ORIGINAL PAPER

Assessing long-term rainfall trends and changes in a tropical watershed Brantas, Indonesia: an approach for quantifying the agreement among satellite-based rainfall data, ground rainfall data, and small-scale farmers questionnaires

Bagus Setiabudi Wiwoho[1] · Ike Sari Astuti[1] (ID) **· Purwanto Purwanto[1] · Ifan Deffinika[1] · Imam Abdul Gani Alfarizi[1] · Hetty Rahmawati Sucahyo[1] · Randhiki Gusti[2] · Mochammad Tri Herwanto[3] · Gilang Aulia Herlambang[1]**

Abstract

The agreement between meteorological data and societal perception is essential in supporting a robust policy making and its implementation. In humid tropic watersheds like Brantas, such consensus is important for water resources management and policies. This study exemplifies an effort to understand the long-term rainfall characteristics within the watershed and to build a common link among the differing data sources: CHIRPS rainfall satellite data, rain gauge data, and farmers perceptions. Six rainfall characteristics were derived using statistical measures from the scientific data and then were translated to a series of structured questionnaires given to small-scale farmers. A consensus matrix was built to examine the level of agreement among three data sources, supporting the spatial pattern of the meteorological data and farmers perception. Two rainfall attributes were classified with high agreement, four with moderate and one with low agreement. The agreements and discrepancies of rainfall characteristics were found in the study area. The discrepancies originated from the accuracy in translating scientific measurements to practical meanings for farmers, complexity of the farming system, the nature of phenomena in questions, and farmers' ability to record long-term climatic events. This study shows an implication that a combined approach to link scientific data and societal data is needed to support powerful climate policy making.

Keywords Rainfall pattern · Rainfall changes · Farmer's perception · Brantas · Satellite data · Watershed

---

✉ Ike Sari Astuti
  ike.sari.fis@um.ac.id

1 Department of Geography, Universitas Negeri Malang, Malang 65145, Indonesia

2 Institut Pertanian Malang, Malang 65141, Indonesia

3 SMAN 1 Kediri, Kediri 64114, Indonesia

1 Introduction

Agricultural systems in humid tropics are characterized by the diversity in practices from fallow management to intercropping and agroforestry and at the same time are challenged by their ecological and social traits such as highly intensive soil weathering, erosion inducing rainfall, and increased anthropogenic threats due to rapid population (Charlton 1987; Sul et al. 2013; Edwards et al. 2017). Tropical agriculture especially the conventional one is also generally marked with intensified small-scale farming, low capitals, and relatively lower resilience to external shocks (Gil et al. 2017; Antoni et al. 2019). Agriculture remains a major sector absorbing around 35% of the national workforce (Ginting and Aji 2015), despite declining shares of agricultural sectors to national products due to increasing industrialization and urbanization. Agricultural farming systems and livelihoods in Indonesia are characterized by their mostly small-scale size, subjectivity to erosion, land conflict, low income, and credit dependence (Adiningsih and Karama 1992; Mohri et al. 2013; Andriyani et al. 2017; Mariyono 2019). Spatial variation of bio-physical systems and diversity in cultural and social capitals exist and suggest the diversity in farming typology (Wiersum 2006).

Among the potential external disturbances, climate change and variability has been regarded as one of the stressors greatly influenced the agricultural production in Indonesia (Naylor et al. 2007). Tropical agriculture is predicted to be one of most affected sectors by the alarming climate change, being projected to be highly exposed to the impacts and to experience more severe declines in production (Cohn et al. 2017; Parker et al. 2019). Numerous reports confirm the escalating concerns of global climate change impacts in the last few decades and will be more severe in the future (IPCC 2018). The predicted climate changes include changes in temperature and rainfall pattern together with their corresponding impacts on water availability, occurrences of pests and diseases, and intensified hazards and extreme weather events, which are all likely to influence the agricultural production (Gornall et al. 2010; Zhai and Zhuang 2012; Chakraborty and Newton 2011). The accredited reports on the predicted impacts of climate change on Indonesia's tropical area include an increase in annual rainfall up to 10% by 2050, and larger variations up to 5% by 2100, especially for Java islands where delayed onsets are predicted and decreased rainfall peaks are expected with wetter rainy seasons and drier dry seasons as well as higher rainfall extreme events (Oktaviani et al. 2011; MFAN 2018).

With the alarming world's climate change and variability impacts, a comprehensive understanding on farmers' perceptions of such changes will be very crucial for an improved, well informed, and effective adaptation planning and practice and policies making and delivery (Hasan and Kumar 2019; Imran et al. 2020; Mkonda and He 2017). It is understood that the threats of climate change impacts on farming systems and farmers' livelihood are uneven and often regionally disproportionate, and result in new challenges for food security and sustainable development achievement (Wossen and Berger 2015). Intergovernmental Panel on Climate Change, IPCC, expected variations land carrying capacity as well as rainfall and temperature changes, which are consequently leading to variations in agricultural productions (Moore et al. 2017). While the scientific perspectives of climate change have much been globally accepted, the perception of community from local experiences about climate and its importance can be more complex and requires better understanding to how the perception is shaped and affected by the community characteristics. Any potential disagreement between what the science has produced and what has been seen and experienced by the farmers will influence the degree of willingness from

community to participate in any measures or strategies in combating the climate change impacts. In recent years, several studies on understanding communal perceptions of climate-related phenomena have been carried out in Indonesia. These include assessment of adaptation strategies for small-scale fishers (Rahman et al. 2021), rice farmers (Sekaranom et al. 2021), citrus farmer (Hasibuan et al. 2020). These works have provided substantial insight into the community response to strategy measures.

Among varying climatic variables, rainfall is the widely studied variable due to its relevance to water availability, soil erosion, and hazards management (Guodaar et al. 2021; Llasat et al. 2008), especially in tropics where rainfall is abundant and impactful. Numerous studies about community's perception toward the changing rainfall patterns primarily took place in less developed and developing countries. More studies are focused on drought-prone regions such as Africa (Guodaar et al. 2021; Mkuhlani et al. 2020; Nnadi et al. 2019; Ayanlade et al. 2018), and tropics in Asia such as in India, Myanmar, Pakistan, and Philippines (Hein et al. 2019; Arshad et al. 2017; Joshi et al. 2014; Combest-Friedman et al. 2012). Despite sufficient literatures on linking the scientific measurements with the societal information, a perspective about spatial pattern of such links is limitedly explored.

Such a deep understanding of the changing phenomenon requires a multi-approach in characterizing the issues. An increasingly accepted approach is a combined approach employing information from people and rainfall data where most studies rely on the use of ground station rainfall data and perception data tabulated from surveys or questionnaires (Guodaar et al. 2021; Ayanlade et al. 2018; Nnadi, et al. 2019). This approach is considered more reliable because the reliance solely on meteorological observation might deviate from the farmer's understanding, leading to a lack of commonalities among the community groups about factors pertaining to climatic changes and how the changes are such as types and magnitudes of indicators and methods for judging the phenomenon (Slegers 2008; Simelton et al. 2013). However, one visible drawback is the lack of spatial understanding, especially when the sites are poorly gauged. Advancement of satellite-based remote sensing rainfall data offers an opportunity to complement the rainfall gauge data in the case of missing data, lacked coverage, and rain gauge errors. At this point, there is no common framework how to integrate varying information from satellite data, meteorological data, and field community data in such a way that is reproducible and can provide insight about the connectivity between satellite, meteorological, and farmer data.

Brantas, a home to 15 cities and regencies, is one of the major watersheds in Indonesia, playing a role in providing ecological and economic benefits for more than 20 million people of East Java, Indonesia (Sunaryo 2002; BPS 2021). Despite its importance, Brantas has been increasingly exposed to varying threats such as deforestation, erosion, floods, and pollution, which were mainly caused by the escalating pressures from rapid population growth and rapid land-use changes (Fulazzaky 2009; Widianto et al. 2010; Mariyanto et al. 2019). Recently, Brantas has been declared as one of the major impaired watersheds (KLHK 2020). Agricultural land uses such as crops farming, horticultural farming, tree farming, and estate farming represent a dominant portion of the Brantas' land uses. In recent years, there have been reports on the increased runoff and declining agricultural production (Setyorini et al. 2017; Hakim et al. 2021). Brantas is recognized as a topographically complex watershed, and hence, variation in rainfall patterns might be expected. To the best of our knowledge, there has been no efforts to investigate the connection between rainfall characteristics as observed by satellite data, meteorological (gauge) data, as well as perceived by farmers in Brantas. Given the above concerns, this study then aims at (1) analyzing rainfall trends and changes using satellite data and rainfall gauges data as the scientific evidence, (2) portraying farmers' perception of rainfall trends and changes, (3) and measuring the

degree of agreement between three sources of information: satellite data, gauge, and farmer's questionnaire.

