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Key Points:
• An automated polynomial fitting-based scheme is implemented for detecting and characterizing linear and nonlinear precipitation change
• Precipitation change is divided into linear and nonlinear (quadratic, cubic, and concealed) trend behavior
• 12.3% of pixel-based precipitation time-series across the globe show a significant trend

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Linear and Nonlinear Trend Analyzes in Global Satellite-Based Precipitation, 1998–2017

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Abstract  Precipitation varies spatio-temporally in amount, intensity, and frequency. Although, much research has been conducted on analyzing precipitation patterns and variation at the global scale, trend types have still not received much attention. This study developed a new polynomial-based model for detecting nonlinear and linear trends in a satellite precipitation product (TRMM 3B43) for the 1998–2017 period at a near-global scale. We used an automated trend classification method that detects significant trends and classifies them into linear and nonlinear (cubic, quadratic, and concealed) trend types in satellite-based precipitation at near-global, continental, and climate zone scales. We found that 12.3% of pixel-based precipitation time series across the globe have significant trend at 0.05 significance level (50% positive and 50% negative trends). In all continents except Asia, decreasing trends were found to cover larger areas than corresponding increasing trends. Regarding climate zone and precipitation trend change, our results indicate that a linear trend is dominant in the warm temperate (77.7%) and equatorial climates (80.4%) while the least linear change was detected in the polar climate (68.9%). The combined results of continental and climate zone scales indicate significant increasing trends in Asia and arid climate over the last 20 yr. Furthermore, positive trends were found to be more significant at the continental scale, particularly, in Asia relative to the climate zone scale. Linear change in precipitation (80%) was the most dominant trend observed as opposed to nonlinear (quadratic [11%] and cubic [9%]) trend types at the global scale.

Plain Language Summary  Ordinary linear regression models have been widely used for trend analysis in many related studies. This procedure implicitly assumes that precipitation changes linearly, which may not always be the case. By using a polynomial fitting-based scheme, the results indicate that 12.3% of pixel-based precipitation time series across the globe have a significant trend, either linear or nonlinear. The linear trend in precipitation is the dominant trend type. The nonlinear trends occur much less frequently and more widely scattered over the globe. However, the nonlinear trends are credible patterns of change in precipitation. In all continents, except Asia, the decreasing trends covered larger areas than the increasing trends. Over lands, the precipitation trend is increasing and observed more frequently in the Northern Hemisphere (especially in Asia). This study provides a large-scale comprehensive perspective of precipitation change and trend types over continents and oceans.

1. Introduction

Since beginning of the weather satellite era in the 1960s, it has been observed that many climatic variables and extremes are changing at both regional and global scale. For this, managers around the globe state an urgent need for reliable and validated details on further changes as a basis for adaptation strategies (Fischer et al., 2013). Precipitation, as a climatic variable, varies from year to year and over decades, with changes in intensity, amount, type (rain vs. snow), and frequency, all of which affect the society and environment (Trenberth, 2011). Improving our knowledge about precipitation changes and potential large-scale trends is necessary for prediction of global and regional hydrological cycles (Treydte et al., 2006). In recent decades, precipitation trend analysis has been of great importance to the scientific community due to the increased awareness of global climate change (Longobardi & Villani, 2009; Mondal, Lakshmi, & Hashemi, 2018). As
well, change in the precipitation and hydrological cycle is of great importance to society as the main driver of water availability in a given region (Tan et al., 2015).

Precipitation changes in the tropical region have so far been reported from two viewpoints: (i) some researchers suggest that dry regions get drier and wet regions get wetter, “dry-gets-drier” and “wet-gets-wetter” (Held & Soden, 2006; Huang, Xie, et al., 2013; Seager et al., 2010) and (ii) others propose that increased precipitation where the rise in sea surface temperature (SST) exceeds the mean SST in the tropics, “warmer-gets-wetter” (Chadwick et al., 2013; Huang, Xie, et al., 2013; Xie et al., 2010). Although, there is little evidence supporting the concept of “dry-gets-drier” and “wet-gets-wetter” (Greve et al., 2014), spatial aggregation of precipitation seems necessary to achieve an improved understanding of global precipitation trends (Fischer et al., 2013; Nguyen et al., 2018). Furthermore, it is crucial to achieve an insight as to how the global precipitation has varied during the last decades, not only for recognizing past climate change and variability, but also for considering proper future climate projections (Gu, Adler, & Huffman, 2016).

