{cases} +1;\, se\ xj > xi \\ 0;\, se\ xj = xi \\ -1;\, se\ xj < xi \end{cases}$$

Equation (2)

When n is greater than or equal to 10, the variable S can be compared with a normal distribution, in which its variance, Var (S), can be obtained from Equation 3, where ti represents the number of repetitions of an extension i.

$$Var(S) = \frac{n(n-1)(2n+5) - \sum_{i=1}^{P} tj(i)(i-1)(2i+5)}{18}$$

Equation (3)

P is the number of linked groups and tj is the number of data values in the group; thus, the values of Var (S) and S are used to calculate the ZMK, obtaining positive, negative or null trend parameters as a result.

$$ZMK = \begin{cases} \dfrac{S-1}{\sqrt{VAR(S)}}\ se\ S > 0 \\ 0\ se\ S = 0 \\ \dfrac{S+1}{\sqrt{VAR(S)}}\ se\ S < 0 \end{cases}$$

Equation (4)

Thus, similar to the Mann-Kendall test, Spearman's nonparametric test is usually used to verify trends in temporal series (Abdul and Burn 2006; Partal and Kahya 2006).

This method is based on the calculation of the correlation coefficient in order (ranks) of x and y, related pair by pair. Thus, according to Equation 5, the Spearman coefficient is calculated as follows:

$$Ps = 1 - \frac{6}{n^3 - n} \sum_{i=1}^{n} (Rxi - Ry)^2$$

Equation (5)

Where Rxi is the order of element Xi in the series in natural order; Ryi is the order of element Yi in the series in increasing form; and n is the number of elements of the sample. With this, the coefficient is a random variable with a symmetrical distribution, with the mean and variance shown in Equation 6:

$$E(ps) = 0\ e\ Var(ps) = \frac{1}{n-1}$$

Equation (6)

Thus, statistically, the test is given by Equation 7 below:

$$Tn - 2 = \sqrt{\frac{(n-2)(ps^2)}{(1-ps^2)}}$$

Equation (7)

Finally, Sen's slope test, which was proposed by Sen (1968) and was improved by Hirsch et al. (1984) and according to the authors Portela et al. (2011) and Tao et al. (2014), is estimated by means of the Q statistic, according to Equation 8:

$$Qij = \frac{Xj - Xi}{j - i}$$

Equation (8)

Where Xi and Xj are values of the variable under study in years i and j, respectively. Thus, positive or negative results for Q indicate increasing or decreasing trends, respectively. If there are n values in the series analyzed, then the number of estimated pairs of Q is given by the equation below:

$$N = \frac{n * (n - 1)}{2}$$ Equation (9)

Therefore, Sen's slope estimator is the median of the N values of Qij, being insensitive to outliers and nonexistent data, demonstrating a simulated measure of the trends that may come to exist in a historical data series (FERRARI, 2012).

2.4. Fuzzy C-Means

To identify the homogeneous regions of precipitation trends, the non-hierarchical Fuzzy C-Means method proposed by Dunn (1973), then improved by Bezdek (1981) and introduced into science by Zadeh (1965) was applied. The method is also recognised as Fuzzy (Aguado and Catanhede 2010).

The variables selected to introduce in the method were Geographic Coordinates (Latitude and Longitude), Mean Annual Precipitation, the results of Sen's Slope method, Euclidean Distance, and fuzzy parameters.

The fuzzy is known as fuzzy clustering, in other words, is characterized by the basic idea that in a data set X = {x1, x2..., xn} is divided into groups p, and the results of clustering are expressed by the degrees of pertinence, so that, each element can belong to a single group or more.

In this way, an element belongs or not to a given set, where a universe U and a particular element x belong to U and the degree of belongingness mA(x) with respect to a set A belongs to U, such that the function mA(x)= U = {0,1} is called the characteristic function.

To generate the partition of clusters, it is necessary to minimise an equation function through an iterative algorithm, which indicates the degree of pertinence of an element belonging to a particular cluster (Xu and Wunsch 2005). Through an assumption, the algorithm is formed, so that a database X = {x1,x2,x3...,xn), where each point xk, k=(1,2,3...,n) is a vector $\Re p$, n is the total data of the database X and $\Re p$ represents a p-dimensional space of the real numbers, which can be one-dimensional, two-dimensional and/or three-dimensional (Bloch 2005). Thus, the partition matrix for the domain X is arranged through Equation 10:

$$Mfnc = \left\{ U \in Ucn : Uik \in [0,1], \sum_{i=1}^{c} Uik = 1, 0 < \sum_{k=1}^{n} Uik < n \right\}$$ Equation (10)

Where Ucn is the group of real matrices c x n; c is the number of clusters that will be found, arranged 2≤c≤n; U is the fuzzy partition matrix for the domain X; and Uik is the degree of pertinence of xk in Cluster i. In this way, if you sum all the pertinence degrees Uik for a given data, their sum should always be equal to 1, and the sum of all the pertinence degrees should be in the range between 0 and n.

As the fuzzy is fuzzy, at each new iteration new centroids are produced, in this way, the task of generating an indicator that helps to check the convergence between the data is assigned to the objective function (J), defined by means of Equation 11 below:

$$J = \sum_{i=1}^{n} \sum_{j=1}^{p} (Uik)^m * d(Xk, Cj)^2$$ Equation (11)

Where n is the number of data points; p is the number of clusters; Uik is the degree of pertinence of sample Xk to j=th cluster; m is the fuzzy parameter; d is the Euclidean distance between Xk and Cj; Xk is the data vector, where i=1, 2..., n represents a data attribute; and Cj is the center of a fuzzy cluster.

