Finding teleconnections from decomposed rainfall signals using dynamic harmonic regressions: a Tropical Andean case study

Daniel E. Mendoza1,4 · Esteban P. Samaniego2,4 · Diego E. Mora1 · Mauricio J. Espinoza3 · Lenin V. Campozano2,4

Received: 10 November 2017 / Accepted: 11 August 2018
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Abstract
Global climate is a multi-scale system whose subsystems interact complexly. Notably, the Tropical-Andean region has a strong rainfall variability because of the confluence of many global climate processes altered by morphological features. An approach for a synthetical climate description is the use of global indicators and their regional teleconnections. However, typically this is carried out using filters and correlations, which results in seasonal and inter-annual teleconnections information, which are difficult to integrate into a modeling framework. A new methodology, based on rainfall signal extraction using dynamic-harmonic-regressions (DHR) and stochastic-multiple-linear-regressions (SMLR) between rainfall components and global signals for searching intra-annual and inter-annual teleconnections, is proposed. DHR gives non-stationary inter-annual trends and intra-annual quasi-periodic oscillations for monthly rainfall measurements. Time-variable amplitudes of quasi-periodical oscillations are crucial for finding intra-annual teleconnections using SMLR, while trends are better suited for the case of inter-annual ones. The methodology is tested over a Tropical-Andean region in southern Ecuador. The following results were obtained: (1) trans-Niño-Index (TNI) and Tropical-South-Atlantic signals are strongly connected to inter-annual and intra-annual time-scales. (2) However, TNI progressively weakens its relation with intra-annual components; meanwhile, El-Niño-Southern-Oscillation 3 gains ground for such time-scales. (3) Finally, an inter-annual connection with the North-Atlantic-Oscillation (NAO) is revealed. These results are consistent with previous literature, although the TNI and NAO connections are interesting findings, taking into account the differences in the connected scales. These results show the methodology’s capability of unraveling global teleconnections in different space and time scales using attributes embedded in an integral mathematical framework, which could be interesting for other purposes—such as the analysis of climate mechanisms or climate modeling.

Keywords
Stochastic-multiple-linear-regressions · Inter-annual-scales · Intra-annual-scales · Trans-Niño-Index · Tropical-South-Atlantic · ENSO 3 · North-Atlantic-Oscillation

1 Introduction

The understanding of climate phenomena has become one of the fundamental priorities for society due to its importance for the preservation of life on Earth, which is threatened by climate change hazards (Urban 2015). However, global climate is a spatiotemporal multi-scale system, whose subsystems interact in a complex manner (Tribbia and Baumhefner 2004). Furthermore, even when time and space scales are identified in climate, there are no clear physical boundaries between them. In fact, an accurate description is still a challenge nowadays, especially for regional scales in tropical systems, in which particular characteristics strongly influence the spatial and temporal behavior of climate (Khoudier et al. 2012).
The lack of climate knowledge in the tropical systems is mainly a consequence of their multiple dominant climate states. For instance, consider the Hadley (North–South) cell and the Walker (East–West) cell, which are the main circulation patterns in the tropical regions consisting respectively of cloudy ascending and dry descending air masses, driven by sea surface temperature (SST). Consider, also, the meridional migration of the Intertropical Convergence Zone (ITCZ), which causes changes in energy balance, and, consequently, rainfall intensity shifts, with intense seasonality (Schneider et al. 2014). Also, a critical climate phenomenon known as El Niño Southern Oscillation (ENSO) has its origins in the tropical Pacific areas, with influence around the globe (Cobb et al. 2003). All these climatological features actively interact with each other, hindering a clear tropical climate understanding (Ambrizzi et al. 2004).

Additional complexity is introduced by mountain systems in the tropics, as the Andean case (Vuille et al. 2000; Buylaert et al. 2006). This complexity is mainly induced by orographic features altering and forcing the flux patterns to create strong climate variability (Xu et al. 2004; Insel et al. 2010). In turn, these phenomena have attracted scientific attention, leading in certain cases to the use of complex models to unveil the underlying climate processes in these areas. However, modeling inaccuracies have been reported, mainly attributed to the inability of such models to represent regional climate conditions with suitable parameterizations (Lin et al. 2006; Moncrieff et al. 2007; Buylaert et al. 2009; Ochoa et al. 2016).

As a consequence, studying the climate of these sites constitutes a challenge, due to its variability. Nonetheless, important scientific literature describing such climate variability is available for the Tropical-Andean region known as the Paute Basin (Fig. 1). This area is located in the south of Ecuador, between the two parallel mountain ranges in which the Andes are divided. Due to its location, exciting climate effects, such as different rainfall regimes delineated in different regions, and explained by various synoptic climate process, are observed (Campozano et al. 2016).

Indeed, a Uni-modal (UM), Bi-Modal (BM), and Tri-Modal (TM) regimes are found according to a classification based on the analysis of the distribution of annual rainfall...

![Fig. 1 Location of the the Paute_Basin—rainfall stations](image-url)
amounts (Celleri et al. 2007). These regimes are the consequence of extreme climate variability in the region, which is reflected in a strong seasonal behavior. For instance, the rainfall is mainly observed in boreal summer, spring, and autumn months for such regimes. Moreover, these seasonal regimes have also been linked to global states through research on teleconnections (Mora and Willems 2012).

The above-mentioned teleconnection survey carried out on the Paute_Basin uses a specific technique to identify decadal oscillations in regional and global climate signals (Ntegeka and Willems 2008). Relations between rainfall regimes and global patterns—such as ENSO, TSA and SOI signals—are revealed (Mora and Willems 2012). The orientation of rainfall locations plays an important role in the explanation of such teleconnections. Nonetheless, even when these and other findings are important, the application of new methodologies able to identify and integrate such information with complementary information in a comprehensive framework seems desirable.

There are several methodological strategies to tackle the challenge of finding linkages between rainfall and atmospheric–oceanic circulations. We now mention some recent studies to illustrate the diversity of possible approaches. In He et al. (2017), precipitation variability is regarded as a superposition of intrinsic atmospheric dynamics and the interaction of the atmosphere with land and ocean. The study focuses on tropical precipitation variability to identify its oceanic and atmospheric origins. The complexity of the interactions and the different time scales involved are studied by means of numerical simulations. In Krishnamurthy and Krishnamurthy (2016), the multi-channel singular spectrum analysis is used to analyze both observations and simulation results in order to discover mechanisms for teleconnections of the Indian monsoon rainfall with AMO and Atlantic Tri-pole. Finally, Tabari and Willems (2018) use the Quantile Perturbation Method (QPM) to analyze possible atmospheric drivers of extreme precipitation anomaly.

The availability of diverse strategies shows the importance of the teleconnections research for improving the climate understanding through different spatial and temporal scales. Furthermore, the proposal of new techniques dealing not only with the identification of such teleconnections but also with their integration and systematization for practical and scientific purposes—such as climate modeling and the analysis of climate mechanisms—constitutes a meaningful challenge. The main difficulty relies on the conception and abstraction of the complex climate systems in order to represent them on a simpler and convenient form.

The simplification of complex systems is a task that generally implies to make some strong—but hopefully reasonable—assumptions and abbreviations about reality, and still being able to capture certain fundamental mechanisms for a specific purpose—such as obtaining intra-annual and inter-annual variabilities for the search of teleconnections. For example, since the rainfall regimes of Paute_Basin are strongly seasonal, it could be reasonable to represent monthly rainfall signals by additive periodical components. Moreover, a trend component would be convenient as a complement to capture other non-periodical effects. In this way, periodical components could be considered useful signals for intra-annual teleconnection searching; in addition, the trends would be important for inter-annual teleconnection identification.

As a consequence, it is clear that the identification and extraction of intra-annual and inter-annual components of rainfall signals is required in the first place. For these tasks, traditional Fourier approaches are not well suited to achieve such signal decomposition because rainfall time series are usually non-stationary since they are quasi-periodic (Bloomfield 2004). In addition, although wavelets are widely applied in the climate field due to their ability to perform time–frequency analysis, they are difficult to integrate in a modeling framework. Therefore, alternative mathematical tools are needed to associate local climatic behavior and global influences systematically.

Dynamic harmonic regression (DHR), on the other hand, is capable of capturing relevant climatic phenomena by decomposing a time signal into essential components within a stochastic setting (Young et al. 1999). In this way, this stochastic tool can deal with the non-stationary nature of rainfall signals, allowing them to be separated into (1) quasi-periodic oscillatory signals and (2) trends. Thereafter, quasi-periodic signals representing intra-annual cyclical regimes, as well as trend signals representing inter-annual and longer time variations, could be linked to external global drivers to reveal temporal characteristics of regional rainfall climate.

Since teleconnections are usually detected by filtering global signals (making them slow and smooth in time), the rainfall trends could be directly linked to them by mere correlations and linear models. However, it is not reasonable to connect quasi-periodical signals directly with global states because they could belong to a different time series class in some cases. For instance, it seems unlikely that such quasi-periodical rainfall signals would be associated with secular (with no trace of periodicity) global ones, as it is the case for some of them. Therefore, another method for the searching of teleconnections has to be found for intra-annual signals.

The answer for the description of teleconnections between the intra-annual behavior of rainfall and global signals can be found in the time-variation of amplitudes and phases of periodical components. Specifically, non-stationarity can be observed in the time-varying amplitude, which constitutes an envelope of the rainfall peaks for each periodical component. Since this amplitude envelope is smooth and slow in time, it could be used for searching intra-annual teleconnections with filtered global signals directly.
In view of the above considerations, this paper focuses on the use of the non-stationary properties of quasi-periodic rainfall signals in order to explore relations with global climate indices (teleconnections). Furthermore, this paper proposes a complete methodology for teleconnection searching, using statistical and stochastic techniques that allow for the analysis of rainfall patterns and their global drivers in separate intra-annual (seasonal regimes) and inter-annual (trends) time-scale signals. Thus, the regional seasonality and their interaction with global indicators are unveiled using an integral and simple mathematical form. To explore the capabilities of this methodology, the description of rainfall climate in the Paute Basin, located in southern Ecuador, is tackled due to the complexity of the underlying atmospheric processes.

2 Materials

2.1 Study area and climate description

The Paute River Basin (Fig. 1) is located in the south of Ecuador, in the inter-Andean depression which separates the Western and the Real cordilleras (Coltorti and Ollier 2000). The basin has an area of 6481 km², and its elevation ranges between 900 and 4200 m a.s.l. It supports several ecosystems, such as the Neotropical Alpine Wetland ecosystem, which is regarded as a water provider due to its hydrological features (Célleri and Feyen 2009). The biodiversity in the basin is rich. In fact, two national parks, namely, El Cajas and Sangay, are entirely and partially within the basin limits, respectively. Also, the basin is an essential spot for hydropower generation in the Ecuadorian region, supplying nearly 1100 MWh of its energy.

The climate behavior in the Paute Basin is strongly seasonal and spatially variable, with three main regimes identified for the area. The UM regime is characterized by a rainfall distribution mainly concentrated in the June–July–August (JJA) months (boreal summer). According to Célleri et al. (2007) and Campozano et al. (2016), this seasonal rainfall behavior is actively present at the outlet basin and windward slopes of the eastern cordillera, which is influenced by the well-known Andean Occurring System (AOS). Despite the subsidence conditions present in this tropical area for the JJA season, low cloud formation and easterly winds intensification (Walker anomaly) in the eastern cordillera induce advection, forcing the water vapor to rise through and above the mountains, with rainfall generation as a consequence.