2 Methods

2.1 Study area

Brantas signifies a typical urbanizing watershed in a humid tropic. Laid on an area of 11,832 km^2, Brantas is home to 15 cities and regencies in East Java Province (Fig. 1), with a total population of exceeding 21 million people in 2020 (BPS 2020). This population accounts for around 14% of the province's population, with a rapid population growth of per year, and uneven population distribution. Despite increasing industrialization and urbanization, Brantas remains a watershed with dominance in varying agricultural land uses from wetland (rice-farming) to dryland farming systems such as crops, trees, gardens, horticultures, and livestock. However, there has been observed declining trends of agricultural roles in terms of productions, labors, and shares of total domestic products from agricultural sectors (Rusliyadi and Libin 2018). Agricultural practices are distributed across the watershed, from upland to lowland. Climatically, Brantas is characterized by the Am Köppen–Geiger's classification system with distinct monsoonal influence in rainfall patterns, with the range of total annual rainfall between 1200 and 3600 mm. Brantas is topographically complex with seven mountain complexes exist and has elevation range from
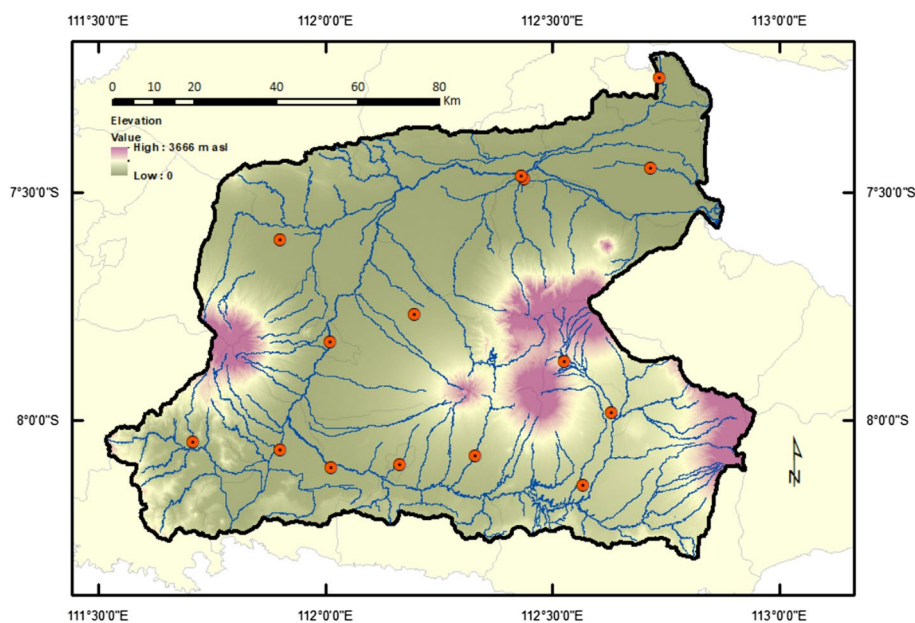

Fig. 1 Study area, with the background of elevation, cities in Brantas watershed, and main river networks of Brantas watershed. Orange circles symbolize cities and regencies within the watershed; blue lines portray the main rivers

0 m above sea level (asl) to more than 3500 m asl, making Brantas exhibit orographic influence on the mountainous regions.

2.2 General approach

In this study, we developed a framework to bridge between the three sources of data, namely satellite rainfall data, meteorological rainfall records, and farmers' perception of rainfall characteristics. First, we defined the characteristics in questions and manifested them into technical information that can be extracted from all the three data sources. Figure 2 depicts the general framework for this study. In order to build consistency of the objects in questions, we determined three main aspects of rainfall, which are trends, changes, and pattern. These three attributes were retrieved from all the rainfall data sources as specified in Fig. 2. We utilized satellite data from 1995 to 2020, to match the availability of ground rainfall data. Each of the data source and analysis was then described in the following section.

2.3 Rainfall and satellite-based data sources and analysis

The first step in the framework is defining the criteria of rain characteristics in questions and translating these into practical meaning to all three data sources into a common ground. Since rainfall dataset from gauges and from satellite is in the same unit, thus the task is then how to bridge the information gathered from satellite—gauge data and from the farmers. We set up several key features describing rain characteristics. We summarized primary rain characteristics in which rainfall data from satellite, rain gauges, and farmers were compared (Table 1).
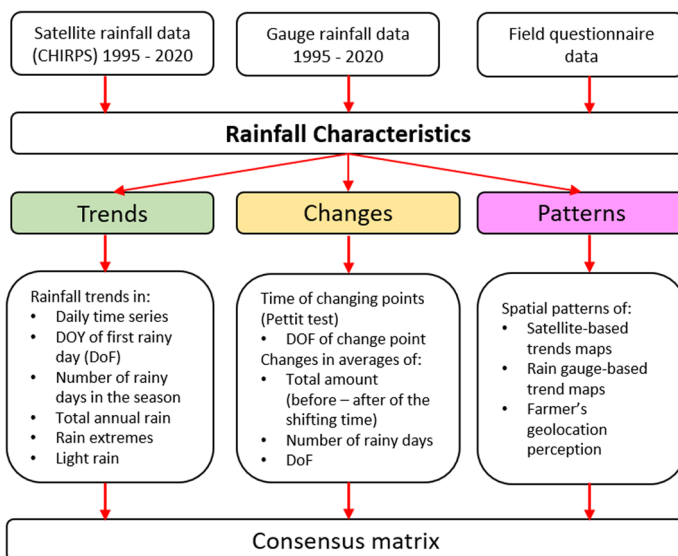

Fig. 2 Workflow of general approach in this study

Table 1 Rain characteristics examined from satellite data, rain gauges, and farmers

Rain characteristics	Satellite and gauges	Farmers
Trends in numbers of rainy days	*Trends in number of rainy days* Increased N rainy days Decreased N rainy days No trends/no change	*Question: What do you perceive about the period of rainy season or number of rainy days?* Longer rainy period (more rainy days) Shorter rainy period (fewer rainy days) Fluctuate period (no trends) No idea
Trends in starts of rainy season	*Trends in annual Day of First rain (DoF)* Increased DoF trends Decreased DoF trends No trends/no change	*Question: What do you feel about rain onset changes?* Starts earlier Starts later Fluctuated (No trend) No idea
Trends in rainfall amount	*Trends in annual total amount of rainfall* Increased trends of total annual rainfall Decreased trends of total annual rainfall No trends/no change	*Question: What do you perceive about rain amount changes?* Decreased amount Increased amount Fluctuate/no trends/no change No idea
Estimates of time of change	*Classification of Breaking point from Pettit test* Class 1 (last 5 years) Class 2 (last 10 years)	*Question: Since when you perceived the changes started to occur?* From the last five years From the last ten years No idea
Trends in number of days with rain extremes (> 50 mm)	*Trends in rain extremes (R50)—rain exceeding 50 mm* Increased trends Decreased trends No trends/no change	*Question: What do you perceive about occurrences of rain extremes events?* Increased Decreased No trend/fluctuate No idea
Trends in light rain events (< 5 mm)	*Trends in light rain events* Increased trends Decreased trends No trends/no change	*Question: What do you perceive about occurrences of light rain events?* Increased Decreased No trend/fluctuate No idea

We collected daily rainfall data from all water resource agencies in East Java, and we obtained around 201 stations. First screening was done to these stations by filtering the coverage of at least 25 years of data. Further filtering was done by assessing the completeness of the data and removed all stations having missing data higher than 5% of the total observations (daily records for 25 years). We also checked for the unusual extreme values (> 400 mm/day). Final screening resulted in daily rainfall data from 201 stations. For the satellite rainfall data, we utilized daily CHIRPS rainfall estimates and retrieved the period the same as that of meteorological data. We selected the CHIRPS data as it was found to be more reliable for the study area, compared to other satellite rainfall products, and presents in the highest spatial resolution (~ 5 km) (Wiwoho et al. 2021). We used the locations of the rain gauges to extract the CHIPRS data. The rainfall datasets were downloaded using Google Earth Engine, in a rain rate unit (mm/day) and converted to rain depth (mm) similar to rain gauge data unit.

2.3.1 Rainfall trends from daily time series measurement

The filtered daily rainfall data from both gauges and satellite were then extracted at each pixel corresponding to the location of gauges. The data were then shifted to follow the water year (started from 1st October at the current year to the 30th of September of the following year). The shift was carried out to enable quantification of the rainy season periods and other measures specified in Table 1. In each water year, we calculated the date of first rain (DoF) and number of rainy days. The rainy day was defined as a day having a rain depth at least 1 mm. To determine the increase or decrease trend, we calculated the Mann–Kendall time series to daily and monthly data from gauges and satellite. The Mann–Kendall test is a nonparametric statistical test to test for the absence of a trend, and this has been widely used to the hydro-climatic data (Yue et al. 2002; Chiew and Siriwardena 2005; Ahmad et al. 2015). Mann–Kendall test was used for viewing whether there is a trend in a data series based on relative rankings of the time span data; the Mann–Kendall statistical test formulas are as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{v} \text{sgn}(x_j - x_i) \tag{1}$$

where $\text{sign}(X_j - X_k)$ is a sign function that has a value of 1 if sign > 0 and if sign < 0 the variable S is represented by mean $\mu S = 0$ and variance; the test for variable Z will relate to S with the following formula.

$$Z_c = \frac{S-1}{\sqrt{\text{Var}(S)}}, \ S > 00, \quad S = 0 \frac{S+1}{\sqrt{\text{Var}(S)}}, \ S < 0. \tag{2}$$

The Mann–Kendall test accepts the null hypothesis if $-Z < Z_{cr} < Z$, where Z_{cr} is the critical value of the statistical normal distribution, and the Z value is the normal distribution and α is the level of significance. The level of significance is determined from the values of Z and α, if Z is positive the movement of the rainfall trend is up and is negative if the movement of the rainfall trend falls, evaluating trend results can be combined with a two-tailed computed probability (P) compared to the confidence level set from the normal distribution curve (Gebremicael et al. 2017). To obtain more practical information, each of the results from MK test was classified based on the following rules (Table 2).