Then, the objective function J is minimized, and the pertinence degrees Uik are generated according to Equation 12:

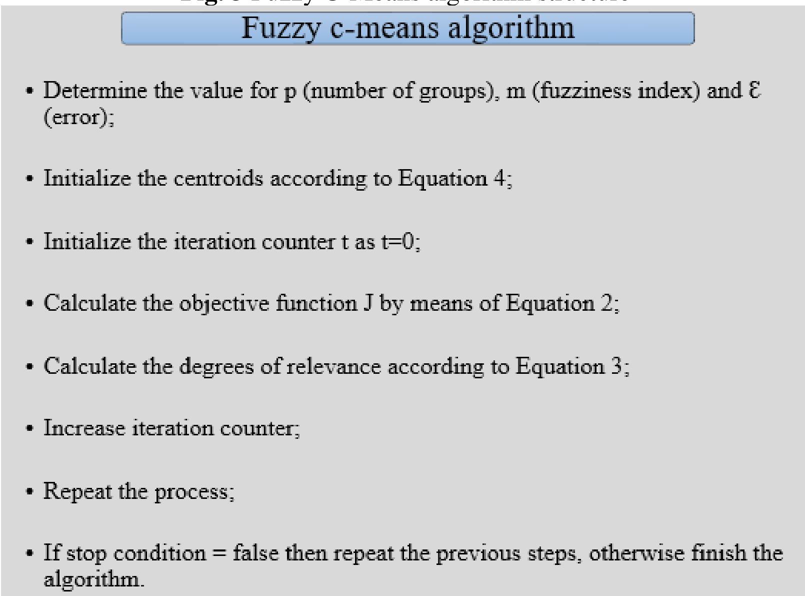
$$\mathrm{Uik} = \left[\sum_{k=1}^{c} \left(\frac{\mathrm{d(XkCj)}}{\mathrm{d(Xk, Cj)}} \right)^{2/(m-1)} \right]$$ Equation (12)

Cj is a vector called a centroid (Pedrycz and Vukovich 2004), which can be obtained through Equation 13:

$$Cj = \frac{\Sigma(\mathrm{Uik})^{\mathrm{m}}\,\mathrm{Xk}}{\Sigma(\mathrm{Uik})^{\mathrm{m}}}$$ Equation (13)

As the degrees of pertinence are defined by the highest degree of correlation, the algorithm needs some execution steps (Fig. 3) (Nascimento et al 2000). It is necessary to establish some rules, according to Bezdek (1992), and in this manuscript, it was adopted some following those applied by Gomes, Blanco and Pessoa (2018).

Fig. 3 Fuzzy C-Means algorithm structure



Source: Bezdek (1992)

2.5. Validation Indices

All grouping processes produce a solution even when the original data do not have any substructures (Tan; Steinbach; Kumar 2005).

The C-means method, because it is a free choice method of group formation, can generate several solutions, which are reapplied several times to avoid local minima of the objective functions, and to minimize these questions, validation indices are used to evaluate the results generated by clustering algorithms (Halkidi; Batistakis; Vazirgiannis 2002).

Therefore, in this work, validations were performed through the Pakhira-Bandyopadhyay-Maulik (PBM), silhouette (SIL), Dunn (D), Davies Bouldin (DB) and Xie Beni (XB) indices. Table 1 shows the indices and their equations.

Table 1 Validation rates and their equations

Index	Source	Equation
Davies Bouldin (DB)	PAKHIRA et al. (2004).	$DB = \frac{1}{K} * \sum_{i=1}^{K} Ri, qt$
Silhouette (SIL)	ROUSSEAW (1987)	$s(i) = \frac{bi - wi}{\max(bi, wi)}$
PBM	PAKHIRA et al. (2004).	$PBM = (\frac{1}{k} * \frac{E1}{Ek} 8 * Dk)^2$
Dunn (D)	PAKHIRA et al. (2004).	

		$Vd = \min_{1\leq s\leq K}\{\min_{1\leq t\leq K, t\neq s}\{\frac{\partial i(Cs,Ci)}{\max_{1\leq k\leq K}\Delta j(Ck)}\}\}$
Xie Beni (XB)	PAKHIRA et al. (2004).	$S = \frac{Jm}{n * (dmin)^2}$

The use of these indexes is necessary because, according to Tan, Steinbach and Kumar (2005), all clustering processes produce a solution, even when the raw and original data do not have any substructures. The C-Means method is a free choice method of group formation, and to avoid erroneous decisions, the applicability of validation indexes become of great value to enrich the results generated by the clustering algorithms (Halkidi; Batistakis; Vazirgiannis 2002).

There are two strands as to the applicability of the indices, some minimize their coefficient to obtain the best result, such as Davies Bouldin and Xie Beni, and others maximize, such as Dunn, Silhuett and PBM.

The PBM index has as main objective to maximize the index to obtain the optimal number of cluster, in other words, the maximum value is selected for the best partition (Pakhira et al. 2004). As for the Silhouett method (Rousseeuw 1987), the width of the silhouette evaluates the quality of the clustering, considering both compactness among data (distance between data points within the same group) and separation (distance between data points in two neighbouring groups).

Dunn's method (D) (Dunn 1974) is defined as S and T, two non-empty subsets in the RN. The Davies Bouldin (DB) index (Davies and Bouldin 1979) is a function of the ratio of the sum of the dispersion within the cluster and the separation between clusters. The dispersion in the i-th cluster is calculated according to its equations. In turn, the Xie Beni (XB) index (Xie and Beni 1991) is considered a fuzzy clustering index, from which its generalised version is obtained through its equation.