For the BM regime, rainfall is mainly observed in the months of March–April–May (MAM) and September–October–November (SON) (boreal spring and boreal autumn, respectively). During these months, strong convective conditions carrying moisture from the Amazon basin are present. A regional analysis determines that this rainfall regime is present mainly along the sheltered valleys, where subsidence takes place during the JJA months, inhibiting convective processes during boreal summer (Célleri et al. 2007; Campozano et al. 2016).

Finally, in some regions in the Paute Basin, a TM regime presents rainfall peaks during the seasons of MAM–JJA–SON. This regime is present in the entire basin; however, it is stronger in the lower-to-highland transitions on the east and west areas. The process of rain generation is thought as a combination of convective and advective operations; therefore, the regime is described as a transition zone (Célleri et al. 2007; Campozano et al. 2016).

The Ecuadorian Andean rainfall has shown a positive correlation with Tropical South Atlantic (TSA) conditions, which implies a southward ITCZ migration with enhanced moisture advection. On the other hand, negative associations with the Pacific states have been detected, which are explained by atmospheric connections. For instance, ENSO positive events are indicative of anomalous equatorial circulations, inhibiting convective activity for the tropical South America (Vuille et al. 2000). For the Paute Basin, connections of ENSO and TSA with the regimes of precipitation are argued; however, topographical features become highly influential, especially aspect and altitude (Mora and Willems 2012). Although ENSO plays an essential role in rainfall behavior, TSA exerts a powerful influence in the region, which is responsible for a notably positive rainfall gradient present along the west-east direction (Buytaert et al. 2006).

The climate conditions of the Paute Basin makes of it an interesting natural laboratory. Moreover, the scientific climate literature available about this region allows the construction of progressive climate understanding. Therefore, this becomes a strategic area for testing new and more advanced mathematical techniques for teleconnections searching and climate modeling. In this way, previous scientific knowledge will be compared and contrasted to show the usefulness and power of the new methodology here proposed.

2.2 Data

Data from 14 rainfall stations, provided by the Ecuadorian National Institute of Meteorology (INAMHI), was used for the analysis (Table 1). Daily accumulated values were monthly aggregated. Since considerable differences in time extent are present among all rainfall datasets, a fixed matching period of 30 years (January/1980–December/2010) was chosen—except for the Labradoro_M141 station, for which a longer data set (January/1964–December/2012) will be considered additionally to test the sensitivity of the methodology to the length of the data, which will be explained later.
Finding teleconnections from decomposed rainfall signals using dynamic harmonic regressions:…

Table 1 Rainfall stations in the Paute river Basin

| Station name | Code | Rainfall regime | Elevation (m a.s.l) | Aspect | Year average (mm) |
|--------------|------|----------------|--------------------|--------|------------------|
| CHANIN       | M414 | TM             | 3020               | East   | 1702             |
| Guala-Ceo    | M139 | BM             | 2360               | North  | 729              |
| Cuenca       | M067 | BM             | 2516               | South  | 846              |
| Biblian      | M137 | BM             | 2640               | East   | 852              |
| Ricaurte     | M426 | BM             | 2545               | South  | 894.6            |
| Sayausi      | M427 | BM             | 2780               | Southeast | 988.1  |
| Palmas       | M045 | UM             | 2400               | Northwest | 1587  |
| Sigsig       | M424 | TM             | 2600               | North  | 753              |
| Penas        | M217 | UM             | 2000               | East   | 3076             |
| Paute        | M138 | BM             | 2289               | South  | 753.8            |
| Labrado      | M141 | TM             | 3260               | South  | 1280             |
| Jacarin      | M197 | BM             | 2700               | Northeast | 719   |
| Mazar        | M410 | UM             | 2450               | East   | 1305             |
| Cumbe        | M418 | BM             | 2720               | Northwest | 681.4 |

Moreover, the chosen period of 30 years ensures the maximum amount of data distributed in all rainfall stations; in this way, less than 5% of missing data was present in 12 of the 14 stations. Monthly gaps were estimated using Multiple Linear Regression with neighboring stations showing the highest correlation coefficients (Villazón and Willems 2010). Regressions were applied for each month, so estimated data for a specific month in a site was obtained only with data from other locations corresponding to the same month.

On the other hand, monthly climate weather patterns are provided by the National Oceanic and Atmospheric Administration (NOAA). The weather patterns (external signals) used in this study include the following data sets: Pacific Decadal Oscillations (PDO), North Atlantic Oscillation (NAO), Atlantic Multidecadal Oscillation (AMO), Bivariate ENSO Time Series (BEST), Multivariate ENSO Index (MEI), ENSO-3.4, ENSO-3, ENSO-1.2, Oceanic Niño Index (ONI), Trans Niño Index (TNI), Tropical Pacific Sea Surface Temperature (EEOF_SST), Quasi-Biennial Oscillation (QBO), Southern Oscillation Index (SOI), Tropical Northern Atlantic Index (TNA), Tropical Southern Atlantic Index (TSA), Atlantic Tripole Sea Surface Temperature (EOFA_SST), Atlantic Multidecadal Oscillation (AMO), Caribbean Index (CAR) and Madden-Julian Oscillation (MJO). These signals represent a large part of the Pacific and Atlantic climate variability; therefore they are probably the most important patterns for the studied region. The same period as the rainfall data extent was selected for these signals.

3 Methods

The methodology proposed in this work aims at the identification of intra-annual and inter-annual teleconnections with global states. It is a six-step process, which will be thoroughly explained in this section. A key part of this methodology is signal extraction employing DHR. Therefore, DHR will be treated first, in order to give a perspective of its fundamentals and properties.

3.1 Dynamic harmonic regressions (DHR)

DHR is a well-known technique for signal extraction within the framework of time series analysis theory. This stochastic tool uses spectral analysis, introducing the concept of Time-Variable-Parameters (TVP’s). The TVP’s take advantage of Recursive Estimation techniques, which allow time-evolving parameters in linear models. Such a time variation is described considering Gauss–Markov Random Walk processes (RW), which are better explained in Young et al. (1999), Bryson (1975), Young (2000, 2012). The parameter evolution is attained under optimal conditions (hyper-parameter optimization). Since the interest of this research is oriented towards an application, a brief description of the DHR technique is given here, starting with the general additive model shown in Eq. (1):

\[ y_k = T_k + S_k + \epsilon_k; \quad \epsilon_k \sim N(0, \sigma^2) \]  
\[ (1) \]

where \((T_k)\) and \((S_k)\), respectively, correspond to trend and seasonal (or cyclical) components, in the k-th time-step. In turn, \((\epsilon_k)\) denotes a Gaussian error term with zero mean and \((\sigma^2)\) variance. It is important to mention that \((T_k)\) is a Time-Variable parameter (TVP). Therefore, the trend can be considered as a Gauss–Markov process, as given in Eq. (2):

\[ T_k = \alpha(T_{k-1}) + \epsilon_k; \quad \epsilon_k \sim N(0, \sigma h^2) \]  
\[ (2) \]

Equation (2) describes an Autoregressive-Random-Walk (ARW) process, which is a particular case of a more General Random Walk (GRW) model (Young 2012). As shown, ARW considers a self-dependence of the k-th time step with respect to its immediate antecedent. A Gaussian fluctuation \((\epsilon_k)\), with zero mean and constant variance \((\sigma^2)\), introduces randomness. The terms \((\alpha)\) and \((\sigma)\) are known as hyper-parameters, and their optimization is required to describe time evolutionary processes, as mentioned below in this section.

On the other hand, the \((S_k)\) component expressed in Eq. (1) is the summation of \((Rs)\) quasi-periodic signals, each one associated with their corresponding \((w)\) frequency. Equation (3a) shows the mathematical expression of this:

\[ S_k = \sum_{i=1}^{Rs} \left[ a_{i,k} \cos(w_i k) + b_{i,k} \sin(w_i k) \right] \]  
\[ (3a) \]
As a consequence, we arrive to
\[
S_k + T_k = \sum_{i=0}^{\infty} \left( a_{i,k} \cos (w,k) + b_{i,k} \sin (w,k) \right),
\]
where \( a_{0,k} = T_k \) when \( w_0 = 0 \) (3b)

Since the trend component is also a TVP parameter, this can be linked to a zero frequency \( (w_0=0) \) term, allowing Eq. (1) to be rewritten so as to include it in the sum of the harmonics expression, as shown in Eq. (3b). In this way, the trend has been conveniently included in the general expression, being the \( (a_0) \) parameter linked to the zero-frequency component.

In the meantime, the temporal variation of harmonic coefficients obeys also an ARW process. Therefore, Eq. (2) is rewritten as shown in Eqs. (4a, 4b) to describe \( (a_{i,k}, b_{i,k}) \) coefficients as TVP parameters:
\[
a_{i,k} = a_i(a_{i-1,k}) + \epsilon_{i,k-1}; \quad \epsilon_{i,k} \sim N(0, \sigma_{h_i}^2)
\]
\[
b_{i,k} = a_i(b_{i-1,k}) + \epsilon_{i,k-1}; \quad \epsilon_{i,k} \sim N(0, \sigma_{h_i}^2)
\]
(4a)
(4b)

It has to be noticed that the parameters \( (a_i, \sigma_{h_i}^2) \) are equal for \( (a_i, \sigma_{h_i}^2) \) parameters within a specific \( i \)-th harmonic component, which is an imposed condition in ARW models. Under these circumstances, the spectral analysis used for identification of frequencies \( (w_i) \) and hyper-parameter optimization is facilitated. For instance, if the ARW is regarded as a differential process, it is straightforward to show that Fourier-transform of these parameters \( (a_i, b_i) \) is given by Eq. (5):
\[
f(w) = \frac{1}{2\pi} \left\{ \frac{\sigma_{h_i}^2}{[1 + a^2 - 2a \cos(w)][2 - 2 \cos(w)]} + \sigma^2 \right\}
\]
(5)

Of course, after applying the Fourier Transform, the frequency space \( (w) \) is the new domain. The \( (\sigma_{h_i}^2) \) parameter represents the variance of the ARW model, while \( (\sigma^2) \) is the total DHR variance model. Having in mind that Eq. (6a) represents the \( i \)-th harmonic component (Hi) of \( (S_i) \),
\[
H_{i,k} = a_i,k, \cos (w,k) + b_i,k, \sin (w,k)
\]
then the \( i \)-th frequency response obtained from the Fourier-transform properties is represented by Eq. (6b):
\[
f_{H_i}(w) = \frac{1}{2\pi} [f(w+w_i) + f(w-w_i) + \sigma^2]
\]
(6a)
(6b)

In this way, it can be shown that the pseudo-spectrum of the complete DHR model is given by Eq. (7):
\[
f_{i}(w) = \sum_{i=0}^{\infty} \left[ \sigma_{h_i}^2 f_{H_i}(w) \right]
\]
(7)

Equation (7) has to be fitted to an observed spectrum of the treated time series. This observed spectrum could be obtained from an Autoregressive (AR) process representing such a series. The order of the AR process is determined according to the Akaike-coefficient (AIC), which is related to the entropy maximization principle (Akaike 1974, 1977; Beamish and Priestley 1981). After that, the Fourier Transform of the AR process represents the empirical (observed) spectrum. In this empirical-spectrum, the fundamental and harmonic frequencies are shown smooth and sharpened (as shown in Fig. 2c), eliminating some spurious harmonics (Ghil et al. 2002; Young et al. 1999). Finally, the cost minimization function presented in Eq. (8) allows the desired hyper-parameters optimization:
\[
J_e = \sum \left[ \log \left\{ f_{\epsilon}(w) \right\} - \log \left\{ f_{i}(w) \right\} \right]^2
\]
(8)

In the previous expression, \( f_{\epsilon}(w) \) represents the mentioned empirical spectrum obtained from the AR process. Here, logarithmic transformations ensure optimal fitting of sharp peaks of components, as well as good agreement in the lower parts of the spectrum. This delivers better results for this kind of optimization problems, which fulfills conditions of continuity and convexity, as is expressed in Young et al. (1999).