Several studies have been carried out on global precipitation trends and variability analyzes using different data sets and methods. Trenberth (2011) investigated changes in precipitation trends by taking into account climate change parameters and indicated that the change in precipitation is more related to the variability of atmospheric circulation that can be affected by a warming climate. Westra et al. (2013) investigated the existence of trend in precipitation (annual maximum) using Mann-Kendall nonparametric and generalized extreme value approach using a global precipitation data set of 8,326 land-based gage stations over a 30 year period. The results indicated an increasing trend in close to two-thirds of gages with a statistically significant association to global average of near-surface temperature. Ren et al. (2013) studied the global precipitation trend using model simulations and a historical precipitation observation (reconstruction) during the 1900–2005 period. They found a significantly upward trend in global oceanic precipitation, subpolar, equatorial, and regions, and a significant decreasing trend in the subtropics for both precipitation reconstruction and model simulations. Gu, Adler, and Huffman (2016) found significant trends in precipitation and temperature during the satellite era (1979–2012) and reported that following the increase of anthropogenic greenhouse-gases, precipitation tends to increase approximately along the climatological intertropical convergence zone (ITCZ) and decrease in the subtropics in both hemispheres and in the south of the equator. Wang et al. (2016) compared monthly precipitation in the Global Precipitation Climatology Project (GPCP), Climate Prediction Center, National Centers for Environmental Prediction, and CMAP (Merged Analysis of Precipitation) reanalysis data sets with decadal trends of annual maximum difference of global precipitation over the 1979–2008 period. They reported a decreasing trend in the CMAP and reanalysis data sets and a flat trend in the GPCP data set due to balance between increasing trend over the subtropical ocean and decreasing trend along the equatorial ocean. Adler et al. (2017) focused on a comparison of the GPCP and new satellite observations such as Tropical Rainfall Measuring Mission (TRMM) and CloudSat to relate with GPCP mean values over the ocean, as well as a basis for reviewing the variations and magnitudes of precipitation over the past 36 yr. They explored the long-term trend of global precipitation and the impact of El Niño/Southern Oscillation (ENSO) and volcanic activities on global precipitation mean. Their findings revealed that the variation of global precipitation during the satellite era was tied to ENSO events, with substantial decrease after major volcanic eruptions, and small increase during El Niño. They found no throughout significant trend for atmospheric water vapor and surface temperature relative to the global mean. Nguyen et al. (2017) explored the global precipitation trend using Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks- Climate Data Record (PERSIANN-CDR) and Coupled Model Intercomparison Project, Phase 5 (CMIP5) precipitation products at different spatial scales using the Mann-Kendall test from 1983 to 2015. The results indicated that annual precipitation for 24 countries (out of 201 countries) showed a significantly decreasing trend, whereas for 20 countries a significantly increasing trend. Furthermore, the annual precipitation for 80 countries showed a nonsignificantly decreasing trend and for 76 countries a nonsignificantly increasing trend (Nguyen et al., 2018). Golian et al. (2019) compared several satellite-based, reanalysis, and observation-based precipitation data sets for drought studies and trend analysis at global scale. They reported that different climatologies (data lengths) could significantly affect the drought characteristics due to the dependency of the precipitation trend to the length of data record.
Error characterization of satellite-based precipitation products is necessary for achieving insightful performance (Prakash, Mitra, AghaKouchak, & Pai, 2015). The TRMM Multi-satellite Precipitation Analysis (TMPA) products have been validated across the world, uncertainties and product errors have been reported, and they are considered one of the most popular precipitation data sets for a range of applications (Prakash, Mitra, AghaKouchak, & Pai, 2015). The TMPA products exhibited higher accuracy at lower latitudes and in flat terrain areas, both in terms of quantitative and qualitative performance, whereas larger errors (both over- and under-estimation) were detected at high latitudes and in areas with greater terrain changes (X. Chen & Huang, 2020; Hashemi, Nordin, et al., 2017; Jiang et al., 2016). As such, the TMPA has a regional dependence to the climate and topography, although it provides adequate quality information at multiple temporal scales (Mantas et al., 2015). It is noteworthy that all environmental data sets including precipitation, either ground- or satellite-based, contain uncertainties. For example, ground-based precipitation data sets are sparse at global scale and have uncertainty from measurement techniques, wind-induced under-catch effects, and siting limitations to land areas. The TMPA 3B43 product used in this study incorporates bias-corrected surface precipitation gauge analyzes, so it should take advantage of gauge information where available, and the multi-satellite scheme everywhere.