3. RESULTS AND DISCUSSION

3.1. Spatial Analysis and Precipitation Trends

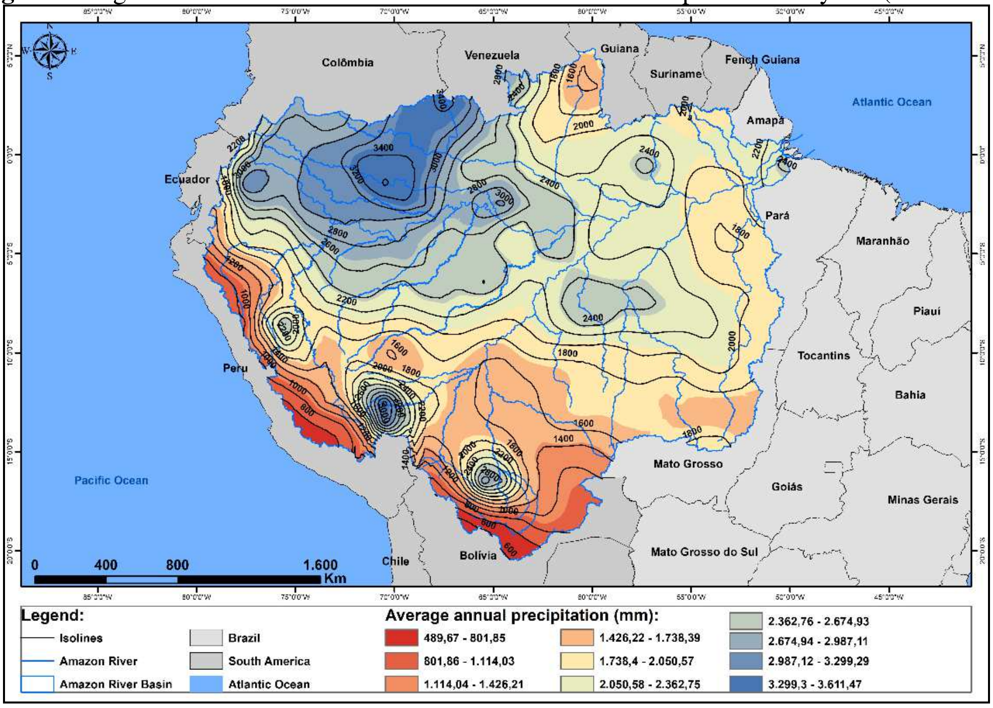
This study is based on several international articles that addressed topics on hydrology, climatology and meteorology, and which adopted data measured by meteorological satellites as a data source.

In recent years, satellites have improved, becoming the primary choices for some studies, such as those by Getirana et al. (2011) and Limberger and Silva (2018), the latter being from the GPCC that is the most suitable for analyzing precipitation in the Amazon.

In a recent study developed by Haghtalab et al. (2020), the GPCC, together with the CHIRPS satellite, are the ones that best estimate satellite precipitation data for Amazonia, which was confirmed in a study by Funk et al. (2015).

As an example of its expansion and improvement, in the work developed by Schneider et al. (2014), the GPCC had a database with 67,200 monitoring stations, and in work developed by Rustemeier et al. (2019), it already had a base with more than 75,000 stations, confirming its improvement in recent years. Fig. 4 shows the results obtained in the spatialization of mean annual precipitation in the Amazon River Basin for a period of 39 years (1982–2021).

Fig. 4 Average annual rainfall over the Amazon River basin for a period of 39 years (1982-2021)



Source: Authors

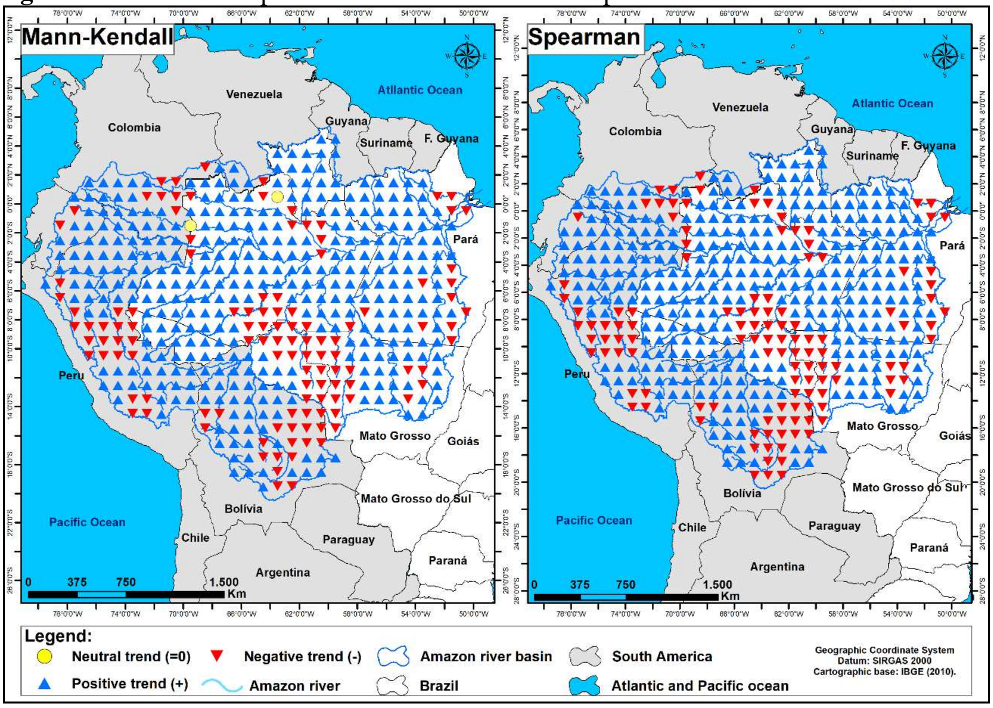
The highest precipitation regime was found in the northwestern part of the study area, in Colombia and in part of Amazonas State in Brazil, ranging from 2,000 mm to rates above 3,500 mm.