Once the optimal hyper-parameters are obtained, the next step consists in their implementation in a Recursive Least Squares algorithm, which uses those parameters to estimate TVP coefficients for every pair of harmonic coefficients \( (a_i, b_i) \). This is achieved through the well-known Kalman-Filter and the Fixed-Interval-Smoothing (KF/FIS) algorithms, whose explanation is omitted here. However, the reader can check the equations and their features in Young et al. (1999) and Young (2012).

Finally, by trigonometric relations it is possible to show that the time-variable parameters \( (a_i, b_i) \) describe time-variable amplitude and phase of each \( i \)-th periodical signal integrated into the cyclical part of the model, as indicated in for the Eqs. (9a, 9b, 9c):
\[
a_{i,k} \cos (w,k) + b_{i,k} \sin (w,k) = A_{i,k} \sin (w,k + \phi_{i,k})
\]
(9a)
\[
A_{i,k} = \left[ \left( b_{i,k} \right)^2 + \left( a_{i,k} \right)^2 \right]^{1/2}
\]
(9b)
\[
\phi_{i,k} = \tan^{-1} \left( \left( \frac{a_{i,k}}{b_{i,k}} \right) \right)
\]
(9c)

For the set of Eqs. (9a, 9b, 9c), \( (A_i) \) and \( (\phi_i) \) represent the time-variable amplitude and phase of its corresponding \( i \)-th seasonal component. It is in these parameters and their
time changing properties where teleconnections could be explored. However, we only will consider the amplitudes for the analysis due to their continuity and smoothness. Also, it has been noticed that every \( w_i \) frequency inside a DHR model could be interpreted as monthly periodical components when these are multiplied by \( 2\pi \). Therefore we shall identify seasonal intra-annual components by their monthly periodicity rather than frequency.

After applying the DHR technique, several outputs are obtained, such as an inter-annual trend, intra-seasonal quasi-periodic oscillations with their time-variable amplitudes (TVP’s of amplitudes), and phases. An example of these outputs is shown in Fig. 2, which corresponds to the “Labrado_M141” rainfall signal decomposition by DHR. The frequency domain estimation, hyper-parameter optimization, and KF/FIS algorithms are implemented in the MATLAB-CAPTAINT toolbox (Taylor et al. 2007), which is freely available at http://www.es.lancs.ac.uk/cres/captain/.

3.2 Teleconnections searching methodology

Let us now describe the complete procedure to objectively find teleconnections between regional climate and global states. It can be summarized in the following steps:

1. Rainfall signal decomposition
2. GCS smoothing
3. Correlation analysis
4. Multiple linear regressions
5. Intensity of influence analysis
6. Sensitivity analysis to data-length

Fig. 2 DHR results for Labrado_M141 station. a Observed monthly rainfall (solid-grey), simulated DHR monthly rainfall (solid-black), trend (solid-white); b 12 month component (quasi-periodic signal), 12-month amplitude (envelope); c empirical spectrum (solid-grey), simulated Spectrum (dashed); d phase variation for 12 month component (solid-black)
3.3 Rainfall signal decomposition

The DHR simulation is applied over the 14 rainfall time series inside the area of study. As mentioned, to evaluate the external influence of the Global Climate Signals (GCS) over the Paute region, the amplitudes of seasonal components and trend components (hereafter labeled as ATC components) obtained from the DHR technique are analyzed, as exemplified in Fig. 2a, b.

3.4 GCS smoothing

The mathematical nature of TVP algorithms causes smoothness over the temporal variation in all ATC of rainfall signals. Therefore, to better quantify any existent relation between ATC local features and GCS, a smoothing process is also applied to the global patterns to filter out high frequencies which may affect the measurement of the relationship using common correlation metrics (Owens 1978).

The smoothing process is achieved employing an Autoregressive-Plus-Trend (APT) model for secular global signals. However, if a global signal shows intra-annual periodic features, the DHR technique is applied. In both cases, a General-Trend (GT) is obtained, which represents the desired smoothed global signals. It is worth emphasizing that the GT signal is defined as a long-term inter-annual component (without any evidence of intra-annual periodicity); in this way, it is objectively calculated by the DHR technique, thus ensuring the extraction of the desired secular inter-annual signal (Watson 1986).

For the non-periodic GCS, the order of the APT model, which defines the fluctuations, is estimated through the mentioned AIC parameter (Akaiake 1974). In turn, the model for the GT is handled as an IRW process, which is a particular case of the more general GRW models better described in Young (2012). Crucial spectral information corresponding to periodicities greater than twelve months is included in ENSO signals (Gaucherel 2010); therefore, the inter-annual quasi-periodical signals identified by the DHR methodology are included within the GCS smoothed set. This consideration is applied under the hypothesis that any signal with inter-annual frequency scales may be of influence on the studied region acting as a hidden external global driver.

3.5 Correlation analysis

The GT of global signals (hereafter labeled as GCS signals for practical reasons) and ATC series inside the Paute basin are homologated within the same scale to measure the linkages. Since these signals do not necessarily have a normal distribution, a scalar value from 0 to 1, based on percentile ranking position, is defined as a transformation for every time-series involved in the analysis. An appropriate metric that measures this ordinal correlation is the well-known nonparametric Kendall’s-tau coefficient, which is applied on every combination pair between ATC and GCS (Kendall 1938; Abdi 2007).

The transformation leads to obtaining surrogate signals with its nonlinearity information removed, which could affect the quantified connections measured by common correlation methods (Hlinka et al. 2014). The ordinal scale is also convenient for visual inspection of the relations through time, which complements the correlation analysis. It has to be noticed that only three frequency components (12, 6 and 4 quasi-periodic components) of every the rainfall signals are reliably used for the purposes set forth herein. These elements are the most influential over the total rainfall, and they meet the Nyquist-frequency criterion, avoiding aliasing (Percival and Walden 1993). This methodology is also established as a benchmark for comparison with the proposed Multiple-linear-regression methodology explained below.

3.6 Multiple linear regressions

Although the individual linkages between ATC and GCS measured by correlations provide important information about existing teleconnections, this information alone does not meet the objectives of this study. In that respect, it is probable that more than one climate mechanism is involved for each ATC component since they implicitly have information from all hydrological seasons (DJF, MAM, JJA, SON). Therefore, instead of pursuing isolated relations between the ATC components and GCS signals, the idea is to combine these effects. These combinations of global influences have been already reported for other climate variables in the ecuadorian-high-mountain systems (Veetil et al. 2014).

To address the objectives set out here, a Stochastic-Multiple-Linear-Regression (SMLR) is applied as a fundamental part of the methodology, which entails a simple mathematical way to explain intra-annual and inter-annual variability of the rainfall spectral attributes, which would be handled by a combination of global states. Its mathematical form is the following:

\[
\text{ATC}_k = \sum_{i=1}^{m} x_i (\text{GCS}_i k) + \varepsilon_k + \epsilon_k \\
\varepsilon_k = a_1 (e_{k-1}) + a_2 (e_{k-2}) + \cdots + a_n (e_{k-n}) \\
\epsilon_k \sim N(0, \sigma^2) \\
\text{ATCD}_k = \text{ATC}_k - \varepsilon_k
\]

As shown in the Eq. (10a), ATC signals from every rainfall series act as dependent variables, and the external signals (GCS) act as independent predictor variables. On the other hand, as indicated by Eq. (10b), an autoregressive
expression \((e_k)\) obtained from a Gaussian \((e_k)\) noise with zero mean and constant variance \((\sigma)\) gives the expression its stochastic character. The order of this autoregressive expression is determined according to the AIC criterion through the “R” package (Hyndman and Khandakar 2008). Here again, the \((k)\) index is used to indicate the \(k\)-th time step.

Since an essential part of this methodology focuses on hypothesis-testing; an identification of the most important (independent) variables to be included in the model is followed to avoid the counterproductive effects related to overfitting and multicollinearity (Meloun et al. 2002). This identification consists in:

1. A Stepwise (SW) procedure based on AIC criteria is applied over each SMLR model, which is freely available in “R” (Hocking 1976; Ripley et al. 2013). Despite some criticism, this is a well-known and widely applied algorithm for variable selection, under the assumption of ignorance of an underlying theory (Whittingham et al. 2006; Flom and Cassell 2007; Symonds and Moussalli 2011). Three methods, which are Backward, Forward, and Simultaneous SW procedures, are tested in order to better discern the most important variables within a model (Kubus 2014). Thus, as long as the intersection between them is not less than 80\%, the subset of variables that will be integrated into the model will be the one that shows the lowest AIC performance among the three methodologies. On the other hand, if the intersection is less than 80\%, the union of the different subsets will be kept, taking care in this way not to sacrifice valuable information.

2. After the selection of variables, a second procedure to avoid multicollinearity is carried out. An algorithm based on Variance Inflation Factor (VIF) parameter will select the final set of variables. The algorithm selection is based on the exclusion of those variables which show a VIF greater than a threshold, as indicated by Naimi et al. (2014), Miles (2014) and Imdadullah et al. (2016). A VIF threshold of 10 as a maximum tolerance is chosen, which has often been considered as a reasonable value. However, other perspective and suggestions are given in O’brien (2007) and Dormann et al. (2013).

Thereafter, only when the more relevant variables are incorporated in a linear model, the use of marginal hypothesis testing allows the analysis of the influence exerted by GCS on ATC components. This is explained in the next section.

3.7 Intensity of influence analysis

SMLRs models are grouped according to ATC signal. In this way, four model sets are classified, which correspond to the trend set (ATC_trend); and the 12, 6, and 4 monthly amplitudes set (ATC_12, ATC_6, and ATC_4). ATC_trend set of models represent large time rainfall evolution, which is handled by GCS patterns, while the ATC_12,6,4 set of models is interpreted as the regulation that GCS exerts on the seasonal rainfall extremes (by controlling the amplitude of quasi-periodical components). Thus, the analysis performed within ATC_trend group will be carried out to unveil inter-annual teleconnections; while the analysis performed in the remaining groups will furnish information on intra-annual teleconnections.

For establishing the intensity of influence that every GCS signal exerts over ATC components, a statistical significance T-test (marginal test) in each SMLR model is calculated for each GCS variable within it. Summation of all T-test values for a specific GCS signal within a group could be interpreted as the Intensity Influence Factor (IIF) exerted by such a GCS signal in that group (i.e. all T_test values of GCS_TNIs will be added for ATC_trend group, obtained a total influence of TNI signal for inter-annual trends, etc.). So, depending on whether and IIF was obtained from ATC_trend group of models, or from ATC_12, 6, 4 groups, they will be interpreted as inter-annual or intra-annual IIF factors.

Finally, rankings of influence are performed. In this way, the IIF is ranked inside each group of models. With these, an ordinal indicator of GCS influence is achieved for intra-annual and inter-annual time-scales.