The global precipitation trend and variation can be summarized as follows: (1) the selected methodology for trend analysis in many related studies focused on statistics such as the Mann-Kendall and linear regression slope, and visualizing precipitation time series, (2) although fine spatial resolution data sets were used in the recent studies, a majority used lower temporal (annual time series) and spatial resolution data sets such as 2.5° × 2.5° grid cells, and (3) almost all precipitation trend studies focused on the trend direction in terms of increasing and decreasing trend and trend magnitude at specified significance levels. Note that linear regression models or statistic tests used for precipitation time series analyzes are typically applied to compute rates of precipitation variation and change. The ordinary linear regression method implicitly assumes that linear or gradual precipitation changes, which may not always be the case. To consider nonlinear changes in precipitation, it is necessary to apply a nonlinear fitting model for precipitation data records. Thus, the goal of this study is to apply an automated trend classification algorithm for analyzing linear and nonlinear trends in global monthly satellite pixel-based precipitation data set (TRMM product 3B43) over the 1998–2017 period. Specifically, this study aims to detect the precipitation trends and classify these into linear and nonlinear types at global, climatic, and continental scales.

2. Materials and Methods

2.1. TMPA Data Set

Prior to 1979, there are no uniform observations of precipitation over either inland or oceans. For this, research efforts have begun to extend the focus on global precipitation observations, including oceans, during the last decades (1979-present) when global satellite-based precipitation estimates were initiated (R. F. Adler et al., 2008; Gu & Adler, 2013; Gu et al., 2007, 2016; John et al., 2009). TRMM was the first dedicated satellite precipitation, organized as a joint mission of the Japan Aerospace Exploration Agency (JAXA) and National Aeronautics and Space Administration (NASA), launched in 1997 to study quasi-global precipitation for climate and weather research purposes (Huffman, Adler, Bolvin, Gu, et al., 2007; Kummerow et al., 2000). The TRMM precipitation products have been extensively used in global hydrometeorological studies. In particular, the TMPA intercalibrates precipitation estimates from the global constellation of passive microwave satellites to the TRMM 2B31 Combined Radar-Radiometer product, as well calibrates estimates from geosynchronous infrared brightness temperatures, and merges all of these into 3 h 0.25° × 0.25° data sets covering 50°N-S, with calibration that includes monthly gauge analyzes (Huffman, Adler, Bolvin, Gu, et al., 2007). The spatio-temporal performance of various TMPA products against ground-based measurement has been thoroughly validated both globally (Xu, Chen, Moradkhani, et al., 2020) and regionally such as in Greece (Feidas, 2010; Nastos et al., 2016), United States (Chen, Hong, Gourley, et al., 2013; Habib et al., 2009; Hashemi et al., 2017, 2020; Prat & Nelson, 2014; Qiao et al., 2014; Zhao & Yatagai, 2014), Bangladesh (Islam and Uyeda, 2005), India (Brown, 2006; Mondal, Lakshmi, & Hashemi, 2018; Prakash, Mitra, Pai, & AghaKouchak, 2016), Ethiopia (Worqlul et al., 2014), Saudi Arabia (Almazroui, 2011), China (Chen, Hong, Cao, et al., 2013; Huang, Chen, et al., 2014; Li et al., 2012), Angola (Pombo et al., 2014), Philippines
(Jamandre & Narisma, 2013), Eastern Africa (Dinku et al., 2007), and Iran (Darand et al., 2017; Javanmard et al., 2010; Moazami et al., 2014).

The TMPA Version 7 provides three types precipitation products at different temporal resolution: monthly (3B43), daily (3B42), and 3-hourly (3B42) encompassing quasi-global precipitation data at 0.25° × 0.25° grid cell size (Huffman et al., 2007, 2010). Starting in October 2014, routine production of the TRMM TMPA shifted from month-to-month calibration by 2B31 to a climatological calibration because the TRMM Precipitation Radar was turned off as part of the end-of-mission process.

The transition from TMPA to IMERG (Integrated Multi-satellite Retrievals) for GPM began in 2015 for the 1998 to the present. Further information on this can be found in the technical documentation available by Huffman and Bolvin (2018) and Huffman (2019). Here, we used the TMPA Version 7 3B43 research products at monthly time scale, also called “TRMM and Other Data Precipitation Data Set,” with a spatial resolution of 0.25° × 0.25° grid cell size covering the latitude band 50°N-S (576,000 pixels) over the period 1998–2017.

2.2. Trend Type Classification

We performed an automated trend classification analysis developed by Jamali et al. (2014) to detect and classify trends in the near-global precipitation data set. The method consists of a three-phase step for detecting and classifying linear and nonlinear (quadratic, cubic, and concealed) trend types. In the case that quadratic or cubic trends do not show any significant net change in precipitation time series during the study period, they are recognized as concealed trend. In other words, concealed trends that possess significant quadratic or cubic curves with an overall net change in precipitation over the time period are insignificant.