The lowest precipitation records were distributed along the Andes Mountains, in Ecuador and Peru, in the subbasin of the Solimões River, and in Bolivia in the subbasin of the Madeira River. These results are similar to those in the studies by Villar et al. (2009), Arvor et al. (2017) and Paca et al. (2020).

As the main objective of this study was to analyze the precipitation trends in the basin for each point of the GPCC grid, the 3 tests proposed in this study were applied. Thus, a total of 1464 tests were performed, where the objective was to analyze the precipitation trend in the study area.

Therefore, the Mann-Kendall and Spearman tests were spatialized (Fig. 5) for the best visualization of the behavior of trends in the study region.

Fig. 5 Results of the nonparametric Mann-Kendall and Spearman tests for each GPCC station



Source: Authors

Of the 488 stations, the Mann-Kendall test showed 368 stations with positive rainfall trends and 2 stations with neutral trends. equal to 0 (zero) and 118 with negative trends. In the Spearman test, 365 stations showed positive trends and 123 showed negative trends, and there were no null records in this test.

Therefore, analyzing the results presented in Figure 5, a negative trend was noted in the central portion of the study area; more specifically in the arc of deforestation of the Brazilian Legal Amazon, similar to the results in the study by Lira (2019).

These negative trends may have been associated with the removal of native vegetation cover, a fact that is a determinant of precipitation. According to a study by Haghtalab et al. (2020), these areas had annual decreases 30% more frequently than the rest of the time series, and this detection of change points had abrupt reductions in daily precipitation in these regions after 1998, 1995, and 1992, which were all years of severe drought throughout the basin, especially in the northeast. These were all ENOS years, which, combined with anomalous warming in the Atlantic Ocean, may have caused less precipitation across the basin.

Nevertheless, in this central portion near Porto Velho, there was a significant increase in extreme drought events in 1989, with the detection of significant change points in 1997, which was a year of extreme drought.

Another important result to be highlighted is related to the mouth of the Amazon River, where both tests showed negative trend results, which could have changed the entire local climatology, causing responses in changes in the hydrological cycle and climate change, generating a decrease in runoff, and changing the total precipitation and quantities and temporal distribution of runoff, as well as the amount of water, changes in the quotas of the river, hydrodynamics and the entire trophic structure of biological communities (Tejadas et al. 2016).

In tropical rivers, ecological and climatic patterns regulate habitat preference, resource availability, and ecological structure (Braga et al. 2012; Correa and Winemiller 2014; Mortillaro et al. 2015; Prudente et al. 2016); for this reason, investigations regarding climate change are necessary in several studies.

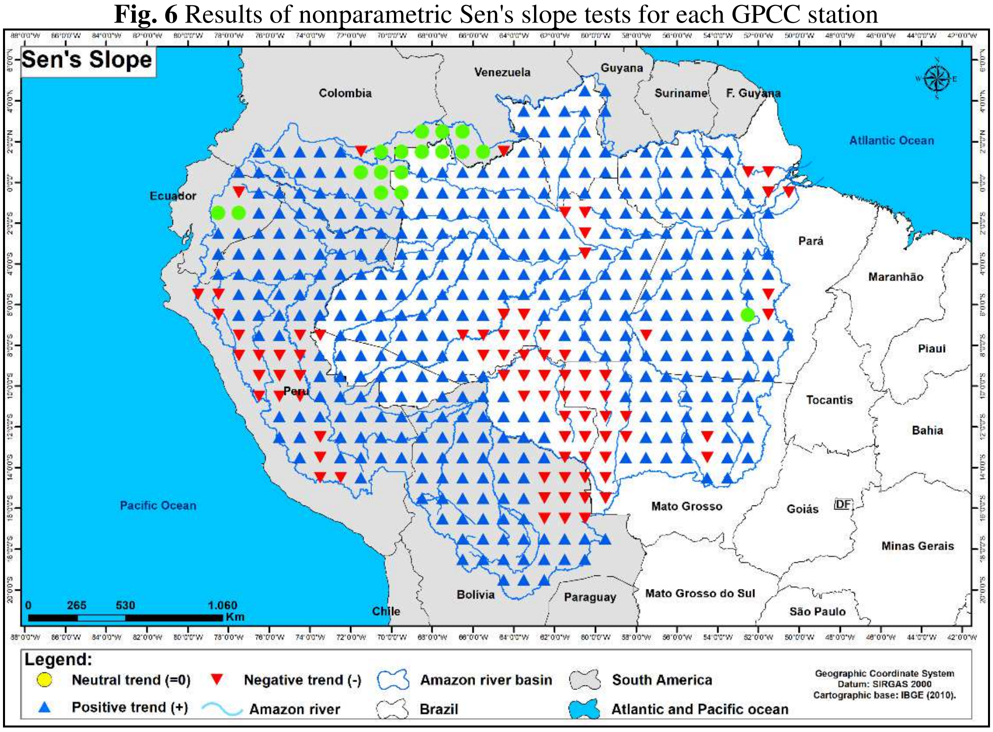
Another example related to climate influence is fish reproduction, which has been highlighted in the Amazon region, where the onset of rainfall has been related to the formation of dry or floodable areas, resulting in an increase or reduction in food availability, similar to studies by Sánchez-Botero and Araújo-Lima (2001) and Leite et al. (2006).