3.8 Sensitivity analysis to data-length

Since the methods used here are statistical-based, and because of the complexity of climate dynamics interactions itself; an intrinsic strong dependence on the amount of information is present in the proposed methodology. In that sense, the sensitivity of the methodology to data-length is a matter of interest that has to be properly addressed. Therefore, a larger period of monthly-rainfall information (1964–2012) for one rainfall station (Labrado_M141) is subjected to the same analysis of variable selection. Thereafter, a comparison of the final set of chosen variables for both periods (i.e. 1980–2010 and 1964–2012) is carried out for the mentioned location.

3.9 Some considerations and cautions on this methodology

1. The analysis based on SMLR models focuses on the deterministic part of ATC signal which is linearly explained by GCS global patterns (i.e. the ATCD part shown in Eq. 10c). Here, an implicit independence assumption is made between the error \((e_k)\) and GCS signals; which in turn means that \((e_k)\) are also independent of such GCS signals. This consideration allows meeting
some statistical requirements of the noise ($e$) component (pointed out later in 4) for the correct application of the stepwise procedure, and posterior variable procedure elimination based on VIF. However, although the models are based on such ATCD part, the ATC notation has been retained for simplicity.

2. Stepwise procedure under AIC parameter ensures good parsimony. However, the authors are aware that the identified model could not be the “best” in statistical terms. Nonetheless, since the selection-variable process considers three different methodologies, the authors are optimistic that a significant part of the variables included in the models is part of the optimum set.

3. Any lag time effect was not incorporated for the searching of GCS and ATC relations. This consideration inherently hypothesizes a direct month-to-month relation between GCS and ATC signals. This assumption is justified since the signals are smooth and slowly varying in time (GCS trends and ATC components). Therefore the inclusion of monthly lags will not significantly change the results.

4. Assumptions made in KF/FIS for signal extraction, SMLR for the step-wise procedure, as well as hypothesis-testing requires uncorrelated Gaussian errors, with zero mean and constant variance. Therefore a normality, autocorrelation, and heteroskedasticity tests are needed for the residuals in every DHR modeling. The Shapiro–Wilk, Durbin–Watson and Breusch–Pagan tests are respectively used for normality, autocorrelation, and heteroskedasticity. These tests are widely applied and extensively treated in Breusch and Pagan (1979), Farebrother (1980) and Royston (1982).

5. Due to limitations related to the accessibility to rainfall information in the region, this work evaluates the sensitivity analysis to data-length based on the analysis for one rainfall site on the Paute_basin. Nonetheless, the authors acknowledge that, under any perspective, the reliability of the results using the proposed methodology will increase according to the quality and quantity of information used. However, the authors are also optimistic that this study provides a clear perspective of the capabilities of the method, even in the case of data limitations.

4 Results and discussion

4.1 DHR modeling and rainfall signals decomposition results

Figure 3a, b, represents the worst and best DHR fitted rainfall models. Eleven of the 14 adjusted models show a high Coefficients of Determination (R2-around 0.8), except for Gualaceo_M139, and Chanin_M414 stations, which show R2 values of 0.54 and 0.49 respectively. However, both rainfall stations are spectrally well represented as shown in Fig. 3c, d.

The last result could suggest that, although ARW model (Eq. 2) embedded in DHR is useful, other GRW model type could be more efficient in the worst cases (Young 2012; Young et al. 1999). Nonetheless, the well fitted spectral models suggest strong dynamic temporal similarities between fitted and observed time series, even when these time series show some degree of disagreement (especially for extremes).

A Kendall’s tau test was carried out between the simulated and observed signals to verify dynamical similarities (Kendall 1938; Abdi 2007). This non-parametric test is oriented to measure ordinal correlation, and thus attenuating the extremes. Therefore, higher Kendall’s tau values could be interpreted as good dynamical representations between the observed and fitted series, while the opposite corresponds to low Kendall’s tau values.

The summarized results in Table 2 show high and significant Kendall’s tau values for every rainfall series, which strongly supports the DHR capacity for capturing the temporal rainfall dynamics. Since the DHR is mainly used for signal decomposition here, and the signals are rescaled from 0 to 1, the aforementioned high Kendall’s tau values confirm the reliability of the proposed methodology, even when the models do not highly perform in R2 terms. Indeed, it is this rescaling process the one that attenuates the extremes in the signal, thus concentrating the model mainly in its temporal dynamics.

On the other hand, the required homoscedasticity for errors, testing by Breusch-Pagan statistic (BP) is violated for almost all the cases. A homoskedastic null hypothesis is established for BP test, and therefore values under the significance level (0.05) show evidence of heteroskedastic errors (not constant variance for modeling errors). It should also be noted that normality and autocorrelation requirements are in some cases violated according to Shapiro–Wilk and Durbin–Watson tests. The former test assumes normality, while the last assumes non-autocorrelation null hypothesis (Royston 1982; Farebrother 1980; Breusch and Pagan 1979). However, for the purposes of this study, we are more interested in the fact that the final models represent very well the temporal dynamics.

In fact, beyond the dynamic signal modeling achieved by DHR, the empirical and fitted spectral signals can consistently capture seasonal features, which characteristically corresponds to the regional rainfall regimes for the studied area (Celleri et al. 2007). For instance, Fig. 4a shows the spectral signal of a rainfall station with a UM regime, while Fig. 4b shows one signal representing the BM regime. These rainfall stations are known with the names of Peñas_M217,
Finding teleconnections from decomposed rainfall signals using dynamic harmonic regressions:…

Fig. 3 Upper graphs: observed and simulation rainfall. Lower graphs: empirical spectrum, and simulated spectrum obtained by DHR. Observes values (solid-grey). Simulated values (solid black and dashed) a, c for Cumbe_M418; b, d for Chanin_M414

Table 2 Kendall_{tau} test (τ), Shaprio–Wilk test (SH), Breusch–Pagan test (BP), Durbin–Watson test (DW)

| Station Name  | Code Code | (τ)   | p   | SH   | p    | BP   | p    | DW   | p   |
|---------------|-----------|-------|-----|------|------|------|------|------|-----|
| CHANIN        | M414      | 0.847 | 0.000 | 0.993 | 0.075** | 28.030 | 0.000 | 2.146 | 0.162** |
| GUALACEO      | M139      | 0.771 | 0.000 | 0.992 | 0.036 | 15.178 | 0.000 | 1.958 | 0.658** |
| CUENCA-AEROPUERTO | M067 | 0.753 | 0.000 | 0.992 | 0.048 | 41.394 | 0.000 | 2.344 | 0.001 |
| BIBLIAN       | M137      | 0.774 | 0.000 | 0.995 | 0.305** | 19.952 | 0.000 | 2.258 | 0.012 |
| RICAURTE      | M426      | 0.797 | 0.000 | 0.996 | 0.504** | 9.251 | 0.002 | 1.934 | 0.527** |
| SAYAUSÍ       | M427      | 0.789 | 0.000 | 0.996 | 0.590** | 15.493 | 0.000 | 2.090 | 0.399** |
| PALMAS        | M045      | 0.825 | 0.000 | 0.997 | 0.785** | 30.486 | 0.000 | 1.853 | 0.147** |
| SIGSIG        | M424      | 0.787 | 0.000 | 0.989 | 0.008 | 34.000 | 0.000 | 2.052 | 0.636** |
| PEÑAS COLORADAS | M217 | 0.777 | 0.000 | 0.998 | 0.867** | 5.292 | 0.021 | 1.970 | 0.733** |
| PAUTE         | M138      | 0.770 | 0.000 | 0.991 | 0.018 | 2.843 | 0.092** | 2.165 | 0.120** |
| LABRADO       | M141      | 0.781 | 0.000 | 0.984 | 0.000 | 11.035 | 0.001 | 2.127 | 0.223** |
| JACARIN       | M197      | 0.796 | 0.000 | 0.992 | 0.054** | 22.378 | 0.000 | 2.023 | 0.844** |
| MAZAR         | M410      | 0.775 | 0.000 | 0.993 | 0.085** | 12.209 | 0.000 | 2.244 | 0.019 |
| CUMBE         | M418      | 0.786 | 0.000 | 0.981 | 0.000 | 63.227 | 0.000 | 2.184 | 0.079** |

*On the right, the p value corresponding to each statistical test is shown. The (**) indicates p values (for SH, BP, and DW) without strong evidence to support the null hypothesis rejection under a 0.05 of significance level.*
and Jacarin_M197 rainfall stations respectively, and can be spatially located according to Fig. 1. As noticed, the locations of the last stations correspond to the previously defined areas for UM regime and BM regime according to the scientific literature (Celleri et al. 2007; Campozano et al. 2016).

DHR modeling finally leads to obtaining seasonal time-variable Amplitudes and Trends (ATC components) for each rainfall signal. A total of 56 ATC time series were obtained from the 14 rainfall series used here. Thus, a general Trend and three time-variable Amplitudes enveloping the 12, 6 and 4 quasi-periodical signals are available for the analysis of inter-annual and intra-annual teleconnections, respectively.

For convenient notation, any specific ATC component will be distinguished using the same ATC label followed by the monthly periodicity in case of seasonal components, or the name of “trend” for the remaining case (i.e. ATC-12 denotes the Amplitude variation of a 12 quasi-periodical component). Figure 5 shows an example of the use of this notation, for which the name and the code number of the specific rainfall station are also previously attached for a precise local distinction.

4.2 GCS smoothing results

APT methodology to obtain GT components from global trends was applied for almost every GCS signals with the except for the ENSO type since they show strong periodicities inside its time series as was revealed by DHR technique. GT components of ENSO 1.2, ENSO 3 and ENSO3.4 obtained by DHR technique represent the smoothing forms for these global signals. Also, the monthly quasi-periodical components of 30, 36 and 40 months, belonging to ENSO 1.2, ENSO 3 and ENSO 3.4 signals respectively, were included within the GCS since their periodicities are greater than 1 year. This consideration follows the mentioned hypothesis of hidden inter-annual frequencies influencing on the studied region.

In this way, a total of 20 GCS signals integrate the smoothed GCS set of global patterns. Sixteen of them comes from the trends obtained by ATP process, three are GT obtained DHR, and the remaining three correspond to the mentioned 30, 36 and 40 monthly periodic components of ENSO 1.2, 3 and 3.4 signals. Hereafter, any specific smoothed GCS signal will be labeled with its specific name to differentiate them. For example, for TNI or ENSO 1.2, the notation of their smoothing form will be GCS_TNI or GCS_ENSO 1.2 respectively. However, if the series responds to a quasi-periodical part of a global signal, a parenthesis containing the monthly periodicity will be specified [i.e., for the 30 months quasi-periodical signal coming from ENSO 1.2, the label will be GCS_ENSO 1.2(30), and so on].

4.3 Correlation results

A Kendall_tau threshold value of 0.3, with a p-value less than 0.05 are chosen to consider any direct relation between ATC and smoothed GCS signals as significant. After the computation of these statistics GCS_TNI global signal is revealed as the one with the greatest relation over the ATC_trends; although its influence only appears considerable related with three rainfall locations, which are identified as CUMBE_M418, GUALACEO_M139 and MAZAR_M410 stations. Also, under the same threshold value GCS_EOFA signal is the second most relevant signal over the same ATC_trends, which are significant on CUENCA_M067, GUALCEO_M139, and PAUTE_M138 stations.