Table 2 Codes of MK result classification and the associated meaning

Code	Description	Marked as
1	If the p value is ≤ 0.05, slope is positive	Significantly increased
2	If the p value is ≤ 0.05, slope is negative	Significantly decreased
3	If the p value is > 0.05, slope is positive	Insignificantly increased
4	If the p value is > 0.05, slope is negative	Insignificantly decreased
5	If slope $= 0.00$ (no change)	No trends (no change)

2.3.2 Rain event classes, amount, and time of changing

In addition to trends analysis to daily rain gauge data, we also examined the trends of the rain event classes. In this regard, we classified the rain events: the lightest and the heaviest based on the following classes (Table 3) (WMO 2008). We used these light and heaviest classes as these are generally easier to perceive by lay meteorological observes.

We plotted the classes on annual basis time series in order to observe trends of classes. This approach permitted identification of rain event distribution from year to year. In addition, we also quantified the temporal total annual amount of each rain gauge during the period of study. To investigate the start of change, we first identified gauges having significant MK trend as explained in Sect. 2.3.1. From these selected stations, we then calculated Pettit test using R platform. Pettitt test (Pettitt 1979) is a test identifying the changing time of the time series data. Further, the starts of change identified from the Pettit test were tabulated for all stations. The Pettitt test has been widely applied to examine the changes in hydro-climatic phenomena such as trends in river sediments (Zhang et al. 2008), rainfall patterns (Kundu et al. 2015), and the changing temperature (Ghasemi 2015). The mode of identified Pettit's' breaking point year was then used as the baseline to determine the before-after period. To understand the difference between these two periods, average of total annual rainfall, starts of rainy season, and number of rainy days were used as the key attributes for comparison.

2.4 Questionnaires for farmer's perception about rainfall pattern and adaptation measures

We collected farmer's perception data through the dissemination of questionnaires. The questionnaires distribution and response collection were carried out in June–July 2021. At initial stage, we used information on number of farmers or agricultural labors derived from agricultural statistics (BPS 2020), which was around 1,844,426 farmers unevenly distributed in 14 municipalities within the watershed. From these 14 regions, we selected only those with more than 25% of farmer population. Proportional sampling was initially applied to the villages within from these 14 regions to have around 250 farmers. However, the condition under

Table 3 Classes of rain events used in this study

No	Rain even classes (mm)
1	0–5
2	> 50

COVID-19 pandemic was not favorable. Due to large social restrictions of COVID-19 (semi-lockdown), we could not obtain a full closure to engage with people and thus as some of farmers or local agencies were not willing to interact with people outside their villages in addition to village border closings. With this situation, we were only able to gather permission from 73 villages, which were then used to evenly allocate the potential respondents (targeted farmers). With heavy social restriction, we did have limited timeframe to conduct farmer interview, and therefore, we decided to choose the farmers based on convenient sampling. In this case all the farmers who were found in the farms during the interview period were willing to participate, which finally resulted in only 211 respondents. We acknowledge the limitations of the convenient sampling for the possibility of not fully representing the agricultural household population's characteristics due to significant constraints in financial resources and pandemic situation. However, since this study was intended to provide an initial assessment and given the relatively high sample size, we considered this approach was sufficient.

The descriptive statistics of the farmers' socio-economic setting ("Appendix 1") reveal that the majority of the farmers are between 36 and 55 years old (52%), with 3–6 family members. The majority of education level is primary school (44%) followed by secondary school (38%) and only 14% of which obtained higher education. Most farmers are categorized as low-income farmers with average monthly income that is below 200 USD (73%), with the majority who has a farming with size ranging from 0.25 to 1.00 ha (48%) and followed by very small size farming less than 0.25 ha (40%). Most of them own the farm (64%), while around 21% are the land renters. Based on their farming experience, most of them (58%) have experience more than 10 years as a farmer.

The questions were delivered in a multiple choice for ease in giving responses. The questionnaires record the socio-economic, physical setting as well as the details of farmers perception. We divided the questions into two types, first about the personal details such as age, education, types of farming, quality of farming, number of family members, and addresses. The second section was about the details of perceptions. These included the questions about trends, changes, patterns, impacts, and adaptation measures taken to deal with the perceived changes. To minimize difficulties in getting access to local farmers, we recruited third-year geography students association living in 14 regions during their online study to serve as enumerators. At this level, the students have already owned sufficient knowledge about agricultural livelihoods. To ensure the same interpretation among the enumerators, we performed a training for all enumerators and carried a Q&A session during the training for confirming any issues or confusion. "Appendix 1" summarizes the characteristics of the farmer's livelihoods.

2.5 Quantifying the degree of agreement of three sources of information

To deduce the agreement of each information source about rainfall characteristics, the variables listed in Table 1 were used as the key parameters. The degree of agreement was determined from how well three sources of rain data describe and agree on the defined rainfall characteristics. Table 4 presents an overview of the agreement level.

2.6 Comparing spatial patterns of satellite rainfall, gauges, and farmer's perception

To compare the performance of satellite data and gauge data, we derived information of rainfall gauge data spatially by plotting spatially the 201 selected gauges data. We mapped

Table 4 Level of consensus of each rainfall characteristics as identified from three sources

Degree of consensus	Description
High	If majority of observations (> 50%) from all three sources (satellite-based rain data, rain gauges, farmer's perception) show the same ideas (i.e., all shows increased trends)
Moderate	If one of majority groups from all sources show different ideas
Low	If all majority groups show different ideas

the information pertaining to rain characteristics using the coordinates of the gauge's locations. To map the spatial orientation of the farmers' perceptions, we geotagged the locations of the villages of the respondents and linked this information to map the perception about rain characteristics. This approach enabled a visual comparison of the spatial pattern of the phenomena from satellite data, gauges, and farmers. We selected three primary rain characteristics, which are trends of total annual rain (rain amount), trends of starts of rainy seasons, and trends of number of rainy days.

3 Result

3.1 Rainfall characteristic trends as observed by CHIRPS and gauges data

Trends of daily rainfall series (1996–2020) from satellite and gauges are presented in Table 5. Overall, based on the *p* values of MK trend analysis, most of locations showed no statistically significant trends. Among 201 stations, only 8% of gauges data and 4% of CHIRPS data showed significantly increased trends and only 1% showed a significant decrease in the last 26 years. In a broader view, most of the data reveal increasing trends of rainfall, with more than 80% of the 201 locations either from gauge or CHIPRS indicated wetter days.

The increased in rainfall depth is more clearly depicted in Fig. 3. This figure portrays the increasing trends of rainfall depth from 1996 to 2020. The CHIRPS data evidently showed a larger gradient than that of the gauge data. Increased daily rain magnitudes correspondingly led to the increase of total annual rain amount as depicted in Fig. 3.

Figure 4 shows that both CHIRPS and gauge data observed increased trends of rainy days. "Appendix 2" shows that most of rain gauge stations experienced increased trends, around 74% (22% of which were increased significantly). Similar to this, CHIRPS data

Table 5 Summary of Mann–Kendall test on daily data from CHRIPS and 201 rain gauges

Types of results	CHIRPS		Rain gauge	
	Number	%	Number	%
Showing significant positive slope (*p* value $\leq$ 0.05, slope > 0)	10	4.98	17	8.46
Showing significant negative slope (*p* value $\leq$ 0.05, slope < 0)	0	0.00	2	1.00
Not significant with positive slope (*p* value > 0.05, slope < 0)	177	88.06	171	85.07
Not significant with negative slope (*p* value > 0.05, slope < 0)	14	6.97	11	5.47
No observed trends (slope = 0)	0	0.00	0	0.00

showed even a larger portion with 100% of locations experiencing increased trends (24% of which significantly increased). "Appendix 3" confirms this finding. Around 78% of gauge locations exhibit increased number of rainy days, while all 100% CHIRPS pixels in gauge locations experience elevated rainy days.

The changes in rain amount and number of rainy days evidently did not result in changes in the onsets of the rainy season. Figure 5 reveals that both CHIRPS and gauge data did not show a clear trend. "Appendix 4" shows that only 3% of 201 gauges and CHIRPS locations showed significantly increased trends of DoF, indicating accelerated onsets of rainy seasons. Around 80% of rainfall locations are from gauges and CHIRPS pixels.

Observing trends of rain depth classes provides a deeper understanding of the changes in rainfall distribution, especially the rainfall trends at the highest class (extreme class: > 50 mm) and lowest class (< 5 mm). Figures 6 and 7 portray the trends of number of days having extreme rain (> 50 mm) and number of days having light rain (< 5 mm). From both data, the positive trends were observable. It is obvious that the wetter condition was attributed to the increased number of both rainy days and days having heavier rains.