In the Andean portion, the study by Haghtalab et al. (2020) showed that for 2001, only one site had a significant increasing/drying trend (region G in their study and a region with a negative trend in this study), and the general trend of increase was clearly recognizable. In this study, the results were different, showing that there was a decrease presented by the two tests applied, which indicates that there is an inconsistency in the data.

In the northernmost Andean portion, the results presented by the 2 tests showed trends of increasing precipitation; according to Haghtalab et al. (2020), this region showed that precipitation during the dry season doubled after 2012 compared with the previous average of 11 extreme events.

Thus, Sen's slope was applied, which is a nonparametric method that has been used to quantify the magnitude of the precipitation slope (changes per unit time) as opposed to the step count of MK's tau and Spearman's rho statistics. Therefore, Fig. 6 illustrates the results of the statistics applied by Sen's method.

Fig. 6 Results of nonparametric Sen's slope tests for each GPCC station



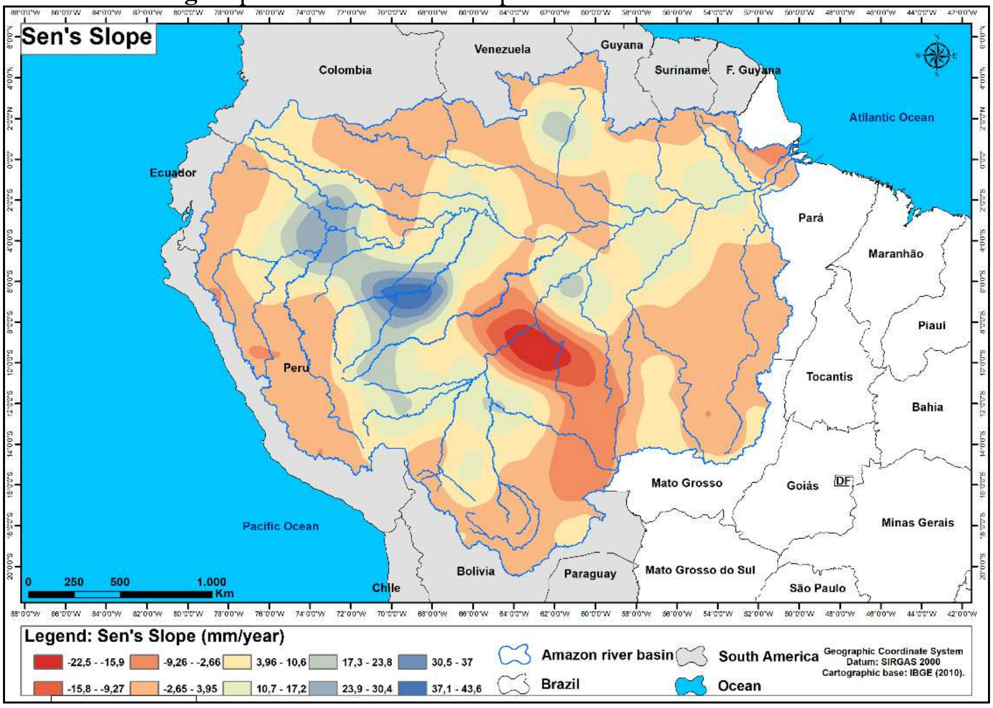
Source: Authors

It can be noted that the three tests applied in this study showed similar results; however, stations farther north of the study area based on the Mann-Kendall and Spearman methods showed trends in rainfall, but Sen's estimator showed null trends, demonstrating that there was no increase or decrease in rainfall volumes in recent years.

Another important fact is that the central portion of the hydrographic basin showed a negative trend in the three methods, and as mentioned previously, this fact was related to deforestation in this area, which accelerated significantly during the 1990s and early 2000s in the Brazilian Amazon, reaching an annual rate of 27,423 km² in 2004 (INPE 2004).

Furthermore, major changes in the regional use and occupation context have been strongly associated with deforestation and forest degradation in the region (Monte-Mor 2013), thus affecting the local climate system (Song et al. 2015). Thus, as the objective of Sen's method is to quantify the trends throughout the year, the spatialization of the values obtained from the stations was made (Fig. 7).

Fig.7 Spatialization of Sen's slope for the Amazon River Basin



Source: Authors

Most of them show statistically significant increasing trends, with the exception of the central part of the basin, whose negative trend was very strong (between -22.5 and -2.66 mm/year), which could indicate a water crisis in this location, which, according to Haghtalab et al. (2020), suffered from a drought in 2015, unlike in 1993 when the region had high humidity.

Other data presented are in the area of Santa Cruz de La Sierra, Bolivia, indicating strong results of negative precipitation trends, ranging from -9.26 mm/year to -2.66 mm/year, demonstrating a considerable decline in precipitation throughout the year, where Haghtalab et al. (2020) stated that there was a sharp decline to 2.2 mm/day after 2016, increasing the number of dry days during the dry season by 0.3 days/year, or 11 days in total during the 37 years analyzed, with extreme rates for these years and for 1984, 1988 and 2011.

The mouth of the Amazon River presented a negative trend, and by means of Sen's slope test, it was verified that it presented a marked negative trend, between -15.9 mm/year and -22.5 mm/year. Considering a 10-year estimate, precipitation values for this region can change considerably, decreasing by more than 150 mm.

Aceituno (1988), Marengo and Hastenrath (1993), CPTEC (1998) and Marengo et al. (2000) showed a tendency of decreasing precipitation in the entire northern Amazonian area, especially during very intense El Niño years, such as 1982–83 and 1997–9, which was evidenced in this research.