For ATC_12, GCS_EOFA and GCS_PDO signals are the most influential ones, although only highlighted in two rainfall locations for each one. Seasonal ATC_6 signals are related with GCS_TSA signals and GCS_ENSO 3 mainly, and both of them with four significative presence above the threshold criteria. However, ATC_4 have a link only with GCS_TSA signals in three locations.
Since less than 4% of the total Kendall-tau values are above the threshold value, and less than 1% are above 0.5, then simple Kendall-tau correlation reveals weak external teleconnections.

### 4.4 SMLR results

The SMLR models applied between ATC and GCS signals (for the period of 1980–2010) show again interesting results. For instance, an "Adjusted Coefficient of Determination" (R$_{adj}^2$) (Srivastava et al. 1995), reveals that from the 56 SMLR performed models, 40 of them surpass the 0.5 R$_{adj}^2$ value. The last means that more than 70% of the models are linearly explained in more than a half of its variability only by GCS signals (i.e. the deterministic part as shown by Eq. 10c). Moreover, from the 16 remaining models with less than 0.5 of R$_{adj}^2$, 14 surpass 0.4 of R$_{adj}^2$ value.

The latter points out that, even in the worst cases the explanation of ATC signals by a linear combination of GCS patterns are considerable. Figure 5a, b shows the best and worst fitted SMLR models. For RICAURTE_M426-ATC_6, the R$_{adj}^2$ is slightly superior to 0.80, while for CHANIN_M414-ATC_4 the R$_{adj}^2$ is 0.32.

The SMLR regressions show the exerted control of GCS signals over Trends and Amplitudes of oscillatory seasonal rainfall components. These results support the underlying hypothesis in which the methodology is based. However, after variable selection employing Stepwise processes, a performance reduction regarding R$_{adj}^2$ coefficient is observed. For instance, an R$_{adj}^2$ decrease from 0.8 to 0.75, and from 0.32 to 0.25 can be seen for RICAURTE_M426-ATC_6 and CHANIN_M414-ATC_4 rainfall stations respectively.

This performance reduction is not considered high in most cases. In summary, an average R$_{adj}^2$ change of 0.11 with a standard deviation of 0.07 describes such a reduction effect in concise way. Interestingly, the minimum and maximum reduction are present for the mentioned RICAURTE_M426-ATC_6 and CHANIN_M414-ATC_4 models respectively, whose linear modeling performance is also shown in Fig. 5c, d.

![Observed and fitted SMLR models for ATC signals.](image-url)
4.5 IIF results

Tables 3, 4, 5 and 6 in “Appendix” summarize information for ATC_trend, ATC_12, ATC_6 and ATC_4 groups of SMLR models respectively. For instance, their regression coefficients, T-values, as well as their Intensity Influence Factors (IIF) are shown for each group of models. Therefore, any analysis performed for these results has to be referenced to its correspondent Appendix-table henceforth.

Observing the marginal tests (T-values), some of them appeared as not significant (considering a significance level of 0.05). Therefore, one should doubt about the importance of these variables within the final model according to what is suggested by its marginal-hypothesis-testing. Nonetheless, since the set of variables that integrate any model is finally chosen according to (AIC) parameter rather than marginal test analysis, these effects are possible due to the different statistical criterion concepts between both. For instance, AIC criterion ensure a good parsimony in the model, which is the total behavior caused by the variables and its interactions within a model, rather than isolated performances. Nonetheless, mathematical relations can be found between one and another criterion. However, the objective here does not contemplate the analysis of such an affairs, but the reader should refer to specific literature for details (Hocking 1976; Seber and Lee 2012).

On the other hand, while it is true that a model is composed of several GCS signals, an analysis of the higher ranked ones will allow contrasting these results with previous findings. These reviews are essential to test the ability of the new methodology for finding teleconnections. However, it should be mention that such results are based on the deterministic portion of the SMLR models (as is expressed in Eq. 10b with the notation of ATCD). Furthermore, it has to be recognized that 30 year monthly-data could be considered as limited sets for establish strong connections in climate variability. However, this limitation will be discussed later in more detail.

4.6 NAO link analysis

Interestingly, a high ranked IIF is given to GCS_NAO signal over ATC_trend group (inter-annual group). This GCS signal is included in the final set of variables in almost all SMLR-trend models and has a positive effect in all of them (Table 3 in “Appendix”). However, the same does not have any presence in the rest of intra-annual ATC groups. This result could be explained by Tropical-rainfall trends and NAO connections previously found (Giannini et al. 2001).

Indeed, it has been argued that negative ENSO states (La NIÑA) have a significative resembling to positives NAO states (Pozo-Vázquez et al. 2001). At the same time, an increase of precipitation directly related with “La NIÑA” state has been previously reported for the same Andean-Tropical systems (Mora and Willems 2012; Hastenrath 1990). In turn, these increase of rainfall precipitation on these regions are positively connected to NAO pattern. This relation is one of the reasons why ENSO has been suggested and used as mechanisms of influence for NAO states and its predictability (Scaife et al. 2014).

On the other hand, the inter-annual relation between the rainfall and GCS_NAO show the sensibility of the proposed methodology for capturing far global states interacting with small climate areas, such as the case of the Paute region. It is reasonable to think that teleconnections are weakened spatially, especially for mountainous areas, which due to their morphology interfere with the transport of the flows. However, the methodology is proficient to highlighting this kind of teleconnections in slow varying time trends.

4.7 TNI link analysis

The GCS_TNI signal is connected with ATC_trend, ATC_12, and ATC_6 groups. This effect suggests a strong GCS_TNI governing pattern over inter-annual and intra-annual time-scales. In a first sight, a definite positive influence over the rainfall Trends, as well as for the 12-periodic rainfall Amplitudes is observed (Tables 3, 4 in “Appendix”). However, a negative control for the 6-month component is detected, but less pronounced (Table 5 in “Appendix”).

Figure 6a is impressive. For instance, from the positive relations shown between GCS_TNI and ATC_trend, PEÑAS_M217 rainfall station (located in the northeast part of the basin) is the less affected. However, the CUMBE_M418, which is diagonally opposite to the previous location, shows the highest relation intensity concerning GCS_TNI trend.

PEÑAS_M217 station is characterized by a single rainfall season, linked to advective rainfall generation processes mainly (Campozano et al. 2016). Therefore, a null or even negative GCS_TNI influence over PEÑAS_M217 is reasonable since an intensification of TNI is linked to the weakening of easterlies winds, which are the trigger for such advective processes in that location. Nonetheless, for the southwest location (CUMBE_M418) the direct relation with rainfall amounts could obey to a Walker circulation anomalies. In general, GCS_TNI signal connection seems to follow a decreasing southwest–northeast pattern.

Figure 6b, which depicts the relation between GCS_TNI and ATC_12, shows an inverted directional pattern relative to trend relations illustrated in Fig. 6a. Here, ATC_12 components follow a progressively decreasing intensity of relation towards the south, which would mean a strong influence over the north locations.

Interestingly, a negative relation between ATC_6 and GCS_TNI was found and is illustrated in Fig. 6c. If the
origin of this rainfall component is different from the one that is connected to ATC_12; then GCS_TNI controls such a rainfall process in an opposite way. This negative pattern seems to have a slight increasing intensity in the west-east direction.

So far, the influence of TNI on the region is a new finding for the studied region. Indeed, while it is true that particular ENSO signals have been previously linked to rainfall behavior on the Ecuadorian-Andean mountains according to the enunciation of Vuille et al. (2000), the authors here are not aware of any relation with TNI signal previously reported for this specific area.

Since TNI signal measures the difference between ENSO 4 and ENSO 1.2, it represents the gradient of the temperature evolution for the complete ENSO area (Trenberth and Stepaniak 2001). Therefore, the teleconnections with GCS_TNI signal suggest that the rainfall changing in the Paute area obeys an evolutionary process from the entire Pacific ENSO, rather than specific ENSO areas. In this way, a gradual modulation response of rainfall according to GCS_TNI states is important for prediction, as has been appropriately suggested for this global signal, and already used for such a purpose (Kennedy et al. 2009).

4.8 TSA link analysis

For starting, Fig. 6d reveals positive relations between ATC_trend signals and GCS_TSA. This positive influence is consistent with previous scientific reports for the Ecuadorian Andean regions (Vuille et al. 2000; Servain 1991).

For other components, GCS_TSA are connected to the 12-monthly quasi-periodical(ATC_12) signal of PENAS_M217, SIGSIG_M424, and JACARIN_M197 as shown in Fig. 6e. Since the first two locations lie within the UM
regime inside the study area, the rainfall generation is controlled mainly by an advective process, which reacts according to TSA states (Celleri et al. 2007; Campozano et al. 2016). These means that the 12-monthly quasi-periodical components in this areas seems to be more likely linked to an advective process, which is firmly controlled by TSA trend.

JACARIN_M197 does not belong to UM regime region. However, it is connected with TSA by morphological features (specifically the northeast orientation, Table 1), rather than by regional regimes (Mora and Willems 2012). Therefore, positive modulation of TSA over 12 monthly quasi-periodical signal of the mentioned rainfall location is consistent with previous literature.

The rainfall locations of LABRADO_M141, BIBLIAN_M137, PAUTE_M138, and GUALACEO_M139 are negatively related with GCS_TSA for 12-monthly quasi-periodical components. Since a rainfall origin is mainly linked with convective climate effects for these areas, an opposite effect of TSA is reasonable and consistent with previous findings (Celleri et al. 2007; Campozano et al. 2016).

Finally, Fig. 6f shows a clear positive influence of GCS_TSA on ATC_6 signals for the northeast rainfall locations, and negatively for the southwest locations, with exception of PALMAS_M045 and SIGSIG_M424.

4.9 ENSO link analysis

Another interesting global pattern that shows itself as influential on the area is GCS_ENSO 3. Even when this global climate variable is not strongly related with ATC_trends group, this is an important signal for intra-annual rainfall components, which is similar to what is reported in Mora and Willems (2012) for hydrological seasons (DJF–MAM–JJA–SON).

For instance, GCS_ENSO 3 is positively and negatively related with ATC_12 according to Fig. 6g. Moreover, as shown in Fig. 6h, i, a dominant positive influence for ATC_6 and ATC_4 groups is present. According to previous literature, for the season of MAM, ENSO_3 is positively related with inter-andean and western rainfall locations, with exception to the locations with an east orientation (Mora and Willems 2012). This exception is shared by this study and reflected for JACARIN_M197 and BIBLIAN_M137 stations in the ATC_6 component.

ENSO 3.4 has been previously linked to drought variability in the Ecuadorian Andean systems (Vicente-Serrano et al. 2017). In this research, ENSO 3.4 signal is influential for all the ATC rainfall components, although it seems to be stronger for ATC_trends and ATC_6.

Additionally, important connections between GCS_ENSO 1.2 and the Andean-rainfall systems in Ecuador has been argued (Vuille et al. 2000; Mora and Willems 2012; Tobar and Wyseure 2018). In this research, ATC_trends components show weak positive and negative connections with GCS_ENSO 1.2. The positive influence is revealed for the east and west cordilleras (LABRADO_M141, PALMAS_M045), while a negative influence is found for the inter-andean valley locations. Negative influence of GCS_ENSO 1.2 are mostly present in the inter-andean valleys (CUENCA_M067, RICAURTE_M426). In that respect, in Mora and Willems (2012) positive relations for high stations in the west cordillera (LABRADO_M141) are described, although in contrast for the eastern part (PALMAS_M045, PEÑAS_M217) a strong negative influence is argued.