As opposed to heavy rains, in the last 25 years, there has been a decrease in the number of days with daily rain depth fewer than 5 mm. Figure 7A and B depicts this condition where clear decreasing trends are observed from CHIRPS and rain gauge data. Around 70% of gauge locations and almost 100% CHIRPS location exhibit negative slopes ("Appendix 6").
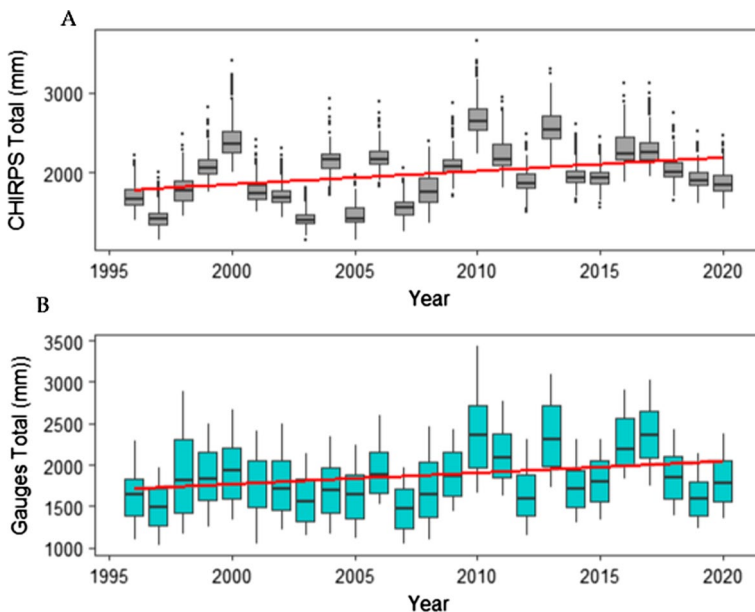

Fig. 3 Trends of total annual rain depth (in mm) during 1996–2020. The red line trends represented the mean value of the data distribution in each year
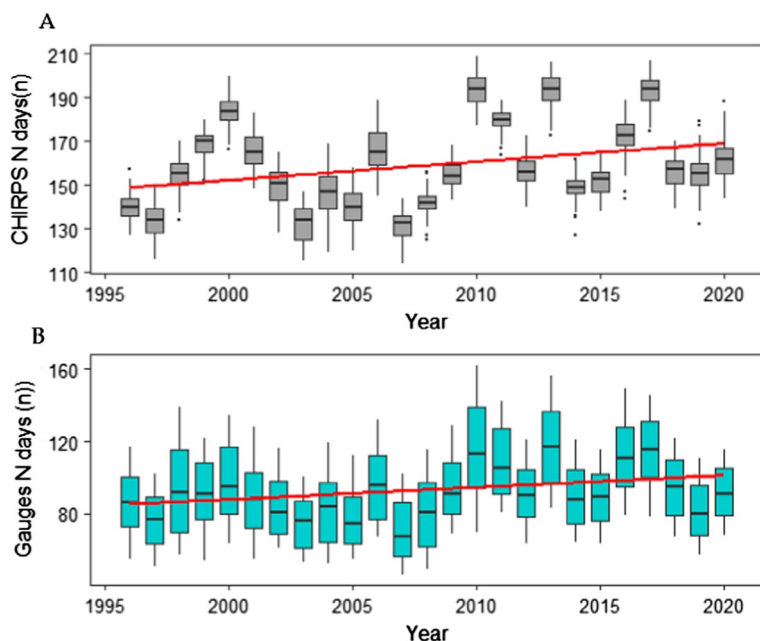
Fig. 4 Trends of number of rainy days as observed by CHIRPS satellite data and rainfall gauge data (averaged over 201 stations)
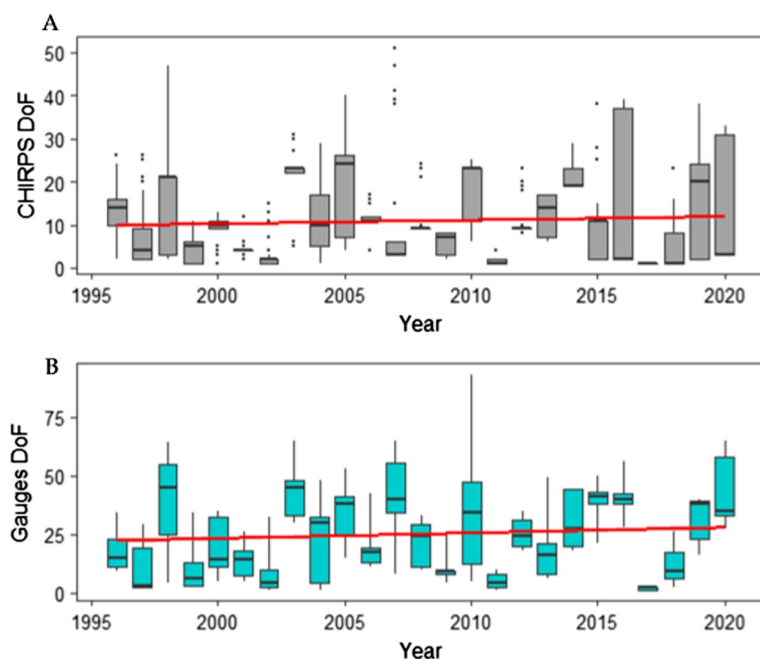

Fig. 5 Trends of rainy season onset (DOY of first rain) comparison between CHIRPS satellite data and rainfall gauge data ($n = 201$ locations)
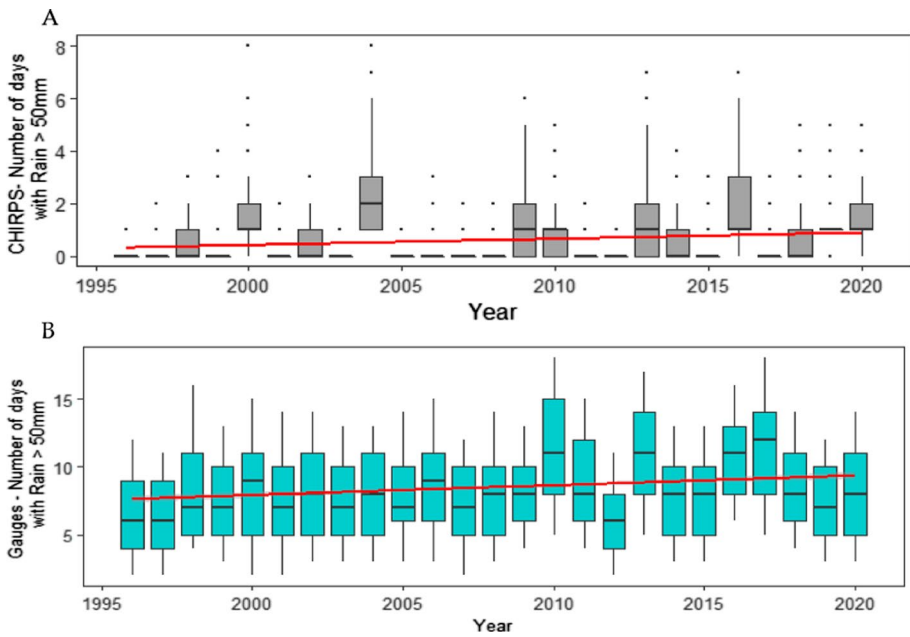
Fig. 6 Trends of number of days receiving rain higher than 50 mm in a day ($n = 201$ locations)
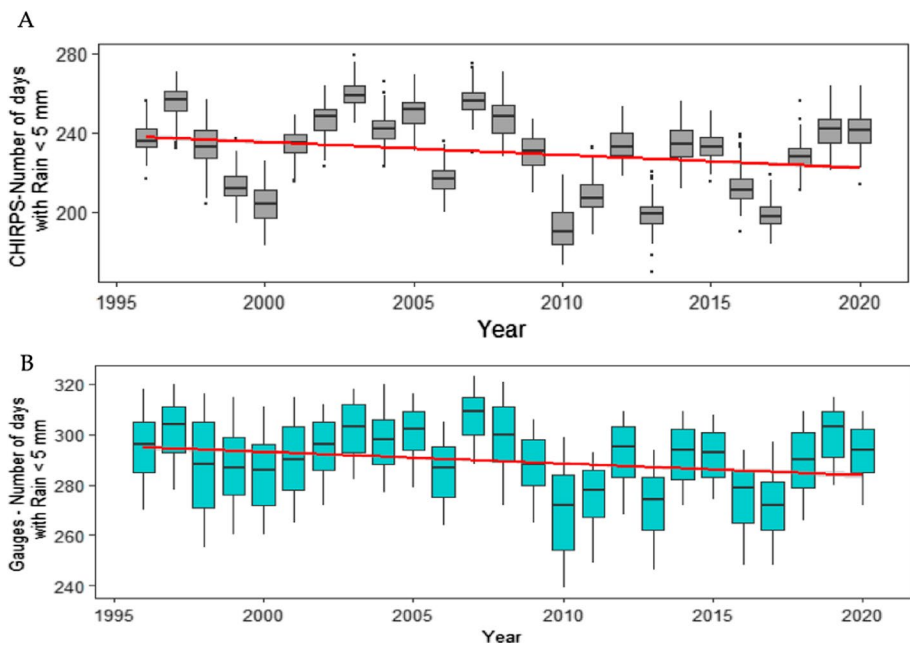

Fig. 7 Trends of number of days with light rain events 1995–2020. Each boxplot was derived from 201 rain gauges

3.2 Rainfall characteristic changes as observed by CHIRPS and gauges data

The Pettitt test *K* value indicates the break point in the data time series. Table 6 summarizes the break point year from both CHRIPS and gauge rainfall data. In most locations, the period identified as the break point commonly longer than 10 years ago, accounting for 54% of the 201 gauges' rainfall. Around 40% of the gauges show that the changes are relatively more recent with the break point year occurred after 2015 (mode value 2009). On the other hand, CHIRPS identified differently with 100% occurred in year 2009.

The differences between before and after the break point year at mode value from CHRIPS and gauge data (2009) are presented in Fig. 8. Changes in averages of total annual rain, starts of rainy season, and number of days before and after the break point year (2009) were as below.

The biggest change was the change in average total annual rainfall, which is from around 1700–1800 mm/year (both CHIRPS and gauge) to around 2000 and 2100 mm/year. A considerable change in number of rainy days is also found in both datasets. While CHIRPS rainfall shows a change of approximately in 18 days higher in after period, the gauge rainfall data show a change of approximately 15 days higher in the after period. The only small change was the start of the rainy season (DoF), with 2 days later than the average DoF in the before period for gauge rainfall (1.28 day later for CHIRPS rainfall data).

3.3 Farmer's perception on rainfall characteristics and generic adaptation strategies

Table 7 presents the summary of the perception about rain characteristics.