According to Nogueira (2008), the negative anomalies of precipitation that occurred in 1982–83 indicate that anomalous warming in the equatorial East Pacific reduced rainfall at the mouth of the Amazon River, and this warming reached up to 5 °C during the evolution of the El Niño of 1982–83 and the El Niño of 1997–1998. In addition to this event, there may have been other influences not studied.

In the border areas between Peru and Colombia, the results of the test showed an increase in local precipitation, in which these regions had large occurrences of extreme rainfall events, when in 2012, there were 29 events, and from this year, their occurrence was well above normal.

The bluer bands in the results are located mainly in the state of Amazonas, Brazil. This fact is due to the great conservation of the Amazon biome with areas of difficult access; dense forests, streams, creeks and rivers preserved; low population density; and use and occupation of native soil, thus maintaining high rates of humidity and precipitation over the years.

One should also highlight the northern portion of the watershed, where there is a greater amount of rainfall per year, whose trend is to continue raining more, which can further change the climatological normals of the regions formed there, as in studies by Davidson et al. (2012), Lira (2019), and Haghtalab et al. (2020).

3.2. Homogeneous Regions of Precipitation Trends

To form homogeneous regions of precipitation trends, the variables listed in Section 2.4 were introduced in the fuzzy C-means model.

After applying the FCM, the degrees of pertinence of each variable, the number of iterations and the value of the objective function for the different analyses were obtained; thus, to define which is the best grouping, validation indices were again applied to avoid incorrect analyses (Tan; Steinbach; Kumar 2005), generating their respective results for each grouping. The table 2 shows the results of the indices.

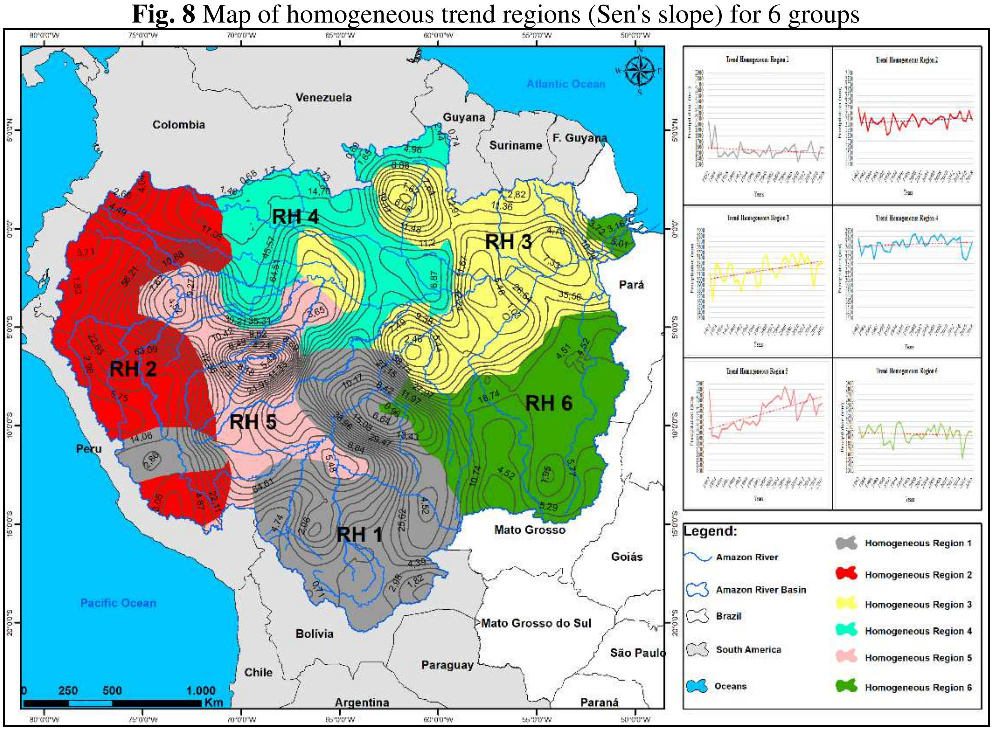
Table 2 Best grouping according to the validation indices

Grupo	Indice				
	Davies–Bouldin	**Dunn**	**Silhouette**	**PBM**	**Xie-Beni**
2	0,1318	0,0569	0,2701	0,6727	0,5882
3	0,1136	0,051	0,3146	0,8425	0,4119
4	0,106	0,051	0,3079	0,8339	0,3524
5	0,1067	0,051	0,2986	0,8312	0,2999
6	0,1173	0,0485	0,3157	0,9084	0,2575
7	0,1283	0,0569	0,2601	0,5416	0,238
8	0,13	0,0569	0,2552	0,4516	0,2222
9	0,1182	0,0569	0,273	0,408	0,1946
10	0,1195	0,061	0,2703	0,3714	0,1712

The index results demonstrate that variable behaviors are best demonstrated in 6 groupings. These groups formed and validated through these indices represent the homogeneous trend regions (Sen's slope).

Each station had a degree of relevance to a particular group and was spatialized to form homogeneous regions of precipitation trends (Fig. 8).