The first step starts with testing the suitability of fitting a cubic model by evaluating and establishing the statistical significance of the fit (a coefficient in $ax^3 + bx^2 + cx + d$ passes a t test at $\alpha = 0.05$) and presence of both a local minimum (downward and then upward change) and local maximum (upward and then downward change) in the cubic polynomial, respectively. If at least one of these tests fail, the process jumps to the next step where a quadratic polynomial is evaluated (see next paragraph). However, if these criteria are met, a first order polynomial is fitted and if found to be statistically significant (a coefficient in $ax + b$) then the cubic trend is assigned. If the linear coefficient is insignificant, a concealed trend (of cubic type) is assigned.

If the cubic model fails, a quadratic model is tested and the analysis proceeds in the same way with the exception that only one local maximum or minimum is sought. If the criteria are met, a first order polynomial is fitted and if found to be statistically significant, a quadratic trend is assigned, otherwise, a concealed trend (of quadratic type) is assigned. The concealed class, therefore, contains cubic or quadratic trends with statistically insignificant linear slope coefficients. This class includes all cases with one significant pattern of increase and then decrease (or decrease and then increase) in precipitation (i.e., concealed quadratic) as well as cases with a pattern of significant decrease-increase-decrease behavior (or increase-decrease-increase) in precipitation (i.e., concealed cubic), but where there is no net increase or decrease over the whole period.

If all cubic and quadratic tests fail, then the fitting a linear model is tested to the pixel-based precipitation time series. Finally, if the linear model is detected to be statistically significant, it is classified as a linear trend, otherwise it is classified to the no-trend class (for more details see Jamali et al., 2014).

2.3. Data Preprocessing

Spatial variability of global precipitation can vary substantially from one place to another, which makes it difficult for comparison. For instance, some regions receive lower than 1 mm rainfall during a year as opposed to areas with more than 2,000 mm year$^{-1}$. Rainfall in some areas may change at a very low rate, that is, one or lower than 1% over two decades, while some areas’ rainfall can change by over 100 percent during two consecutive years. These issues are more profound in global scale precipitation analysis due to a large spatio-temporal variation. To remove any likely errors in the analyzes, two conditions (filters) were used before data evaluation. First, a polynomial model was fitted to every pixel time series having a precipitation range (maximum-minimum) amount of >1 mm. Second, the polynomial model was fitted to every pixel's
time series data having a precipitation range (maximum-minimum) more than 0.05 from its median during the 20 yr (1998–2017) study period. This means that we did not fit a polynomial model to pixel values that change less than that 0.05 of median value; this was defined as no change. Note that the median was used, instead of average, as the median is less influenced by the precipitation extremes. Furthermore, we used 0.05 of the median as part of classifying changes in precipitation with the increase of an average change between −5% and +5% (“No change”), change between −5% and −20% (“Small decrease”), change between 5% and 20% (“Small increase”), change less than −20% (“Large decrease”), and change of greater than 20% (“Large increase”) following the practice in IPCC (2001). As a matter of clarification, if there are two pixels with precipitation of 10 and 1,000 mm increase to 20 and 1,010 mm, respectively, by the end of the study period (0.5 mm per year or in total 10 mm during 20 yr), the results of the statistical test and polynomial fitting, without filtering/regularization, may show a significant trend for both pixels. However, the first pixel value significantly changed, by 100%, while the second one only changed by 0.01%. By applying the filter, the polynomial fitting disregards the second case and moves on to the next pixel and neglects the impact of that pixel in the overall analysis. In addition, to ensure the normality of the precipitation data set, we used the Jarque and Bera (1987) method with the null hypothesis implying that the sample follows a normal distribution with unknown variance and mean. More than 80% of pixel-based precipitation time series were shown to follow a normal distribution at the global scale and at 0.05 significance level.

We need to clarify that the trend is considered as the rate of the average change during the selected time period. In other words, the detected trend only describes the changes over the selected time frame, which is in this case 20 yr. Although a longer-period data set may provide more insight concerning historical changes, we think it is interesting to focus on the relatively recent changes in precipitation over this time period.

2.4. Trend Types in Different Climate Zones and Continents

We conducted the precipitation trend analysis at three different scales (i) global, (ii) continental, and (iii) climate zone. As the precipitation trend variation is inherently related to climate zone boundaries that do not necessarily follow political boundaries and continental borders, we used the world map of Köppen–Geiger climate classification to extend our analysis beyond the political boundaries. The climate zone classification was published by Wladimir Köppen for the first time in 1900 and updated by Rudolf Geiger in 1961. The latest version of this classification was recently produced considering global temperature and precipitation observations and is available at http://koeppen-geiger.vu-wien.ac.at/shifts.htm (Kottek et al., 2006; Rubel & Kottek, 2010). In this classification, five main climates are recognized, including equatorial, warm temperate, arid polar, and snow. We considered the five main climate zones as well as global and continental borders to compute the percentage of pixels having significant trend, to determine an increasing or decreasing trend, and to identify the trend types at each scale.