Furthermore, intra-annual ATC_12 and ATC_6 components show a strong negative relation with GCS_ENSO 1.2 for the west and east rainfall locations in which (UM) regime is present (PEÑAS_M217, PALMAS_M045, JACARIN_M197, LABRADO_M141). Stronger negative influence of GCS_ENSO 1.2 is present for ATC_6 than for ATC_12. This could be related to what is reported by Mora and Willems (2012) in the sense that a negative relation between ENSO 1.2 and the eastern part of the basin is stronger for SON period than for JJA. In that case, it is possible that ATC_6 is mainly representing the MAM–SON rainfall seasons, while ATC_12 could be describing JJA rainfall seasons.

An important observation between ATC_4 component and GCS_ENSO 1.2 is the intense and homogeneous negative connection between them in the studied area Fig. 7a. This is important mainly because ATC_4 could be a surrogate representation of a specific oscillatory climate variable related with rainfall, which is strongly driven by GCS_ENSO 1.2. For instance, such a climate variable could be the specific-humidity, which shows a 4-monthly periodical behavior as previously described for the study zone in Campozano et al. (2016). In such a case, the model components of the framework are related to a specific physical process, which could be analyzed to improve the climate understanding.

Till here, teleconnections with ENSO 3 and TNI signals, are interesting findings, which were identified using the proposed methodology. For instance, both global variables complement each other to describe the ENSO phenomena in an extended regional manner (Trenberth and Stepaniak 2001). More important, since both of them are potentially predictable, it would be possible to use these as global variables controlling rainfall, under the DHR modeling technique. All these findings are supported by previous literature in the same area (Mora and Willems 2012), especially because of the interesting similarities found for TSA and ENSO 1.2. However, any contrast with previous findings are complementary knowledge, and the reasons are discussed later.
4.10 Other important signals

GCS_PDO oscillation is strongly affecting ATC_12, according to its IIF (Table 4 in "Appendix"). The connection of this signal with intra-annual components rather than inter-annual trends is interesting. For instance, Fig. 7b shows negative and positive links, which seems to have a relation with morphological features, such as Aspect and Position. Indeed, PEÑAS_M217, CHANIN_M414, and PALMAS_M045 which are the stations near to the outlet of the basin, are negatively connected with this signal. JACRIN_M197 rainfall station is also negatively connected with GCS_PDO, which has a Northeast orientation (Table 1).

Also, another signal connected with ATC_6 is the GCS_CAR (Table 6 in "Appendix"). As shown in Fig. 7c, this signal controls the 6 monthly quasi-periodical components positively. The northwest locations seem to be the most affected. Nonetheless, its influence is also active in the inter-Andean valley location.

Previous scientific reports suggest skillful techniques for the prediction of CAR signals (Penland and Matrosova 1998). Therefore, its presence over intra-annual rainfall modes automatically suggests again the possibility of monthly rainfall modeling under the DHR mathematical frame, using the CAR signal in the same way as in the case of TNI and ENSO.

4.11 Sensitivity to data-length results

The sensitivity analysis to data-length carried out for Labrado_M141 station reveals interesting results, which are detailed in the Tables 3, 4, 5 and 6 in "Appendix", corresponding to ATC_trend,12,6 and 4 rainfall components respectively. Such analysis is based on the comparison between the results obtained from the 30-year period used for other analysis in this article (i.e. 1980–2010) versus the results found using a 49-year period (i.e. 1964–2012).
results of this comparative analysis are reported in the following paragraphs.

On the one hand, when the 30-year dataset is used, the variable-selection methodology identifies 9 GCS signals for the ATC_trend model component. On the other hand, 12 GCS signals are identified as important when the 49-year dataset is used. These two sets of GCS variables are almost the same for both data-lengths, except for the cases of GCS_CAR and GCS_MJO, which were ignored when the longer dataset was used. Since larger data contains more information about climate variability, the inclusion of more global climate information to explain the ATC_trend signal is reasonable.

In addition, when the 49-year dataset is used, the general influence of ENSO and Pacific signals are strengthened; particularly for the GCS_TNI, GCS_EOFP and GCS_SOI global patterns. It is worth to mention that GCS_ENSO 1.2 was included only after the increase of data-length. Nonetheless, although the results show changes in the intensity of influence mainly, they still agree with previous literature (Mora and Willems 2012). Furthermore, the inclusion of a new global pattern (GCS_TNA) when the 49-year dataset is used, agrees consistently with earlier reports for the Ecuadorian-Andean region (Vuille et al. 2000).

Similarly, when the 49-year dataset is used, the influence of ENSO and Pacific signals are strengthened for the ATC_12, ATC_6, and ATC_4 components; only the GCS_TNI signal weakens progressively from the highest to the lowest component. Particularly, from all ENSO signals, the participation of GCS_ENSO 4 becomes notorious when the longer dataset is used. Interestingly, the influence of GCS_NAO vanishes in both components for the longer dataset, but the participation of GCS_CAR is confirmed.

Although a strong coincidence in global connections is found for the ATC_trend, 12. 6 components for both datasets (i.e. 1980–2010 and 1964–2012 data sets), the differences could be related to the uncertainty of the ATC components, which in general increases for lower periodicities—although for the sake of brevity, the last is not detailed in this work. Furthermore, any difference found by the sensitivity data-length analysis could be related to the implicit complexity of climate interactions through different time-scales.

4.12 Some comments about previous teleconnections literature for the study region

To the authors’ understanding, the most relevant scientific article on the subject of teleconnections for the same area of study is (Mora and Willems 2012). Therefore, it is reasonable to have used it as an important benchmark for comparison of our results. However, the authors would like to remark that a comparison between our methodology and the one used in this reference should be understood as a search for complementary knowledge. This complementarity is based on the following:

(a) On the one hand, in Mora and Willems (2012), general and seasonal teleconnections are established in decadal time-scales. This is reached using a specific filtering technique—the Quantile perturbation Factor (QPF), which is mentioned as suitable for the identification of decadal-oscillations (Ntegeka and Willems 2008). On the other hand, in our proposal, the non-stationary amplitudes and trends obtained by DHR are used as surrogate signals for inter-annual and intra-annual teleconnections analysis, whose time-scales oscillations include periodicities greater than 1-year, but lower than a decade. In that sense, the involved time-scale for each methodology is different.

(b) The rainfall dataset period used for the Mora and Willems (2012) research (1964–1992) is different from the one used in our research (1980–2010). This could lead, in principle, to different teleconnection results, probably explained by the long-term changes in the dominant climate process involved for rainfall generation.

(c) Finally, in Mora and Willems (2012), four seasonal teleconnections are distinguished. They are established collecting QPF information for each hydrological season (i.e. December–February corresponds to one season, March–May for another season and so on). In contrast, the DHR based methodology represents the “seasonality” by means of quasi-periodicities. Since these quasi-periodical signals are indeed intra-annual oscillations, they implicitly have information from all hydrological seasons, which probably involve more than a few rainfall-mechanisms.

5 Conclusions

The dynamic harmonic regression (DHR) technique was successfully applied to obtain non-stationary trends and quasi-periodical components, which are interpreted as inter-annual and intra-annual rainfall modes, respectively.

Furthermore, a teleconnection analysis was carried out using time-variable amplitudes and trends, which are specific attributes of non-stationary signals. On the one hand, the connections between global climate variables and rainfall trends are interpreted here as inter-annual teleconnections. On the other hand, the links to time-variable amplitudes of quasi-periodical rainfall components are understood
as *intra-annual* teleconnections. In this way, teleconnections for *inter-annual* and *intra-annual* time-scales are distinguished.

Interestingly, *trends* and *amplitudes* are significantly represented in *stochastic-multiple-linear* (SMLR) models that use global variables as *predictors*. After an influence analysis based on marginal hypothesis tests, TNI (*TRANS NIÑO INDEX*), ENSO 3 (*EL NIÑO SOUTHERN OSCILLATIONS 3*), and TSA (*TROPICAL SOUTH ATLANTIC SIGNAL*) are revealed as the most significant signals for *inter-annual* and *intra-annual* time-scales. However, NAO (*NORTH ATLANTIC OSCILLATION*) is importantly connected only to *inter-annual* time scales (*trends*).

The *deterministic* part of the linear models explains more than 0.5 of the *Coefficient of Determinations* in almost all the models. In fact, the *goodness of fit* of these is such that in some cases, the *Coefficient of Determination* is around 0.8. These results also support the underlying hypothesis made here about global states controlling local rainfall patterns. The control is directly exerted in rainfall *trends*, and through the handling of *amplitudes* for seasonal behaviors. In this way, *interannual* and *intra-annual* teleconnections were identified for the studied area.

Moreover, a spatial description of these *teleconnections* and its intensity was possible by ranking the *marginal t-tests* carried out for the variables in SMLR. The spatial description results in relationships with complex and scattered intensities. However, these findings are reasonable since the mountains in the *Andean* systems interact with natural flows introducing additional complexity, ultimately translated in strong spatial climate variability.

While it is true that direct correlations reveal connections with global states; these are not clear in comparison with those found through the proposed SMLR framework. Moreover, other interesting interactions between global variables and local rainfall are kept hidden if simple correlations are used instead of SMLR techniques. For example, a relation between rainfall *Trends* and *North Atlantic Oscillation* (NAO) were found once the SMLR were applied for teleconnections searching.

The *sensitivity analysis to data-length* shows the technique’s capacity to deal with short amounts of climate data. Even when some differences exist, the most significant connections remain for the different datasets used, which supports the robustness of the methodology to deal with data scarcity. More interestingly, considering that specific previous literature reports similar results using different time scales for the analysis of rainfall data, e.g. (Mora and Willems 2012) in decadal oscillations, these results could be considered as complementary knowledge about teleconnections. Furthermore, these similarities also suggest that significant teleconnections could be invariant to the mentioned time-scale effect.

All the above-mentioned facts demonstrate the ability of the methodology to find climate connectivities between far distant climate regimes and complex regional climate, as in the case of the *Paute Basin*. Such findings also support the spatial and temporal complexity of climate interactions, in which global states strongly handle relatively small climate regions in a combined way.

Therefore, the work presented here opens an opportunity to explore the rainfall modeling within a stochastic DHR framework, including global variables as predictors. In this way, *teleconnections* could be translated from a mere description to a modeling framework, with potentialities for physical explanations and analysis.

Finally, this methodology contributes to the study of the interaction and functioning of climate across different time-scales for the Paute Basin, which could be replicated in other climate regions and conditions. Further, this methodology could be useful in other scientific fields, which are typically represented by quasi-periodical signals including non-stationary behavior, when this behavior could be encoding relevant information.

**Acknowledgements** The authors of this work would like to thank Jacinto Ulloa for his valuable technical comments and corrections in the English language.