Fig. 8 Map of homogeneous trend regions (Sen's slope) for 6 groups

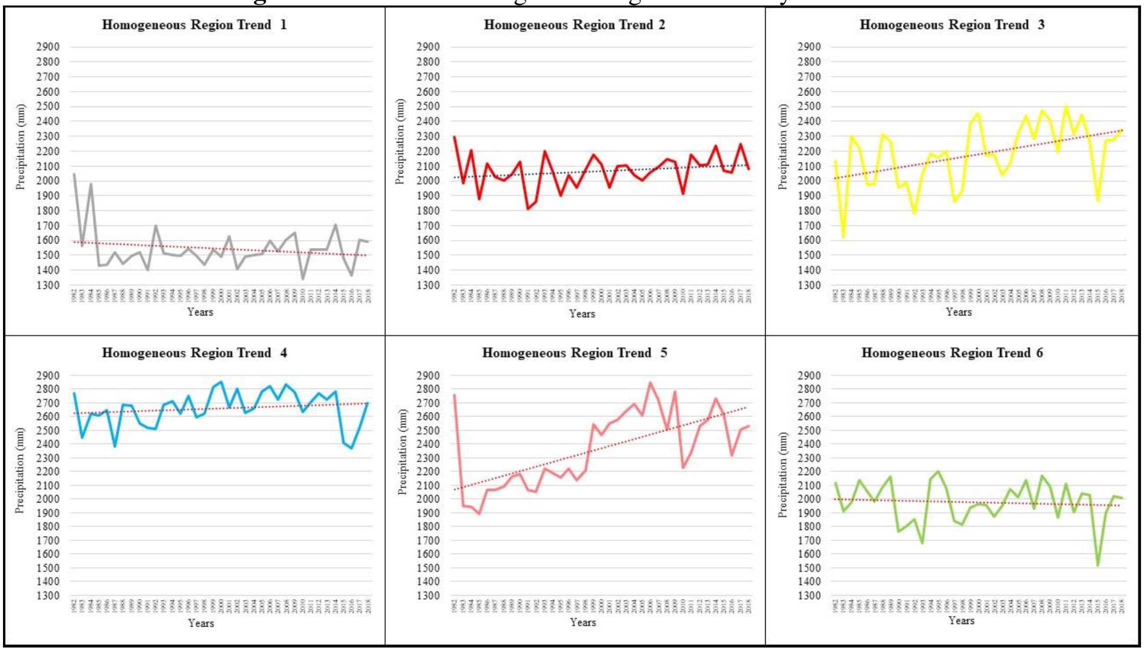


Source: Authors

For the groupings, Region 1 presented 83 stations with 17.01%, Region 2 with 81 stations representing 17.60%, Region 3 with 83 stations and 17.01%, Region 4 grouped 80 stations with 16.39%, Region 5 with 72 stations and 14.75%, which was the smallest region, and Region 6 with 89 stations and 18.24%, which was the largest region.

Thus, Fig. 9 represents the behavior of all trends in each region formed.

Fig. 9 Trend in each homogeneous region formed by the cluster



Source: Authos

In homogeneous Region 1, more to the south of the study area, mostly present in the subbasins of the Madeira and Solimões Rivers, presented results of Sen's slope ranging from -15.79 mm/year to 12.82 mm/year, with an average annual precipitation of 1545.95 mm and an average elevation of 649 meters, being the last in average precipitation values and the second in terms of elevation, respectively, it is also characterized by a long dry season (Davidson et al. 2012).

This presented an average trend with a negative value of -1.17 mm/year, thus the largest with a negative trend, located in the arc of deforestation of the Amazon, and as discussed, the removal of vegetation cover directly impacts rainfall indices, which in turn alters the local climatology.

In 1991, 1992, 2002, 2010 and 2016, the lowest average annual precipitation rates were recorded, and in 1992, an ENOS event occurred, with severe drought in this region. By analyzing the time series, one can see the decreasing slope of precipitation, when in 1982, average precipitation rates near 1600 mm were recorded. Currently, the trends indicate rates near 1500 mm, whose values may be lower with the occurrence of extreme drought events.

These results are consistent with previous studies that identified similar spatial anomalies, such as those in Ronchail et al. (2002), Santos et al. (2015) and Silva et al. (2018).

In the case of RH 2, located in the subbasin of the Solimões River, a variation in Sen's slope between -3.19 mm/year and 13.43 mm/year was observed, with an average annual precipitation of 2068.47 mm and an average elevation of 1138.89, which was the highest of all regions. Despite being at high elevations, RH 2 did not present low average annual rainfall rates, which may be associated with the barriers that the Andes create with precipitation and humidity and differently from what was presented by Haghtalab et al. (2020).

This region has shown changes in precipitation behavior over time, and as discussed by Donat et al. (2016), the spatiotemporal variability in precipitation across the Amazon Basin is more complex than the common refrain of "wet gets wetter and dry gets drier".

The average trend for this region is positive (3.24 mm/year), i.e., In a 10-year estimate, the precipitation trend for this region increased by 32.40 mm, which is representative of hydrological terms.

This indicates that increasing frequencies of heavy rainy days are strongly related to increases in total annual precipitation, as cited by Haylock et al. (2006). Analysis of the time series for this region indicates that in 1982, the mean annual precipitation was just over 2,000 mm, and in 2018, it was estimated to be close to 2,100 mm.

Analyzing the formation of RH 3, located in the subbasins of the Trombetas, Tapajós, Xingu and Negro rivers, it presented a variation of Sen's slope between 1.78 mm/year and 18.69 mm/year, not having negative trend values at any point in this region, an average annual precipitation of 2,177.83 mm and average elevation of 138.57 meters; thus, the least elevated of all regions.

It is possible to observe an accentuated positive trend line for this region, a fact represented in the results of Sen's slope statistic tests, with an average trend of 10.38 mm/year.

Despite presenting a high annual trend value, it was still the second with the highest trend within the hydrographic basin. However, although the indices had high precipitation averages, this area has already suffered from severe droughts in 1983 and 1992 (Davidson et al. 2012), when, according to Grimm and Zilli (2009), the changes in rainfall variability were probably linked to ENSO and other global phenomena, such as SST anomalies in the Southern Tropical Atlantic, the South American low-level jet and the South American Convergence Zone, which affect the rainfall in the western part of the basin and are currently exhibiting greater variability (Liebmann et al. 2004).