Most farmers (98%) perceive that rain has changed with floods and landslides were considered as the most physical impact. However, when it comes to describing the nature of the change, most of them responded inconsistently by choosing "fluctuate/no trends" (66%) instead of choosing "decrease" or "increase." Similar responses were found when they were asked to describe the duration or number of rainy season and starts of rainy season. The most obvious response was the response to changes in rain amount with almost 95% perceived an increase in rain amount trends. When being asked to estimate the start of changes, most farmers found that rain has changed since the last 5 years (79%). The perception of farmers on rainfall classes was shown from the response in classifying the occurrences of extreme rains and light rains. The majority concluded that occurrences of both extreme rains and light rain are decreased.

The variations in responses are also shown in impacts perceived and adaptation measures taken by farmers. Table 8 portrays the general types of adaptation strategies performed by farmers. When being asked what the impacts of rain changes to their farming

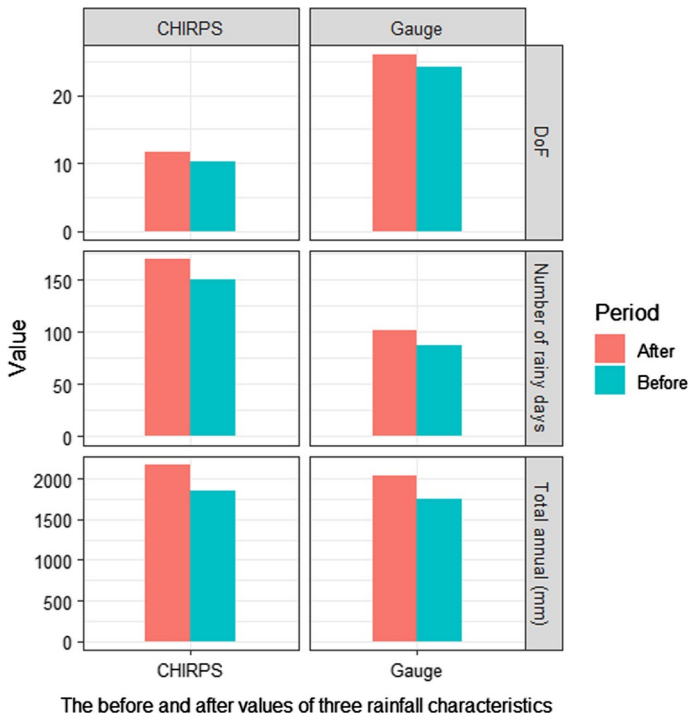| Table 6 Summary of Pettitt's break point year classified by the 5-year and 10-year period	Break-point time	CHIRPS		Gauge	
		n	*%*	*n*	*%*
	> 2015 (since 5 years)	0	0.00	82	40.80
	> 2010 (since 10 years)	0	0.00	9	4.48
	Else (> 10 years ago, before 2010, mode value is 2009)	100	100.00	110	54.73

Fig. 8 The averaged values of three rain characteristics at before and after periods from both CHIRPS and gauge data

are, around 45% blamed the rainfall changes as the cause of increased pest/diseases/weeds, followed by 40% choosing the increased of wild animal attacks.

When being asked whether or not they applied some measures to deal with the impacts, most of them responded as "yes" (85%) and only 15% saying "no." The most popular measures taken by farmers are applying farming inputs, accounting for 37% of the group, followed by changing the plants or cattle (30%). Given the fact that most farmers are economically marginal, it is not surprising to find that 73% of farmers face multiple obstacles (mostly lack of funding and skills) in applying the adaptation measures.

3.4 Assessing the consensus level of rainfall characteristics from different data sources

Based on the proposed consensus matrix as specified in Sect. 2.5 (Table 4), there have been disagreement and agreement among the three data sources as shown in Table 9. Among the six rain characteristics, two rainfall attributes have "High" agreement: trends of total rainfall amount and light rain events, meaning both rainfall parameters from satellite and gauge are in the same direction as that of farmers' perception. Three rainfall attributes, namely trends in number of rainy days, time of change, and trends of extreme rain events, were classified as "Moderate" with farmer's perception became the primary source of disagreement. The only rain characteristics classified as "Low" is the trends in rainy season onset.

Table 7 Summary of farmers' perception about rain characteristics

Rain changes and patterns characteristics	n	%
What do you perceive about rain trends		
Increased	33	15.64
Decreased	20	9.48
Fluctuate/no trends	141	66.82
No idea	17	7.58
What do you perceive about the period of rainy season or number of rainy days?		
Longer rainy period (more rainy days)	34	15.64
Shorter rainy period (fewer rainy days)	20	9.48
Fluctuate period (no trends)	141	66.82
No idea	16	7.58
What do you feel about rain onset changes		
Starts earlier	43	20.38
Starts later	56	26.54
Fluctuate/no trends/no change	105	49.76
No idea	7	3.32
What do you perceive about rain amount changes		
Decreased amount	12	5.69
Increased amount	199	94.31
Fluctuate/no trends/no change	0	0.00
No idea	0	0.00
Since when you perceived the changes started to occur?		
From the last five years	167	79.15
From the last ten years	44	20.85
No idea	0	0.00
What do you perceive about occurrences of rain extremes events?		
Increased (more frequent)	80	37.91
Decreased	131	62.09
Fluctuate	0	0
No idea	0	0.00
What do you perceive about occurrences of light rain events		
Increased (more frequent)	88	41.71
Decreased	120	56.87
Fluctuate	0	0
No idea	3	1.42

In this regard, three data sources exhibit different results. Table 9 compiles the majority of responses for each rain characteristics question.

3.5 Spatial patterns of rainfall characteristics

Figure 9 depicts the spatial patterns of three rain characteristics from three different data sources. In general, there have been different levels of visual agreement from the three

Table 8 Summary of farmers' perception about adaptation characteristics

Question	n	%
What are the impacts for your farming?		
(a) Increased pests/diseases/weeds	113	53.55
(b) Eroded lands	2	0.95
(c) Wild animal attacks	92	43.60
(d) Drought-driven loss	4	1.90
(e) No idea	0	0.00
Types of adaptation strategies carried out		
(a) Applying farming inputs (forages, water, growth controllers, fertilizers, pest drugs)	78	36.97
(b) Changing the plants/cattle	64	30.33
(c) Carrying conservation and farming techniques improvement	32	15.17
(d) Combined at least two	7	3.32
(e) Do nothing	30	14.22
Obstacles in carrying strategies?		
(a) Lack of funding	19	9.00
(b) Lack of skills and experiences	23	10.90
(c) Lack of time and labors	9	4.27
(d) Difficult terrain and farm conditions	6	2.84
(e) Combined at least two responses above	154	72.99
From where you received assistance to deal with the impacts?		
(a) Farmers' association	99	46.91
(b) Government at local and national	12	5.68
(c) NGOs/local communities	35	16.58
(d) Relatives/family	61	28.91
(e) None	4	1.89

sources. The spatial pattern of trends of rainy days between CHIRPS and rain gauge is relatively similar with a dominance of insignificantly increased trends across the watershed. However, most farmers' geolocations show the differing spatial pattern with a dominance of fluctuated trends. On the other hand, the spatial pattern of rain amount trends shows that three data sources have higher agreement. Visual similarity of the spatial pattern across the watershed is quite obvious. This feature is classified as "High" in Table 9. The "Low" classified DoF in Table 9 is also evident in Fig. 9C. Three data sources show considerably different patterns. While CHIPRS data show a dominance of "decreased" trend in the middle to the south of the watershed, the gauge data show a dominance of "increased trends" across the watershed. As opposed to this, farmers perception is dominated by "fluctuated or no trends."

4 Discussion

The study demonstrates work on how three different assessments on a particular phenomenon can be evaluated and examined for their association. The research shows that a qualitative and quantitative characterization approach can be assessed together to provide deeper