**Compliance with ethical standards**

**Conflict of interest** The authors declare that they have no conflict of interest.

**Appendix**

See Tables 3, 4, 5 and 6.
Table 3: Final GCS variables included in SMLR models for each ATC_Trend components of rainfall signals and ranking of influence over the Paute Basin

| Variable   | Coefficient | Standard Error | P Value |
|------------|-------------|----------------|---------|
| PDO        | -0.075      | 0.020          | 0.121   |
| NAO        | 0.096       | 0.012          | 0.013   |
| ENSO       | 0.533       | 0.026          | 0.001   |
| BEST       | 0.266       | 0.021          | 0.001   |
| QBO        | 0.101       | 0.038          | 0.001   |

**Note:** Significant at the 0.05 level.
Table 3 (continued)

|        | LAB-RADO M141 | LAB-RADO M141* | BIBLIAN M137 | CHAÑIN M414 | CUENCA M067 | CUMBE M418 | GUAL-CEO M139 | JACA-RIN M197 | MAZAR M410 | PAL-MAS M045 | PAUTE M138 | PEÑAS M217 | RICAURTE M426 | SAYAUSI M427 | SIGSIG M424 | IFF |
|--------|---------------|---------------|-------------|------------|-------------|------------|--------------|-------------|------------|-------------|-----------|------------|--------------|--------------|-------------|-----|
| SOI trend | -0.248 (15.5) | -0.712 (54.36) | -0.285 (15.7) | -0.074 (3.6) | -0.002 (0.2)** | -0.168 (15) | -0.273 (22) | -0.082 (5.1) | -0.126 (10.8) | -0.577 (34.4) | -0.606 (38.4) | -0.722 (26) | 8 |
| TNA trend | 0.412 (33.39) | 0.82 (52.5) | 0.458 (27.4) | 0.358 (40.8) | 0.808 (69.6) | -0.285 (20.6) | 0.017 (1.8)** | -0.107 (9.2) | 7 |
| TSA trend | 0.306 (34) | 0.571 (115) | 0.185 (30.7) | -0.281 (30.9) | 0.411 (60.5) | 0.365 (38.8) | 0.216 | 3 |
| EOF trend | 0.789 (56.1) | 0.381 (32.21) | 0.43 (42.2) | 0.428 (30.5) | 0.676 | 0.394 (39) | 0.713 | 4 |
| AMO trend | 0.563 (59.3) | 17 |
| CAR trend | -0.331 (28.2) | -0.49 (35.3) | 0.115 (7.1) | -0.085 (10.4) | 0.017 (1.9)** | 0.379 (33.6) | -0.067 (7) | 0.428 | 10 |
| MJO trend | -0.104 (9.5) | -0.447 (39.7) | -0.508 (75) | -0.233 (25.5) | 0.177 (14.5) | -0.237 (25.7) | 0.305 (25.1) | -0.084 | 6 |
|        |               |               |             |             |             |             |             |             |             |             |             |             | 0.081 |             | -0.279 | 0.063 |

*Coefficients of the final chosen variables are shown without closure; while in brackets the marginal T-test values for each ATC_Trend models are contained. The (**) shows the marginal T-test values which are not significant in terms of [p] value (a significance [p] level of 0.05 is considered)

*ENSO3.4 (36), ENSO1.2 (30) and ENSO3(40) are the notational representations of 36, 30 and 40 quasi-periodical components of ENSO signals found by DHR methodology in the GCS smoothing process, and finally attached to GCS set external patterns (regressors for SMLR)

*The column identified with the name Labrado_M141 *corresponds to the results using 49-year monthly data
Table 4 Final GCS variables included in SMLR models for each ATC_12 components of rainfall signals and ranking of influence over the Paute Basin

| Variable | LAB-RADO M141 | LAB-RADO M141* | BIBLIAN M144 | CUENCA M067 | CUMBE M148 | GUALCEO M139 | JACARIN M197 | MAZAR M410 | PALMAS M045 | PAUTE M138 | PEÑAS M217 | RICAURTE M426 | SAYAUSI M427 | SIGSIG M424 | IFF |
|----------|----------------|----------------|--------------|-------------|------------|--------------|-------------|------------|------------|------------|------------|----------------|-------------|-----------|-----|
| INTERCEPT | 0.081          | 0.278          | 0.707        | − 0.137     | 0.56 (18.4) | 0.916        | 0.326       | 1.03       | − 0.234    | 0.689      | 0.174      | 0.763           | 1.379 (68.9) | 0.852     | 1.44 |
| PDO trend| 0.115          | 0.497          | 0.362        | − 0.062     | − 0.01    | − 0.202      | 0.294       | − 0.491    | − 0.121    | − 0.652    |          |                |              |           | 4   |
| NAO trend| 0.168          | 0.467          | 0.247        | − 0.036     | 0.162     | 0.236        | 0.009       | 0.268      | 0.325 (45.7) |          |          |                |              |           | 7   |
| BEST trend| 0.243         | (22.1)         |              |             |           |              |             |            |            |            |           |                |              |           | 19  |
| MEI trend|                |                |              |             |           |              |             |            |            |            |           |                |              |           | 18  |
| ENSO 3.4 trend| 0.181    | 0.601          |              | − 0.292    | 0.277     |              | − 0.515    | 0.147      | − 0.172    |          |                |              |           | 14  |
| ENSO 3.4(36) trend|          |                |              |            |          |              |            |            |            |          |                |              |           | 20  |
| ENSO 1.2 trend| − 0.092   | − 0.207        |              | 0.209      | − 0.146   | 0.189        | − 0.292    | − 0.388    | 0.484      | 0.571      |                |              |           | 11  |
| ENSO 1.2 (30) trend|          |                |              |            |          |              |            |            |            |          |                |              |           | 20  |
| ENSO 3 trend| − 0.021    | − 0.148        | 0.188        | − 0.826    | − 0.401   | 0.374        | − 0.098    | 0.466      | 0.586      | 0.256 (19) | − 0.513     |                |              |           | 5   |
| ENSO 3 (40) trend|          |                |              |            |          |              |            |            |            |          |                |              |           | 20  |
| ENSO 4 trend| − 0.383    | − 0.176        |              | 0.217      |            |              |            |            |            |          |                |              |           | 16  |
| ONI trend|                | − 0.631        |              | − 0.519    |          |              |            |            |            |          |                |              |           | 8   |
| TNI trend| 0.431       | 0.184          | 0.322        | 0.499      | 0.463     | 0.313        | − 0.348    | 0.116      | 0.261      | − 0.096    | 0.249 (30) | 0.264           |              |           | 2   |
| EOF trend| − 0.0277   | (27.61)        |              |            |          |              |            |            |            |          |                |              |           | 20  |
| QBO trend| − 0.121    | (25.24)        |              |            |          |              |            |            |            |          |                |              |           | 17  |
|       | LAB-RADO M141 | LAB-RADO M141* | LIBLIAN M137 | CHANIN M014 | CUENCA M067 | CUMBE M048 | GUALCEO M139 | JACARIN M197 | MAZAR M040 | PALMAS M045 | PAUTE M138 | PEÑAS M217 | RICAURTE M426 | SAYAUSI M427 | SIGSIG M424 | IFF |
|-------|----------------|----------------|--------------|-------------|-------------|-------------|--------------|-------------|-------------|-------------|-------------|-------------|----------------|---------------|---------------|-----|
| SOI trend | − 0.024        | − 0.063        | − 0.253      | − 0.257     | − 0.964      | − 0.607     | − 1.111      | 10          |            |             |             |             |                 |                |                |     |
|       | (2)            | (2.9)          | (20.2)       | (15.6)      | (37.5)      | (43.8)      | (37.5)       |             |            |             |             |             |                 |                |                |     |
| TNA trend | 0.343          | 0.457          | 0.717        | − 0.362     | 0.536        | 0.172       | − 0.144      | 6           |            |             |             |             |                 |                |                |     |
|       | (29.29)        | (42.5)         | (37.4)       | (61.8)      | (55.7)      | (14.1)      | (10.1)       |             |            |             |             |             |                 |                |                |     |
| TSA trend | − 0.434        | − 0.218        | − 0.26       | 0.067       | 0.045       | − 0.138     | 0.296        | 0.365       | 3           |            |             |             |                 |                |                |     |
|       | (74.8)         | (43.24)        | (38.7)       | (11.1)      | (5.3)       | (20.4)      | (31.4)       | (18.8)      | (27.7)      |            |             |             |                 |                |                |     |
| EOF trend | 0.753          | 0.327          | 0.784        | − 0.022     | 0.022       | 0.4         |             |             |             |             |             |             |                 |                |                |     |
|       | (87.2)         | (33.01)        | (75.3)       | (12.4)      | (75.3)      | (1.5)**     | (20.6)       |             |             |             |             |             |                 |                |                |     |
| AMO trend |               |               | 0.103        | 0.578       | − 0.545     | 0.741       | 13           |             |             |             |             |             |                 |                |                |     |
|       |               |               | (12.4)       | (61.2)      | (28.6)      | (53.6)      |             |             |             |             |             |             |                 |                |                |     |
| CAR trend | 0.082          | 0.061          | 0.09         | − 0.351     | − 0.062     | 0.321       | − 0.358      | 0.072       | 15          |             |             |             |                 |                |                |     |
|       | (11)           | (6.06)         | (8.7)        | (18.4)      | (7.2)       | (32)        | (25.7)       | (5.5)       |             |             |             |             |                 |                |                |     |
| MJO trend | − 0.217        | − 0.104        | − 0.575      | − 0.502     | − 0.094     | 0.432       | − 0.332      | 9           |             |             |             |             |                 |                |                |     |
|       | (20.5)         | (12.1)         | (37.5)       | (48.4)      | (10.2)      | (51.5)      | (34.9)       |             |             |             |             |             |                 |                |                |     |

*Coefficients of the final chosen variables are shown without closure; while in brackets the marginal T-test values for each ATC_12 models are contained. The (**) shows the marginal T-test values which are not significant in terms of [p] value (a significance [p] level of 0.05 is considered)

*ENSO3.4 (36), ENSO1.2 (30) and ENSO3(40) are the notational representations of 36, 30 and 40 quasi-periodical components of ENSO signals found by DHR methodology in the GCS smoothing process, and finally attached to GCS set external patterns (regressors for SMLR)