Homogeneous Region 4 is present in the northern Amazon River Basin, mostly in the subbasin of the Negro River and part of the subbasins of the Solimões and Madeira Rivers. This study presented results of Sen's slope varying from -2.97 mm/year to 11.28 mm/year, with annual precipitation averages of 2,657.22 mm (largest region in rainfall indices) and an average elevation of 155 meters.

In this region, the annual rainfall averages were high, and according to the results of Sen's slope test, the trend was increasing, with a rate of 2.73 mm/year, which could make the rainy days even longer. Factors related to the convergence zones, however, include not only these factors, such as the Hadley and Walker circulations, which are associated with a prolongation of the dry season in South America (Agudelo et al. 2018).

It is precisely for this reason that moisture is displaced toward the interior, causing the moisture trends over much of the Amazon Basin to be influenced by a strengthening of the Walker circulation (Barichivich et al. 2018), which were identified in the northern and western parts of the basin.

In the case of homogeneous Region 5, which was present in part of the Solimões River subbasin and part of the Madeira River subbasin, it presented a variation in Sen's slope between 10.93 mm/year and 43.67 mm/year, presenting no negative trend values. This region presented an average annual precipitation of 2,368.52 mm, together with an average elevation of 197 meters.

The precipitation trend line in this region is well accentuated, a fact that is justified by the results presented by Sen's slope estimator, giving a positive result of 19.81 mm/year.

However, despite the positive results, near Porto Velho, Roraima-Brazil, this region presents a "diagonal pattern" of decreasing precipitation in the region, but it was not associated with deforested regions or other major changes in surface cover (Haghtalab et al. 2020).

This structure, which is evident in Silva et al. (2018), has lower significance, and this diagonal pattern of drying shows spatial similarity with correlations of rainfall with the South Atlantic TSM (Yoon and Zeng 2010).

However, around Iquitos, Peru, Haghtalab et al. (2020) found a mean annual precipitation with an increase of 10.8 mm/day over the 37 years of study, with a clear trend, with erratic behavior in extreme dry season events. Most of the increase was due to extreme rainy season events (18 additional events over 37 years).

Finally, the formation of homogeneous Region 6 (mouth of the Amazon River is present in this region) is situated mostly in the subbasins of the Tapajós and Xingu Rivers and a part in the subbasins of the Madeira and Trombetas Rivers.

This region has a Sen's slope variation between -22.74 mm/year and 7.86 mm/year, with an average annual precipitation of 1,975.93 mm and an average elevation of 279 meters.

The precipitation trends for this region are negative according to the results of Sen's slope test, with an average trend of -0.62 mm/year. These results reinforce the hypothesis that at the mouth of the Amazon River, there is a tendency for precipitation to decrease.

Nogueira (2008) states that some precipitation anomalies may have influenced this region, where the length of the dry season increased in most regions east of the basin to 9 months (Li et al. 2006).

However, correlations with other factors make the results more complex. For example, the eastern region is highly influenced by ENSO (Marengo 2004; Coe et al. 2009), and the long dry season is also driven by subsidence connected to the ITCZ (Fu et al. 2001) and SSTs (Yoon and Zeng 2010).

4. CONCLUSION

The behavior of rainfall in the Amazon River Basin is constantly changing, where most of the Amazon area has undergone climatic changes. In general, the western regions tend to be wetter, while the eastern and southern regions tend to be drier.

In the collection and analysis of data, it was found that the GPCC meteorological satellite data were fundamental and valid for the information obtained in this study and can be used in new climatological analyses, as well as the applicability of the tests used in the formation of homogeneous regions (fuzzy C-means), validating the groups by the indices of validations because they managed to form distinct groups, with precipitation averages and well-defined trends and with a spatialization of the regions consistent with several studies presented in this manuscript.

To the best of our knowledge, this is one of the few studies to form homogeneous regions of precipitation trends for the Amazon River Basin using high temporal and spatial resolution data.

The drivers of the spatial pattern of climate and its variability are complicated in the basin. There are no water limitations thus far for the region; however, regions showing negative trends of precipitation in recent years were observed, which may change the excellent water pattern of the region.

The applicability of the three nonparametric tests demonstrated that there are different precipitation trends in the basin depending on the area. The central portion of the basin, toward the south, presented negative precipitation tendencies according to the methods, a fact that can be related to the Arc of Deforestation in Legal Amazonia, where the removal of native vegetation can be causing a decrease in precipitation in the area, affecting the local climate. In all three tests, the mouth of the Amazon River showed a negative trend in precipitation.

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5.2. Competing Interests

The authors A and B have no financial interests or conflicts of interest on this manuscript.

5.3. Ethics approval and consent to participate

The authors declare that this manuscript is in accordance with the ethical responsibilities of the journal and the Committee on Publication Ethics (COPE).

5.4. Consent for publication

The authors agree with the contents of this manuscript and have all given consent for submission, as well as obtained the consent of the responsible authorities of the institute/organisation where the work was carried out.

5.5. Author Contributions

All authors contributed to the design and development of the study. The preparation of the material, data collection and data analysis were performed by Authors A and B, David Figueiredo Ferreira Filho and Francisco Carlos Lira Pessoa. The first version of the manuscript was written by David Figueiredo Ferreira Filho and both revised the final text. Author B, Francisco Carlos Lira Pessoa, applied the methodology of the work and Author A, David Figueiredo Ferreira Filho, discussed the results. Authors A and B made the conclusion of the work. All authors read and approved the final manuscript.

5.6. Data Availability

The datasets generated during and analysed during the current study are available on the DWD website and can be accessed via the link: https://kunden.dwd.de/GPCC/Visualizer.

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