Table 9 Degree of agreement on rain characteristics from three sources of data

| Rain characteristics	Satellite	Rain gauge	Farmers	Agreement level
Trends in numbers of rainy days	Insignificantly increased/ longer period (91%)	Insignificantly increased/longer period (48%)	Fluctuate/no trends (66%)	Moderate
Trends in starts of rainy season	Insignificantly decreased (57%)	Insignificantly increased (75%)	Fluctuate/no trends (49%)	Low
Trends in rainfall amount	Insignificantly increased (88%)	Insignificantly increased (52%)	Increased (94%)	High
Estimates of time of change	Mode value: 2009 (> 10 years)	Mode value: 2009 (> 10 years)	Since last 5 years/2015 (79%)	Moderate
Trends in number of days with rain extremes (> 50 mm)	No trends/no change (95%)	Insignificantly increased (38%)	Increased (62%)	Moderate
Trends in light rain events (<5 mm)	Insignificantly decreased (98%)	Insignificantly decreased (50%)	Decreased (56%)	High
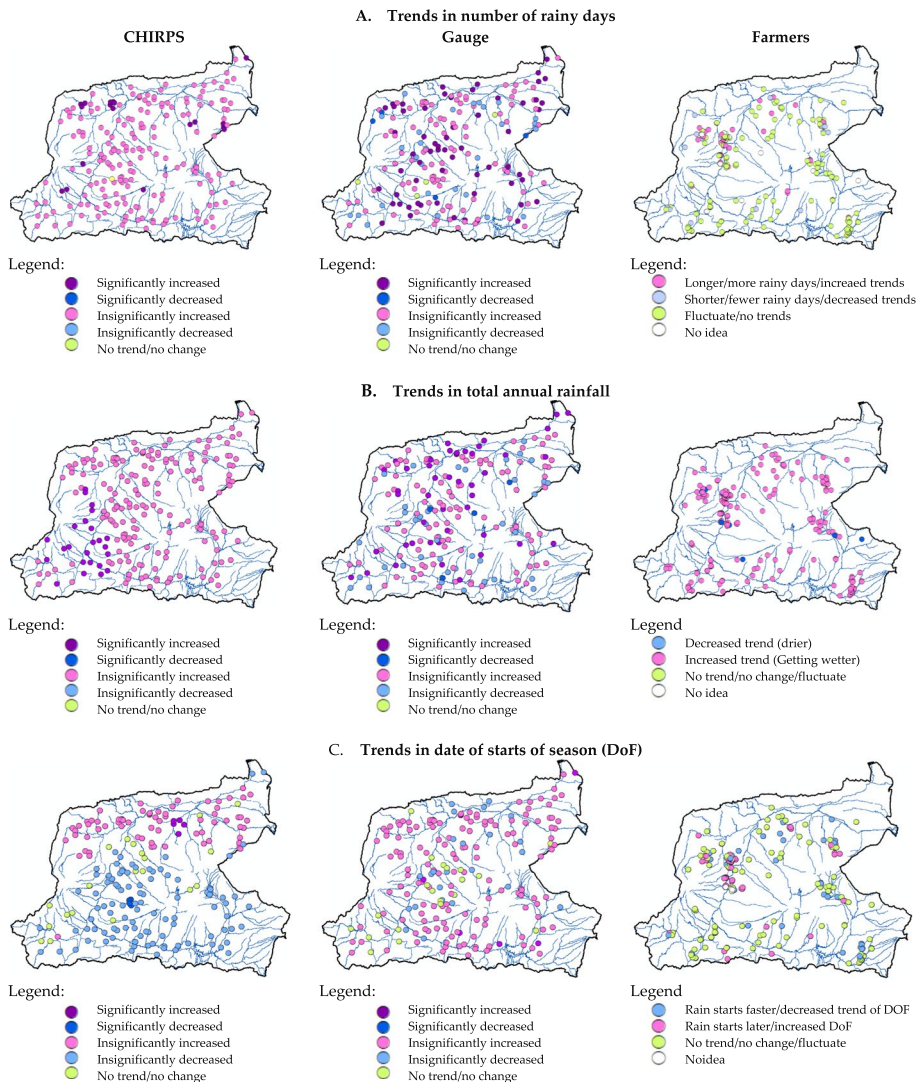
Fig. 9 Spatial pattern of rain characteristics as observed by CHIRPS data, rain gauge data, and farmers' perception

insights into how farming systems are influenced by rainfall changes and an opportunity to develop a link between geospatial data, field data, and farmers data. The six rain characteristics examined in this research reveals differing degrees of agreement among the three data sources. These result in two characteristics assigned as "High," two others as "Moderate," and the rest as "Low."

The two characteristics classified as "High" are the trend in rainfall amount and trends in light rain events. The nature in rainfall trends is linked with large-scale climatic phenomena. Total annual rainfall represents a cumulative portion of rain received. While in rain gauge data and satellite data, this characteristic can be easily examined through statistical

measures, the farmers' recognition to this phenomenon might not be straightforward. The fact that most farmers could generate the same information as that of satellite and rainfall data might not be very surprising. Total annual rainfall is an accumulation of daily rain events. Farmers might observe the elevated rainfall from their daily observation. High rain is visually observable from their intensified rain and can be also approached from the increasing occurrences of floods and landslides. Data from local disaster agencies show that there have been elevated frequencies of water-related hazards (Handayani et al. 2020). Similar to this, the decrease in light rain can be perceived properly by most farmers. However, unlike extreme rains, light rain lower than 5 mm is hard to quantify accurately as the rain might not be noticeable. The farmers' response that corresponds to the observation from gauges and satellite data might be attributed to the association of domination of perceived high rains throughout the season.

In terms of onsets, generalized perception such as 'it's difficult to tell when the rainy season begins' was represented in both rainfall data in terms of interannual variability of onsets. Determination of DoF for farmers might be associated with the start of planting and play a role in decision making of the farming practices (Ingram et al. 2002), and therefore, it is expected that the response is not contradictory to result from satellite and gauge data. However, the result shows that most farmers perception about DoF is different. The inability of farmers on perceiving this phenomenon could potentially be attribute to the fact that the magnitudes of changes in DoF for the before and after period (Fig. 8) were not noticeable, showing very slight change (1–2 days). Farmers' perceptions of rainfall characteristics and meteorological data can be at odds. One cause of disagreements is that farmers may tend to state a more recent break point change than the meteorological data indicates. This is in line with the findings of Marx et al. (2007), who found that perception of massive rain events can be vivid if they occur on a regular basis and became more memorable. Such discrepancies can also stem from the farmers' difficulty in recording long-term patterns and tend to capture more recent ones (Debela et al. 2015). Another potential source of disagreement is the quality of the rainfall data. Despite many similarities between satellite rainfall data and gauge rainfall data, the discrepancy that occurred on DoF between CHIRPS and gauge infers the inability of satellite data capture the rainy days. Many studies reported limitations of satellite CHRIPS data such as insensitivity to light rain and rain influenced by orographic effect (Bai et al. 2018).

Bridging information obtained from scientific data such as meteorological data to community like farmers cannot always be direct since there might be differences among users in deriving the meaning of the information. The fundamental part is how the issue in question can be perceived from differing sources. The first step carried out in this study is defining the issue, which is the changes of rainfall, into a series of quantifiable assessments. The six rain characteristics statistical tests in Table 1 exemplified such an issue description from a meteorological data perspective, and the six questionnaire questions were developed to address the corresponding assessment from meteorological data. For example, the MK test was calculated to identify a trend of a rainfall time series data, and this can be extended to a form of question to farmers about the trend by providing directed response choices: increased, decreased, fluctuate or no trend, and no idea, which can be practically articulated to farmers and can be responded to quite directly. The degree of success in translating the scientific statement into societal perception might be influenced by the complexity of the scientific assessment. In other case, quantitative assessments such as rain extremes might be more challenging for farmers as they might be difficult to qualitatively measure how much is considered extremes. On the other hand, the way farmers capture meteorological events can be influenced by the relative importance of such events to their daily life

context such as the growing season and wood haunting (Guodaar et al. 2021). However, albeit being prone to subjectivity, this study offers a simple approach in solidifying the results from differing sources. The resulting divergence among the local perception and scientific measurement emphasizes the importance of integration for adaptation policy and planning in rural agro-ecological context.

It is well understood that farmer's perception toward the rainfall changes as well as their ability to adapt is influenced by internal and external variables such as their self-capacity, governmental support, technological advancement, and physical land conditions (Smith and Skinner 2002; Kessler 2006). Therefore, variations in farmers' characteristics are expected. Understanding farmer's farming systems, their perception, and acts is essential toward successful climate management in the prone to pressures small-scale systems. It provides not only information the variability of farming systems but also their beliefs and capacity to deal with climatic hazards and accordingly determine their potential resilience in sustaining the system. In this research context, an understanding of local farming systems and the variability is important to investigate the relationship between rainfall data and farmers' perception in the region. Determination of rainy season onset has been the most challenging where "Low" agreement was observed. Studies show the importance of rainy season onset and its link to farmers' choices of plants (Marteau et al. 2011; Ngetich et al. 2014). About 75% of 201 rain gauges observed an increased trend of rainy season onset (rainy season start is getting later), only 26% of farmers responded "later start," while most of them (46%) perceived fluctuations. If we look at further to the variety of eight farming types as specified in Appendix 1, we found that differences in perception appeared in differing farming system types. The differentiation in response apparently was influenced by the differentiation in farming types. Among the 26% of total farmers with correct perception, farming groups with vegetables/horticulture and farmers planting mixed paddy and vegetables showed relatively high portion of correct response ("start later"), which is 39% and 30% of their total groups. This is much higher than farmers with crops, which only 19% of them state the later trends of rainy season onset. Similarly, low portion of correct perception was evident from fruit tree farmers and industrial plant farmers, where none of them stated "later." The differentiation in response apparently was influenced by the differentiation in farming types. In this regard, farmers growing vegetables appear to have a better sense of observing the early rains. This was not surprising, given the fact that vegetables are types of plants needing intensive care in soil tillage practices including plant watering. With the dependence on rainfall and river water, farmers' sensitivity to initial rainfall occurrences became higher. On the other hand, differing perspective was exemplified from farmers with cattle and fruit trees or industrial plants. Cattle do not need water for intensive early growth. Similarly, water supply for fruit trees and industrial plants such as durians, cloves, avocado, and sugarcane is not intensive when these plants are already established.

The findings from this study provide several implications not only for the purpose of scientific development but also for the climate-related policy making and implementations. For the scientific perspective, this study provides a systematic assessment to obtain an initial insight about the variability of farmers' livelihood and their belief toward climatic issues. The variability and spatial patterns of farmer's perception in this study would be a beneficial input for refinement of the sampling design in future studies. This would even be more essential when such studies are expected to be the source of a policy making. Second implication is that the achievement of agreement between scientific data and societal perception depends largely on how to define a common ground for an issue as assessed by scientific measurement, such as rainfall changes, can be translated to a practical assessment

by society without losing much meaning. If the observation from scientists and perceptions from local stakeholders such as policy makers, farmers, and other community members exhibit a divergence, there would be likely a failure in policy design and delivery. While the climate change is increasingly a global concern, a shared understanding about this would inevitably expedites the success in managing the concern.