3. Results

3.1. Global Scale

We detected various trend types, i.e., cubic, quadratic, linear, no trend, and concealed trend, in the global satellite-based precipitation data set at the pixel level for the 1998–2017 period. To visualize general characteristics of the pixel-based precipitation amount across the globe (576,000 pixels), mean annual precipitation (mm) during the recent 20 year period is depicted in Figure 1a. Figure 1b shows the spatial distribution of computed positive and negative monthly precipitation trends at the global scale. According to our findings, about 87.7% (505,227 pixels) of precipitation time series showed insignificant change while 12.3% (70,773 pixels) had significant trend at 0.05 significance level. Among the 12.3%, half showed a significant positive trend while the rest showed a significant decreasing trend (Figure 1b).

From the standpoint of the concept that “wet-gets-wetter” and “dry-gets-drier,” our findings indicate a dominance of positive trend (57%) relative to a negative trend (43%) based on the pixel-based precipitation time series over land for the 1998–2017 period. Similarly, we found a preeminence of a positive precipitation trend (53%) relative to a negative trend (47%) over oceans, seas, and lakes (Figure 1b). Over the ocean, the most negative trend was found to occur over the South Pacific Ocean and Indian Ocean near Southern Australia where the mean annual precipitation is lower than 300 and 500 mm per year, respectively (Figure 1a).
According to our results, all negative changes in precipitation at the global scale followed a linear trend type over the 1998–2017. Furthermore, some parts of the South and South Atlantic Ocean, North Pacific Ocean, and Indian Ocean showed a positive precipitation trend (Figure 1b).

Figures 1c and 2 show spatial distribution and typical examples of different detected trends types (linear, quadratic, and cubic), respectively. The linear trend type is the dominating trend in 80% of the precipitation time series compared to the quadratic (11%) and cubic (9%) trends at the global scale. Furthermore, the positive and negative trends for both linear and nonlinear types had equal percentage over the study period (50% positive and 50% negative). Spatial distribution of linear trends over the ocean and land was 81% and 76%,
Figure 2. Typical annual precipitation time series with detected trend types (positive and negative) of cubic (a and b), cubic concealed (c and d), quadratic (e and f), quadratic concealed (g and h), linear (k and m), and no-trend (n). The dashed lines for concealed trends show nonsignificant linear fits.
respectively. On the other hand, nonlinear trends (including 12% quadratic and 13% cubic) were similarly distributed over the land and ocean areas (Figure 1c).

### 3.2. Continental Scale

Figure 3 depicts the results of trend direction and trend type for different continents. At the continental scale, we observed 16.0%, 10.9%, 15.1%, 9.2%, 14.0%, 3.2%, and 45.0% significant, positive or negative, precipitation trends in Africa, Oceania, Europe, North America, Australia, Asia, and South America respectively (Figures 3a and 4a). For all continents except Asia, we found a higher percentage of decreasing trend compared to increasing trend over the study period. Conversely, in Asia the positive trend (65.1%) dominated over the negative trend (32.3%) (Figures 3a and 4b). Furthermore, we observed the strongest positive trends in countries such as Pakistan, China, Kazakhstan, northwestern India, and southern Afghanistan, relative to the rest of the continent. The results showed that a linear precipitation trend is the dominating trend type over the land areas by more than 70% coverage. The linear precipitation trend type was found to occur most frequently over Europe (84.2%) and North America (82.2%) and the least over Asia (72.6%).

The quadratic trend was the dominant nonlinear trend type over Australia (12.9%), Asia (13.9%), and South America (14.3%) (Figures 3b and 5). For most continents, we observed more negative trend than positive trend, for both linear and nonlinear types. On average, 25%, 15%, and 28% of linear, quadratic, and cubic trend types, respectively, were positive and the remaining were negative. Conversely, in Asia, positive linear (65%), quadratic (66%), and cubic (67%) trends were observed to be the dominant negative trend (Table 1).
Figure 6 shows the distribution of positive and negative trends and trend types for different climate zones. In general, the results indicated that significant trend in precipitation including positive and negative occurred in less than 15% of all climate zones except the polar climate, which was 23.9% (Figures 6a and 7a). Our analyzes revealed that most significant negative precipitation trends occurred in warm temperate (84.3%) and equatorial (74.8%) climates while we found least negative precipitation trends in the arid (36.3%) and polar (41.5%) climates at 0.05 significance level (Figures 6a and 7b). We also detected positive precipitation trend in the arid and polar climates by 63.7% and 58.5%, respectively (Figures 6a and 7b).