*The column identified with the name Labrado_M141 *corresponds to the results using 49-year monthly data
| Variable          | LAB-RADO M141 | LAB-RADO M141* | BIB-LIAN M137 | CHA-M067 | CUENCA M148 | CUMBEM M141 | GUAL-CEO M139 | JACA-RIN M197 | MAZAR M260 | PAL-MAS M045 | PAUTE M138 | PENAS M217 | RICAURTE M426 | SAYAUSI M427 | SIGSIG M424 | IFF |
|-------------------|---------------|----------------|--------------|----------|-------------|-------------|---------------|---------------|------------|-------------|------------|------------|---------------|-------------|--------------|-----|
| INTERCEPT         | -0.182        | 0.17           | 0.016        | -0.319   | 0.26 (17.6)| -0.128      | -0.043        | -0.045        | 0.311      | 1.112       | -0.22      | 0.024      | 0.86 (55.1)  | 1.043       | 0.826       | 3   |
| PDO trend         | 0.244         | 0.036          | 0.351        | 0.263     | -0.07      | 0.356       | 0.073         | -0.28         | 0.261      | -0.261      | 0.086      | -0.086     | 0.143         | 0.144       | 0.216       | 6   |
| NAO trend         | 0.234         | 0.285          | 0.503        | 0.251     | 0.21       | 0.012       | -0.092        | 0.143         | 0.076      | 0.144       | 19.7       | -0.216     | 0.144         | 0.144       | 0.216       | 6   |
| BEST trend        |               |               |              |          |             |             |               |               |            |             |            |            |               |             |             | 20  |
| MEI trend         | -0.678        |               | -0.158       | 0.114     | -0.21      | 0.539       | 0.565         | -0.47         | 0.505      | -0.505      | 0.236      | 0.236      | 0.565         | 0.47         | 0.302       | 23  |
| ENSO 3.4 trend    | 0.341         |               | -0.158       | 0.114     | -0.21      | 0.539       | 0.565         | -0.47         | 0.505      | -0.505      | 0.236      | 0.236      | 0.565         | 0.47         | 0.302       | 23  |
| ENSO 3.4 trend    | 0.341         |               | -0.158       | 0.114     | -0.21      | 0.539       | 0.565         | -0.47         | 0.505      | -0.505      | 0.236      | 0.236      | 0.565         | 0.47         | 0.302       | 23  |
| ENSO 1.2 trend    | -0.998        | -0.36          | 0.086        | 0.155     | -0.352     | 0.172       | 0.013         | 0.341         | 0.204      | 0.404       | 0.039      | 0.234      | 0.18          | 0.144       | 0.216       | 6   |
| ENSO 1.2 trend    | 0.564         | 0.253          | 0.321        | -0.001    | 0.588      | 0.498       | 0.657         | -0.576        | 0.344      | 0.137       | 0.108      | 0.641      | 0.428         | 0.428       | 0.052       | 2   |
| ENSO 3.4 trend    | 0.341         |               | -0.158       | 0.114     | -0.21      | 0.539       | 0.565         | -0.47         | 0.505      | -0.505      | 0.236      | 0.236      | 0.565         | 0.47         | 0.302       | 23  |
| ENSO 3.4 trend    | 0.341         |               | -0.158       | 0.114     | -0.21      | 0.539       | 0.565         | -0.47         | 0.505      | -0.505      | 0.236      | 0.236      | 0.565         | 0.47         | 0.302       | 23  |
| ENSO 3.4 trend    | 0.341         |               | -0.158       | 0.114     | -0.21      | 0.539       | 0.565         | -0.47         | 0.505      | -0.505      | 0.236      | 0.236      | 0.565         | 0.47         | 0.302       | 23  |
| ENSO 3.4 trend    | 0.341         |               | -0.158       | 0.114     | -0.21      | 0.539       | 0.565         | -0.47         | 0.505      | -0.505      | 0.236      | 0.236      | 0.565         | 0.47         | 0.302       | 23  |
| ENSO 3.4 trend    | 0.341         |               | -0.158       | 0.114     | -0.21      | 0.539       | 0.565         | -0.47         | 0.505      | -0.505      | 0.236      | 0.236      | 0.565         | 0.47         | 0.302       | 23  |
| ENSO 3.4 trend    | 0.341         |               | -0.158       | 0.114     | -0.21      | 0.539       | 0.565         | -0.47         | 0.505      | -0.505      | 0.236      | 0.236      | 0.565         | 0.47         | 0.302       | 23  |
| ONI trend         | -0.16         | 0.074          | 0.319        | -0.155    | -0.01      | 0.338       | 0.154         | -0.162        | 0.162      | -0.215      | 0.013      | 0.066      | 0.018         | 0.018       | 0.184       | 5   |
| TNI trend         | -0.16         | 0.074          | 0.319        | -0.155    | -0.01      | 0.338       | 0.154         | -0.162        | 0.162      | -0.215      | 0.013      | 0.066      | 0.018         | 0.018       | 0.184       | 5   |
| EOF trend         | -0.435        |               | -0.315       | 0.315     | 0.315      | 0.315       | 0.315         | 0.315         | 0.315      | 0.315       | 0.315      | 0.315      | 0.315         | 0.315       | 0.315       | 18  |
| QBO trend         | 0.054         |               | 0.214        | -0.16     | -0.212     | 0.006       | 0.018         | 0.018         | 0.184      | 0.184       | 0.184      | 0.184      | 0.184         | 0.184       | 0.184       | 14  |
| SOI trend         | 0.209         |               | 0.209        | 0.159     | 0.382      | 0.209       | 0.209         | 0.209         | 0.209      | 0.209       | 0.209      | 0.209      | 0.209         | 0.209       | 0.209       | 13  |
### Table 5 (continued)

|       | LAB- | LAB- | BIB- | CHA- | CUENCA | CUMBE | GUAL- | JACA- | MAZAR | PAL- | PAUTE | PEÑAS | RICAURTE | SAYAUSI | SIGSIG | IFF |
|-------|------|------|------|------|--------|-------|-------|-------|-------|------|-------|-------|-----------|---------|--------|-----|
|       | RADO | RADO | LIAN | NIN  | M067   | M418  | CEO   | RIN   | M410  | M045 | M138  | M217  | M426      | M427    | M424   |     |
| TNA   |      |      |      |      |        |       |       |       |       |      |       |       |           |         |        |     |
| trend | 0.408| 0.202| 0.172| 0.078|        |       |       |       |       |      | -0.153| -0.282| 0.201      |         |        |     |
|       |      |      |      |      |        |       |       |       |       |      | (30)   | (19.6) | (16.85)    | (34.2)  | 12     |     |
| TSA   | -0.176| -0.158| 0.382| 0.076| 0.597  | 0.143 | 0.256 | 0.614 | 0.235 | -0.182| -0.253| 0.149 |           | (12.9)  |        | 1    |
| trend | (20) | (31.29)| (47.3)| (53.4)| (18.4) | (34.4)| (24.8)| (67.4)| (13.5)| (25.8)| (39.5)| (12.9) |           |         |        |     |
| EOFA  | -0.013| 0.069| -0.252| -0.501|        |       |       |       |       |      | -0.73  | -0.358| 9        |         |        |     |
| trend | (1.34)**| (6.3)| (19) | (47.1)|        |       |       |       |       |      | (66.5) | (20.2)| 4        |         |        |     |
| AMO   |      |      |      |       | 0.617  | 0.171 |       | -0.093|       |       |       |       |           |         |        |     |
| trend |      |      |      |       | (55.6) | (21.8)|       | (5.4) |       |       |       |       |           |         |        |     |
| CAR   | -0.05 | -0.024| 0.451| 0.39  | 0.604  | 0.516 | 0.268 | 0.424 | 0.359 | (35.3)| 0.209 | 4        |           |         |     |
| trend | (3.8) | (2.43) | (45.7)| (34.9)| (50.6) | (51.9)| (24.8)| (32)  | (14.4)|       |       |           |         |        |     |
| MJO   | 0.08 (7.2)| -0.269| 0.044| -0.028| 0.379  | 0.206 | -0.121| 0.008 | -0.305| -0.027| 11     |           |           |         |     |
| trend | (26.8)| (4.5) | (2.2) | (25.7)| (19.5) | (12.3)| (0.9)**|       | (35.8) | (1.8)**|         |           |           |         |     |

*Coefficients of the final chosen variables are shown without closure; while in brackets the marginal T-test values for each ATC, 6 models are contained. The (**) shows the marginal T-test values which are not significant in terms of |p| value (a significance |p| level of 0.05 is considered).

*ENSO3.4 (36), ENSO1.2 (30) and ENSO3 (40) are the notational representations of 36, 30 and 40 quasi-periodical components of ENSO signals found by DHR methodology in the GCS smoothing process, and finally attached to GCS set external patterns (regressors for SMLR).

*The column identified with the name Labrador_M141 *corresponds to the results using 49-year monthly data.
Table 6 Final GCS variables included in SMLR models for each ATC_4 components of rainfall signal and ranking of influence over the Paute Basin

| Variable   | LAB-RADO M141 | LAB-RADO M141* | BIB-LIAN M14 | CHANIN M107 | CUENCA M141 | CUMBER M418 | GUAL-CER M139 | JACARIN M141 | MAZAR M410 | PALMAS M045 | PAUTE M138 | PEÑAS M045 | RICAURTE M426 | SAYAUSI M427 | SIGSIG M424 | IFF |
|------------|---------------|----------------|--------------|-------------|-------------|-------------|---------------|-------------|-------------|-------------|------------|------------|----------------|--------------|--------------|-----|
| INTERCEPT  | 0.772         | 0.422          | 0.284        | 0.182       | 1.191       | 0.954       | 0.555         | 0.605        | 0.284       | 0.84        | 0.09       | -0.141     | 0.669         | 0.098        | 1.028        | 1   |
| PDO trend  | -0.3          | -0.433         | -0.235       | -0.352      | -0.134      | -0.11       | -0.282        | -0.282       | -0.11       | -0.59       | -0.237     | 0.178      | -0.168         | 0.063        | 0.063        | 4   |
| NAO trend  | -0.005         | -0.131         | 0.266        | 0.231       | -0.103      | -0.168      | 0.072         | 0.221        | 0.485       | 0.253       | 0.178      | 0.063      | -0.275         | 0.063        | 0.063        | 4   |
| BEST trend | 0.285         | (17.4)         |              |             |             |             |               |             |             |             |            |            |                |              |              |     |
| MEI trend  |               |                |              |             |             |             |               |             |             |             |            |            |                |              |              |     |
| ENSO 3.4 trend | 0.313         |             | -0.231       | -0.544      |             |             |               |             |             |             |            |            |                |              |              |     |
| ENSO 3.4(t36) trend | -0.605         | -0.328        | -0.06        | -0.398      | -0.585      | -0.378      | -0.236        | -0.189       | -0.433      | -0.322      | -0.011     | -0.168        | 0.072        | 0.221        | 0.485 | 7   |
| ENSO 1.2 trend | -0.605         | -0.328        | -0.06        | -0.398      | -0.585      | -0.378      | -0.236        | -0.189       | -0.433      | -0.322      | -0.011     | -0.168        | 0.072        | 0.221        | 0.485 | 7   |
| ENSO 1.2(t30) trend |             |              |             |             |             |             |               |             |             |             |            |            |                |              |              |     |
| ENSO 3 trend | 0.268         |             | 0.39         | -0.327      | 0.273       | -0.375      | 0.327         | 0.398        | 0.586       | 0.581       | 0.55        | 0.179       | (22)         | 0.212        | 0.664        | 2   |
| ENSO 3(t40) trend |             |              |             |             |             |             |               |             |             |             |            |            |                |              |              |     |
| ENSO 4 trend | 0.457         |             |             |             |             |             |               |             |             |             |            |            |                |              |              |     |
| ONI trend  | -0.366        |             |             |             |             |             |               |             |             |             |            |            |                |              |              |     |
| TNI trend  | 0.154         |             |             |             |             |             |               |             |             |             |            |            |                |              |              |     |
| EOFP trend | -0.429        |             |             |             |             |             |               |             |             |             |            |            |                |              |              |     |
| QBO trend  | -0.08         |             |             |             |             |             |               |             |             |             |            |            |                |              |              |     |
| SOI trend  | -0.08         |             |             |             |             |             |               |             |             |             |            |            |                |              |              |     |
| TNA trend  | 0.093         |             |             |             |             |             |               |             |             |             |            |            |                |              |              |     |
Table 6 (continued)

| Variable | TSA | SMO | CUB | CEM | MIO | M197 |
|----------|-----|-----|-----|-----|-----|------|
| Coefficient | 0.198 | 0.198 | 0.198 | 0.198 | 0.198 | 0.198 |
| Error | 0.198 | 0.198 | 0.198 | 0.198 | 0.198 | 0.198 |
| Trend | 0.198 | 0.198 | 0.198 | 0.198 | 0.198 | 0.198 |

*Coefficients of the final chosen variables are shown without closure; while in brackets the marginal T-test values for the variables which are not significant in terms of p-value (a significance level of 0.05 is considered). The T-test values which are not significant in terms of p-value are shown without closure.*

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