5 Conclusion

This study demonstrates an effort to develop an understanding of the consensus and discrepancies of farmers and two meteorological measurements toward the rainfall changes in a tropical watershed region using a combined quantitative and qualitative approach. The statistical analysis results reveal that during the last 25 years, Brantas river basin has been experiencing an increase in rainfall amount, duration, rain extremes occurrences, and a decrease in light rain occurrences. Among these phenomena, only two rainfall attributes that the farmers perceived in agreement with all satellite data and field measurements. The discrepancies between satellite and field data were purely the differing ability of these two scientific tools in sensing and measuring the rain phenomena. While the discrepancies from the farmers infer the ability of farmers in perceiving and recording long-term rainfall events and in quantifying the phenomena, the ability of farmers in observing climatic phenome is complex and influenced by farmers' inherent and external factors such as farming types. A potential way to reduce the discrepancies is to jointly define the issue in question and derive practical meanings for the lay observers like farmers. The simple approach in this study could potentially be extended and improved for other applications.

Appendix 1: Summary of farmer's socio-demographic setting

Variable	*n*	%
Age		
< 35 years old	27	12.80
36–55 years old	111	52.61
> 55 years old	73	34.60
Number of family members		
< 3 persons	33	15.64
3–6 persons	112	53.08
> 6 persons	66	31.28
Sex		
Male	188	89.10
Female	23	10.90
Level of education		
Never	4	1.89
Primary school	95	45.02
Secondary school	81	38.38
Higher education	31	14.69
Level of income		

Variable	n	%
< 200 USD	157	73.46
200–345 USD	39	18.96
> 345 USD	15	7.11
Types of farming		
Cattle only	20	9.48
Crops	31	14.69
Horticulture	38	18.01
Paddy + crops*	21	9.95
Paddy + horticulture/vegetables	23	10.90
Fruit tree	4	1.90
Industrial plants*	6	2.84
Paddy only*	68	32.23
(*) owned small cattle		
Farming size		
< 0.25 ha	84	39.81
0.25–1.00 ha	102	48.34
> 1.00 ha	22	10.43
Land status		
Self-owner	139	65.86
Renting	45	21.33
Shared	25	11.84
"Bengkok"/rewards (gift)	1	0.47
Labor	1	0.47
Farming experience		
< 5 years	44	20.85
5–10 years	40	18.96
> 10 years	127	60.18

Appendix 2: Summary of MK trends of total annual rainfall time series 1996–2020

Types of results	CHIRPS		Rain gauge	
	Number	%	Number	%
Showing significant positive slope (p value ≤ 0.05, slope > 0)	24	11.94	46	22.89
Showing significant negative slope (p value ≤ 0.05, slope < 0)	0	0.00	4	1.99
Not significant with positive slope (p value > 0.05, slope > 0)	177	88.06	106	52.74
Not significant with negative slope (p value > 0.05, slope < 0)	0	0.00	45	22.39
No observed trends (slope = 0)	0	0.00	0	0.00

Appendix 3: Summary of MK trends of number of rainy days time series 1996—2020

Types of results	CHIRPS		Rain gauge	
	Number	%	Number	%
Showing significant positive slope (p value ≤ 0.05, slope > 0)	18	8.96	62	30.85
Showing significant negative slope (p value ≤ 0.05, slope < 0)	0	0.00	6	2.99
Not significant with positive slope (p value > 0.05, slope > 0)	183	91.04	97	48.26
Not significant with negative slope (p value > 0.05, slope < 0)	0	0.00	32	15.92
No observed trends (slope $= 0$)	0	0.00	4	1.99

Appendix 4: Summary of MK trends of DOY of first rain time series 1996–2020

Types of results	CHIRPS		Rain gauge	
	Number	%	Number	%
Showing significant positive slope (p value ≤ 0.05, slope > 0)	6	2.99	6	2.99
Showing significant negative slope (p value ≤ 0.05, slope < 0)	4	1.99	0	0.00
Not significant with positive slope (p value > 0.05, slope > 0)	69	34.33	151	75.12
Not significant with negative slope (p value > 0.05, slope < 0)	102	50.75	24	11.94
No observed trends (slope $= 0$)	20	9.95	20	9.95

Appendix 5: Summary of MK trends of number of days with extreme rains (rain depth > 50 mm)

Types of results	CHIRPS		Rain gauge	
	Number	%	Number	%
Showing significant positive slope (p value ≤ 0.05, slope > 0)	6	2.99	38	18.91
Showing significant negative slope (p value ≤ 0.05, slope < 0)	0	0.00	11	5.47
Not significant with positive slope (p value > 0.05, slope > 0)	40	19.90	78	38.81
Not significant with negative slope (p value > 0.05, slope < 0)	0	0.00	35	17.41
No observed trends (slope $= 0$)	155	77.11	39	19.40

Appendix 6: Summary of MK trends of number of days with light rains (rain depth < 5 mm)

Types of results	CHIRPS		Rain gauge	
	Number	%	Number	%
Showing significant positive slope (p value ≤ 0.05, slope > 0)	0	0.00	1	0.50
Showing significant negative slope (p value ≤ 0.05, slope < 0)	3	1.49	42	20.90
Not significant with positive slope (p value > 0.05, slope > 0)	1	0.50	42	20.90
Not significant with negative slope (p value > 0.05, slope < 0)	197	98.01	102	50.75
No observed trends (slope $= 0$)	0	0.00	14	6.97

Data availability Data cannot be made available for reasons disclosed in the data availability statement.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The authors declare they have no known financial interests/personal relationships which may be considered as potential competing interests.

References

Adiningsih JS, Karama AS (1992) A sustainable upland farming system for Indonesia. Centre for Soil and Agroclimate Research (RSAR), Bogor

Ahmad I, Tang D, Wang T, Wang M, Wagan B (2015) Precipitation trends over time using Mann–Kendall and spearman's rho tests in swat river basin, Pakistan. Adv Meteorol 2015:1–15

Andriyani I, Jourdain D, Lidon B, Soni P, Kartiwa B (2017) Upland farming system erosion yields and their constraints to change for sustainable agricultural conservation practices: a case study of land use and land cover (LULC) change in Indonesia. Land Degrad Dev 28(2):421–430

Antoni C, Huber-Sannwald E, Hernández HR, van't Hooft A, Schoon M (2019) Socio-ecological dynamics of a tropical agricultural region: historical analysis of system change and opportunities. Land Use Policy 81:346–359

Arshad M, Kächele H, Krupnik TJ, Amjath-Babu TS, Aravindakshan S, Abbas A, Mehmood Y, Müller K (2017) Climate variability, farmland value, and farmers' perceptions of climate change: implications for adaptation in rural Pakistan. Int J Sustain Dev World Ecols 24(6):532–544

Ayanlade A, Radeny M, Morton JF, Muchaba T (2018) Rainfall variability and drought characteristics in two agro-climatic zones: an assessment of climate change challenges in Africa. Sci Total Environ 630:728–737

Bai L, Shi C, Li L, Yang Y, Wu J (2018) Accuracy of CHIRPS satellite-rainfall products over mainland China. Remote Sens 10:362

BPS (2020) Provinsi Jawa Timur Dalam Angka 2020. BPS Provinsi Jawa Timur, Jawa Timur

BPS (2021) Propinsi Jawa Timur Dalam Angka. Badan Pusat Statitisik, Jakarta

Chakraborty S, Newton AC (2011) Climate change, plant diseases and food security: an overview. Plant Pathol 60(1):2–14

Charlton CA (1987) Problems and prospects for sustainable agricultural systems in the humid tropics. Appl Geogr 7(2):153–174

Chiew FH, Siriwardena LW (2005) Probabilistic seasonal streamflow forecasting methods. In: 29th hydrology and water resources symposium: water Capital. Water Capital, Engineers Australia, Rydges Lakeside, Canberra, pp 208–215

Cohn AS, Newton P, Gil JD, Kuhl L, Samberg L, Ricciardi V, Manly JR, Northrop S (2017) Smallholder agriculture and climate change. Annu Rev Environ Resour 42:347–375

Combest-Friedman C, Christie P, Miles E (2012) Household perceptions of coastal hazards and climate change in the Central Philippines. J Environ Manag 112:137–148

Debela N, Mohammed C, Bridle K, Corkrey R, McNeil D (2015) Perception of climate change and its impact by smallholders in pastoral/agropastoral systems of Borana, South Ethiopia. Springerplus 4(1):1–12

Edwards DP, Lim F, James RH, Pearce CR, Scholes J, Freckleton RP, Beerling DJ (2017) Climate change mitigation: potential benefits and pitfalls of enhanced rock weathering in tropical agriculture. Biol Lett 13(4):20160715

Fulazzaky MA (2009) Water quality evaluation system to assess the Brantas River water. Water Resour Manag 23(14):3019–3033

Gebremicael TG, Mohamed YA, Hagos EY (2017) Temporal and spatial changes of rainfall and streamflow in the Upper Tekezē–Atbara river basin, Ethiopia. Hydrol Earth Syst Sci 21(4):2127–2142

Ghasemi AR (2015) Changes and trends in maximum, minimum and mean temperature series in Iran. Atmos Sci Lett 16(3):366–372

Gil JD, Cohn AS, Duncan J, Newton P, Vermeulen S (2017) The resilience of integrated agricultural systems to climate change. Wiley Interdiscip Rev Clim Change 8(4):e461

Ginting E, Aji P (2015) Summary of Indonesia's economic analysis. ADB Papers on Indonesia, pp 1–9

Gornall J, Betts R, Burke E, Clark R, Camp J, Willett K, Wiltshire A (2010) Implications of climate change for agricultural productivity in the early twenty-first century. Philos Trans R Soc B Biol Sci 365(1554):2973–2989