The trend classification map indicated that nonlinear trend (25.5%) extended in a smaller area compared to the linear type (74.5%) (Figures 6a and 7b). We observed that a majority of linear precipitation trends occurred in the warm temperate (77.7%) and equatorial (80.4%) climates while the least linear trends were observed in the polar climate (68.9%). Moreover, 25.5% of the precipitation were detected to have nonlinear trend, characterized by 13.2% and 12.3% quadratic and cubic trend types over the study period, respectively. The trend type analysis showed that about 60.0% of the nonlinear precipitation trend occurred in the polar (31.2%) and arid (28.0%) climate with dominating quadratic type by 21.1% and 15.0%, respectively (Figures 6b and 8).

We observed that the precipitation in the equatorial and warm temperate climates was more influenced by negative linear change (73.1% and 85.6%), quadratic change (79.7% and 86.1%), and cubic change (82.9%
and 73.0%) than other climates. Conversely, we found that precipitation in the arid climate was more affected by positive linear (64.5%), quadratic (65.5%), and cubic (57.0%) trend types among the climates studied (Table 2).

### 4. Discussion

A side study (not shown) demonstrated that PERSIANN-CDR gave very similar trends over land, likely due to the fact that PERSIANN-CDR is calibrated monthly by GPCP SG, which incorporates the same GPCC gauge analysis as TMPA, and it is known that the gauge tends to dominate the monthly analysis of these combined data sets where reasonable gauge coverage exists. There were larger differences in trend between the two over some mid- and high-latitude ocean regions, but these regions were not the focus of this study. As such, we chose to concentrate on analyzing the TMPA. Our results indicated that less than 15% of annual pixel-based precipitation time series had statistically significant trend during the last two decades covering −50 to +50 latitude and −180 to +180 longitude. Similarly, using GPCP data set, Adler et al. (2017) detected no overall significant trend in the mean precipitation at global scale (over ocean and land), unlike the atmospheric water vapor and surface temperature. Although, the global mean precipitation had a near-zero trend, that does not mean that regional precipitation trends are zero as well. As Adler et al. (2017) reported, observed precipitation trends showed a distinctive pattern of negative and positive precipitation change.

![Figure 5. Significant trend type at the 0.05 significance level over the continents.](image)

| Continents   | Linear (%) | Quadratic (%) | Cubic (%) |
|--------------|------------|---------------|-----------|
|              | Positive   | Negative      | Positive  | Negative  | Positive | Negative  |
| Asia         | 64.53      | 35.47         | 66.42     | 33.58     | 67.20    | 32.80     |
| Africa       | 32.82      | 67.18         | 33.53     | 66.47     | 20.83    | 79.17     |
| Europe       | 13.82      | 86.18         | 4.55      | 95.45     | 4.20     | 95.80     |
| North America| 27.82      | 72.18         | 16.20     | 83.80     | 53.80    | 46.20     |
| South America| 28.42      | 71.58         | 23.97     | 76.03     | 12.05    | 87.95     |
| Australia    | 8.13       | 91.87         | 0.00      | 100.00    | 75.00    | 25.00     |
| Oceania      | 23.73      | 76.27         | 12.50     | 87.50     | 2.27     | 97.73     |
with linkages to the change patterns for water vapor and surface temperature (Adler et al., 2017). Our results indicated that 12.3% of the precipitation time series across the globe presented trend, positive or negative, with 0.05 significance level. As well, our study agrees with Nguyen et al. (2018) that no detectable, significant positive trend in global precipitation due to the well-established increasing global temperature using 33+ years of high-resolution global precipitation PERSIANN data set, even as they observed negative and positive trends in precipitation at regional scale.

We observed a band of decreasing trend along the equator in the tropical central-eastern Pacific in the precipitation time series. Precipitation variability in this region is related to an irregular periodic variation in SST and wind over the tropical eastern Pacific Ocean associated to ENSO (Gu & Adler, 2013). Strong precipitation variation appears in the tropical central-eastern Pacific forced by the ENSO-related SST fluctuations during ENSO events (e.g., Gu & Adler, 2011; Sobel et al., 2002; Wallace et al., 1998). Gu and Adler (2013) reported that the precipitation and water vapor pattern changes in the tropical Pacific region seem not to influence the pattern of warming and other mechanisms in addition to global warming that are probably impacting the precipitation trend. Satellite-observed variations and changes in global precipitation during 1979–2014 are intimately linked to ENSO events and major volcanic eruptions (Adler et al., 2017; Gu & Adler, 2011). Variation of precipitation in regional scale due to ENSO is significant, but since it is associated with inter-annual phenomena, this variation does not significantly affect long-term regional changes (Adler et al., 2017). The seasonal variability effect of the ENSO on precipitation pattern can be associated with both the intra-annual migration of the ITCZ and a strong seasonality of El Niño/La Niña peaks (Gushchina et al., 2020; Rasmusson et al., 1982), which are the main causes of extreme precipitation in the tropics.

Figure 6. Trend direction (a) and trend type (b) for different climate zones.
Amirudin et al. (2020) found that the anomalous Walker circulation, which connects the tropical Pacific Ocean and Indian Ocean besides ENSO effects, plays a significant role in determining regional changes and anomalous precipitation patterns. In the tropical central-eastern Pacific, the significant precipitation trend during the last two decades seems to be more related to short-term ENSO events than to long-term change.

The results for continental and climate zone scales indicated dominate positive precipitation trend over Asia and arid climate during in the last 20 yr. Here, the main question arises regarding the drivers of these trends. Over the land areas, the positive precipitation trend was more frequent for the Northern Hemisphere, especially in Asia. It appears that the increasing trend occurs on the larger continents in influenced by the high mountain ranges (Adler et al., 2017). Furthermore, positive trend of precipitation was detected following the continental boundaries (e.g., Asian) rather than the climate zone boundaries (Figures 4a and 7a). Positive precipitation trends predominate over northern and western China (∼+5 mm/year), which are characterized by steep terrain, whereas negative precipitation trends are stronger in the Tibetan Plateau (∼−3.5 mm/year) during the period studied. These results agree with Rodell et al. (2018) who
reported positive precipitation trends in northwestern China (+1.1 mm/year) and negative precipitation trends in the North China Plain and Tibetan Plateau (−2.3 and −1.5 mm/year, respectively) during the last two decades. We found substantial positive precipitation trend at the vicinity of the Himalaya Mountains in Asia, the Earth’s highest peaks, as well as over northern India, Pakistan, and Afghanistan characterized by highly complex topographical features. These results confirm the studies conducted by Mondal, Khare, and Kundu (2015), Kishore et al. (2016), and Mondal, Lakshmi, and Hashemi (2018) as they reported an increasing precipitation trend in northern India in the monsoon season, which is associated with ENSO. Himalayan snow and ENSO have a major role for the monsoon, and the La Niña phase strengthens the monsoon while the El Niño causes a weaker monsoon (Kripalani et al., 2003; Ramesh Kumar et al., 2009). Less winter snow is considered favorable for the monsoon (Kripalani et al., 2003; Mondal, Lakshmi, & Hashemi, 2018). This has been linked to a considerable increase in the frequency and magnitude of precipitation events (Mondal, Lakshmi, & Hashemi, 2018; Goswami et al., 2006). Our research is consistent with Treydte et al.’s (2006) report that in northern Pakistan the twentieth century was the wettest period during the past millennium. They also reported a large-scale intensification of the hydrological cycle coincident with the onset of global warming and industrialization. Moreover, our results indicate that parts of Syria, Iraq, and Iran in the Middle East experienced a significant decreasing trend over the last two decades. Similarly, Rodell et al. (2018) reported a slight decline in the precipitation amount (−1% per year) in this region during the period 1979–2015.

Our findings indicated a decreasing precipitation trend in eastern and southeastern coast of Africa during the last two decades. Rodell et al. (2018) reported similar results indicating a 4% precipitation decrease relative to average precipitation. This has caused a severe meteorological drought leading to a major food shortage in the region during the 2003–2013 period (Rodell et al., 2018; Thomas et al., 2014). Furthermore, our

| Climate Zones   | Linear (%) | Quadratic (%) | Cubic (%) |
|-----------------|------------|---------------|-----------|
|                 | Positive   | Negative      | Positive  | Negative  | Positive | Negative |
| Equatorial      | 26.9       | 73.1          | 20.3      | 79.7      | 17.2     | 82.9      |
| Arid            | 64.5       | 35.5          | 65.5      | 34.5      | 57.0     | 43.0      |
| Polar           | 65.3       | 34.7          | 35.0      | 65.0      | 61.1     | 39.0      |
| Snow            | 50.6       | 49.5          | 38.8      | 61.3      | 57.7     | 42.3      |
| Warm Temperate  | 14.4       | 85.6          | 14.0      | 86.1      | 27.0     | 73.0      |
findings indicate that North and Northwest regions of the Europe experienced a significant decreasing trend over the last two decades. Xu et al. (2019) reported a maximum spatial increase in meteorological drought coverage in Africa and projected substantial increase in drought duration in Africa, Europe, North America, and South America. Golian et al. (2019) also reported similar results indicating that the Middle East, Central and North Africa, and northern Europe suffered from the meteorological drought during 1983–2016.