Guodaar L, Bardsley DK, Suh J (2021) Integrating local perceptions with scientific evidence to understand climate change variability in northern Ghana: a mixed-methods approach. Appl Geogr 130:102440

Hakim R, Haryanto T, Sari DW (2021) Technical efficiency among agricultural households and determinants of food security in East Java, Indonesia. Sci Rep 11(1):1–9

Handayani W, Chigbu UE, Rudiarto I, Putri IHS (2020) Urbanization and Increasing flood risk in the Northern Coast of Central Java—Indonesia: an assessment towards better land use policy and flood management. Land 9(10):343

Hardono GS, Dinamika PDB Sektor Pertanian dan Pendapatan Petani

Hasan MK, Kumar L (2019) Comparison between meteorological data and farmer perceptions of climate change and vulnerability in relation to adaptation. J Environ Manag 237:54–62

Hasibuan AM, Gregg D, Stringer R (2020) Accounting for diverse risk attitudes in measures of risk perceptions: a case study of climate change risk for small-scale citrus farmers in Indonesia. Land Use Policy 95:104252

Hein Y, Vijitsrikamol K, Attavanich W, Janekarnkij P (2019) Do farmers perceive the trends of local climate variability accurately? An analysis of farmers' perceptions and meteorological data in Myanmar. Climate 7(5):64

Imran M, Shrestha RP, Datta A (2020) Comparing farmers' perceptions of climate change with meteorological data in three irrigated cropping zones of Punjab, Pakistan. Environ Dev Sustain 22(3):2121–2140

Ingram KT, Roncoli MC, Kirshen PH (2002) Opportunities and constraints for farmers of West Africa to use seasonal precipitation forecasts with Burkina Faso as a case study. Agric Syst 74(3):331–349

Intergovernmental Panel on Climate Change, IPCC (2018) Global warming of 1.5° C: an IPCC special report on the impacts of global warming of 1.5° C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty. Intergovernmental Panel on Climate Change, Geneva

Joshi S, Kumar K, Joshi V, Pande B (2014) Rainfall variability and indices of extreme rainfall-analysis and perception study for two stations over Central Himalaya, India. Nat Hazards 72(2):361–374

Kementrian Lingkungan Hidup dan Kehutanan KLHK (2020) Rencana strategis direktorat jendral pengendalian das dan hutan lindung tahun 2020–2024

Kessler CA (2006) Decisive key-factors influencing farm households' soil and water conservation investments. Appl Geogr 26(1):40–60

Kundu S, Khare D, Mondal A, Mishra PK (2015) Analysis of spatial and temporal variation in rainfall trend of Madhya Pradesh, India (1901–2011). Environ Earth Sci 73(12):8197–8216

Llasat MDC, López L, Barnolas M, Llasat-Botija M (2008) Flash-floods in Catalonia: the social perception in a context of changing vulnerability. Adv Geosci 17:63–70

Mariyanto M, Amir MF, Utama W, Bijaksana S, Pratama A, Yunginger R, Sudarningsih S (2019) Heavy metal contents and magnetic properties of surface sediments in volcanic and tropical environment from Brantas River, Jawa Timur Province, Indonesia. Sci Total Environ 675:632–641

Mariyono J (2019) Stepping up to market participation of smallholder agriculture in rural areas of Indonesia. Agric Finance Rev 79:255–270

Marteau R, Sultan B, Moron V, Alhassane A, Baron C, Traoré SB (2011) The onset of the rainy season and farmers' sowing strategy for pearl millet cultivation in Southwest Niger. Agric for Meteorol 151(10):1356–1369

Marx SM, Weber EU, Orlove BS, Leiserowitz A, Krantz DH, Roncoli C, Phillips J (2007) Communication and mental processes: experiential and analytic processing of uncertain climate information. Glob Environ Change 17(1):47–58

Mertz O, Mbow C, Reenberg A, Diouf A (2009) Farmers' perceptions of climate change and agricultural adaptation strategies in rural Sahel. Environ Manag 43(5):804–816

Ministry of Foreign Affairs of the Netherlands (MFAN) (2018) Climate change profile Indonesia

Mkonda MY, He X (2017) Are rainfall and temperature really changing? Farmer's perceptions, meteorological data, and policy implications in the Tanzanian semi-arid zone. Sustainability 9(8):1412

Mkuhlani S, Crespo O, Rusere F, Zhou L, Francis J (2020) Classification of small-scale farmers for improved rainfall variability management in South Africa. Agroecol Sustain Food Syst 44(1):7–29

Mohri H, Lahoti S, Saito O, Mahalingam A, Gunatilleke N, Hitinayake G, Takeuchi K, Herath S (2013) Assessment of ecosystem services in homegarden systems in Indonesia, Sri Lanka, and Vietnam. Ecosyst Serv 5:124–136

Moore FC, Baldos U, Hertel T, Diaz D (2017) New science of climate change impacts on agriculture implies higher social cost of carbon. Nat Commun 8(1):1–9

Naylor RL, Battisti DS, Vimont DJ, Falcon WP, Burke MB (2007) Assessing risks of climate variability and climate change for Indonesian rice agriculture. Proc Natl Acad Sci 104(19):7752–7757

Ngetich KF, Mucheru-Muna M, Mugwe JN, Shisanya CA, Diels J, Mugendi DN (2014) Length of growing season, rainfall temporal distribution, onset and cessation dates in the Kenyan highlands. Agric for Meteorol 188:24–32

Nnadi OI, Liwenga ET, Lyimo JG, Madukwe MC (2019) Impacts of variability and change in rainfall on gender of farmers in Anambra, Southeast Nigeria. Heliyon 5(7):e02085

Oktaviani R, Amaliah S, Ringler C, Rosegrant MW, Sulser TB (2011) The impact of global climate change on the Indonesian economy. Food Policy Research Inst., Washington

Parker L, Bourgoin C, Martinez-Valle A, Läderach P (2019) Vulnerability of the agricultural sector to climate change: the development of a pan-tropical climate risk vulnerability assessment to inform subnational decision making. PLoS ONE 14(3):e0213641

Pettitt AN (1979) A non-parametric approach to the change-point problem. J R Stat Soc Ser C (appl Stat) 28(2):126–135

Rahman M, Toiba H, Huang WC (2021) The impact of climate change adaptation strategies on income and food security: empirical evidence from small-scale fishers in Indonesia. Sustainability 13(14):7905

Rusliyadi M, Libin W (2018) Agriculture development programs for poverty reduction evidences from Indonesia and China-comparative study case. Asian J Agric Rural Dev 8(2):104–118

Sekaranom AB, Nurjani E, Nucifera F (2021) Agricultural climate change adaptation in Kebumen, Central Java, Indonesia. Sustainability 13(13):7069

Setyorini A, Khare D, Pingale SM (2017) Simulating the impact of land use/land cover change and climate variability on watershed hydrology in the Upper Brantas basin, Indonesia. Appl Geom 9(3):191–204

Simelton E, Quinn CH, Batisani N, Dougill AJ, Dyer JC, Fraser ED, Mkwambisi D, Sallu S, Stringer LC (2013) Is rainfall really changing? Farmers' perceptions, meteorological data, and policy implications. Clim Dev 5(2):123–138

Slegers MF (2008) "If only it would rain": farmers' perceptions of rainfall and drought in semi-arid central Tanzania. J Arid Environ 72(11):2106–2123

Smit B, Skinner MW (2002) Adaptation options in agriculture to climate change: a typology. Mitig Adapt Strateg Glob Change 7(1):85–114

Sul WJ, Asuming-Brempong S, Wang Q, Tourlousse DM, Penton CR, Deng Y, Rodrigues JL, Adiku SG, Jones JW, Zhou J, Cole JR (2013) Tropical agricultural land management influences on soil microbial communities through its effect on soil organic carbon. Soil Biol Biochem 65:33–38

Sunaryo TM (2002) Integrated water-resources management in a river-basin context: the brantas River Basin, Indonesia. In: Integrated water-resources management in a river-basin context: institutional strategies for improving the productivity of agricultural water management, p 277

Widianto D, Suprayogo S, Id L (2010) Implementasi Kaji Cepat hidrologi (RHA) di Hulu DAS Brantas (No. 121). Jawa Timur, working paper

Wiersum KF (2006) Diversity and change in homegarden cultivation in Indonesia. Tropical homegardens: a time-tested example of sustainable agroforestry, pp 13–24

Wiwoho BS, Astuti IS, Alfarizi IAG, Sucahyo HR (2021) Validation of three daily satellite rainfall products in a humid tropic watershed, Brantas, Indonesia: implications to land characteristics and hydrological modelling. Hydrology 8(4):154

WMO (2008) Guide to hydrological practices. Volume I: Hydrology—From measurement to hydrological information. WMO-No. 168

Wossen T, Berger T (2015) Climate variability, food security and poverty: agent-based assessment of policy options for farm households in Northern Ghana. Environ Sci Policy 47:95–107

Yue S, Pilon P, Cavadias G (2002) Power of the Mann–Kendall and Spearman's rho tests for detecting monotonic trends in hydrological series. J Hydrol 259(1–4):254–271

Zhai F, Zhuang J (2012) Agricultural impact of climate change: a general equilibrium analysis with special reference to Southeast Asia. In: Climate change in Asia and the Pacific: how can countries adapt, pp 17–35

Zhang S, Lu XX, Higgitt DL, Chen CTA, Han J, Sun H (2008) Recent changes of water discharge and sediment load in the Zhujiang (Pearl River) Basin, China. Glob Planet Change 60(3–4):365–380