It appears that the polynomial fitting-based scheme for analyzing linear and nonlinear types of change in precipitation is an effective approach to detect precipitation trend types over the last decades. Compared to other trend analysis methods, the polynomial fitting-based scheme provided more details regarding changes in precipitation time series. Typical trend analysis methods in hydrometeorological studies implicitly assume that precipitation changes linearly and gradually. This may not always be the case (Panda et al., 2019; Song et al., 2019). For example, in the current research, in addition to increasing and decreasing trends, we found nonlinear changes in precipitation time series. In a clustering procedure, we classified global precipitation trends in three significant linear and nonlinear trends. This classification provides an insight into the precipitation changes and variability over the last two decades.

In the precipitation trend analysis at global, continental, and climate zone scales we found 80% of the precipitation trend over the last two decades follow a linear type while 11% and 9% follow the quadratic and cubic trend types, respectively. Our results indicated that the precipitation trend over Asia and South America followed a nonlinear type. Especially, parts of northern India, Afghanistan, and Pakistan where monsoon season affects precipitation patterns, we observed positive linear and cubic precipitation trends. More specifically, we saw that the southern parts of these regions experienced positive linear trend while northern parts were influenced by the positive cubic precipitation trend. In other words, the precipitation in the southern parts of Asia increased linearly, but in the northern parts changed nonlinearly (cubic) during the study period. Furthermore, we found that the positive and negative nonlinear precipitation trends mostly occurred in the arid climate compared to other climates. The quadratic precipitation trend in the arid climate zone seems to be related to the high rainfall variation in the dry climate.

5. Conclusions

At global scale, most precipitation trend studies have focused on the trend direction, increasing or decreasing, and trend magnitude using lower temporal (annual time series) and spatial resolution data sets (e.g., 2.5° × 2.5° grid cells). Ordinary linear regression models or statistics tests have been widely used for trend analysis in many related studies. This procedure implicitly assumes that precipitation changes linearly and gradually, which may not always be the case. The current research used an automated mapping trend classification method to detect different types of trend, linear and nonlinear, for the monthly satellite-based precipitation time series TRMM 3B43 at the 0.25° × 0.25° grid size over the 1998–2017 period. The trend direction and trend types of precipitation were separately considered at the (i) global, (ii) continental, and (iii) climate zone scales, and the relationship between the investigated trend at all scales was evaluated.

Our findings indicated that 12.3% of pixel-based precipitation time series across the globe had significant trend at 0.05 significance level (out of these, 50% had positive and 50% had negative trend). More than 85% of the pixel-based precipitation time series did not show any significant trend over the study period. We found that increasing trend was predominant over Asia and arid climate regions relative to other continents and climate zones. Over land areas, positive precipitation trends were more frequent in the Northern Hemisphere, especially in Asia. For the significant trends identified, linear trend was dominating (80%) followed by quadratic (11%) and cubic trend types (9%).

At the global scale (land and ocean separately), precipitation trends were mainly linear. The linear trend mostly covered Europe (84.2%) and North America (82.2%) whereas the least linear trend was observed over Asia (72.6%). Nonlinear precipitation trends were infrequent at the global scale. We observed a substantial negative precipitation trend in the equatorial and warm temperate climates in linear form, 73.1% and 85.6%, quadratic form, 79.7% and 86.1%, and cubic form, 82.9% and 73.0%, respectively. Conversely, we found that the precipitation trend in arid climate was the most positive (64.5% linear, 65.5% quadratic, and 57.0% cubic) among the climates studied. The quadratic and cubic trends were found in some restricted regions of Asia and South America. We found that the increasing and decreasing nonlinear precipitation trend types mostly
occurred in the arid climate compared to other climates. Larger positive precipitation trend over northern China and western China was prevalent, which areas are characterized by steep terrain, while the negative precipitation trends were more profound in the Tibetan Plateau during the period studied.

Our results provide a large-scale comprehensive perspective of precipitation changes and trend types over continents and oceans during the last two decades. The detected trend only describes the changes over the selected time frame, which was in this case 20 yr, however, a longer-period data set may provide more insight concerning historical changes. The methodology developed in this paper applies a novel and effective polynomial fitting-based scheme that provides a detailed analysis of trend direction and types in the remotely sensed pixel-based precipitation time series at the near-global scale.

**Data Availability Statement**

These data are available at [https://disc.gsfc.nasa.gov/datasets/TRMM_3B43_7/summary](https://disc.gsfc.nasa.gov/datasets/TRMM_3B43_7/summary)
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