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Verification of Weather and Seasonal Forecast Information Concerning the Peri-Urban Farmers' Needs in the Lower Ganges Delta in Bangladesh

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Abstract: Skillful weather and seasonal predictions have considerable socio-economic potential and could provide meaningful information to farmers and decision-makers towards agricultural planning and decision-making. Peri-urban farmers in the Lower Ganges Delta need skillful forecast information to deal with increased hydroclimatic variability. In the current study, verification of European Centre for Medium-Range Weather Forecasts' System 5 (ECMWF SEAS5) seasonal prediction system is performed against ground observations for the Lower Ganges Delta using three skills assessment metrics. Additionally, meteoblue hindcasts are verified for Khulna station according to the peri-urban farmers' needs and an assessment of onset/offset dates of rainy season is also conducted using the same ground observations. The results indicated that the skill of both examined products is limited during the pre-monsoon and monsoon periods, especially in the west side of the Bay of Bengal. However, during the dry winter season, skill is high, which could lead to potential agricultural benefits concerning irrigation planning. Interannual variability and trend indicated that onset dates have become later and that the length of the rainy season reduced. This could increase the pressure on the already challenging situation the farmers are experiencing, in relation to hydro-climatic variability.

Keywords: rainfall; seasonal forecast; SEAS5; meteoblue; onset/offset; sustainable agriculture; Lower Ganges Delta; Bangladesh

1. Introduction

Weather and climate are key drivers for all ecological and economic systems [1,2] and crucial components that affect agricultural productivity and crop efficiency, farmland value and profitability of agricultural systems [3–9]. Bangladesh, because of its unique geographical location, is recognized as one of the most vulnerable countries to climate change [10]. It is expected to become more vulnerable to sea-level rise and cyclones as well as extreme precipitation events. Additionally, due to the increase in temperature and increase in CO_2 levels, agriculture and food security are also under threat. In Bangladesh, agriculture is the backbone of the rural economy, and the agricultural sector contributes more than 15% of the national Gross Primary Product (GDP) and employs more than 40% of the population [11]. Weather and Climate information provision has the potential to play an essential role. However, there is a need to better understand the skill of the information that is provided and what are the implications associated with sustainable farm management.

So far, farmers in the peri-urban areas of the Ganges Delta mainly base their agricultural decision making on traditional practices (e.g., traditional calendars, beliefs) [12–15]. However, increased

hydro-climatic variability that governs the region [16–21] as a result of climate change in combination with monsoon periods [22,23] and scarce and inadequate hydroclimatic information services have severe socio-economic and environmental impacts on farmers. These can no longer rely solely on traditional knowledge to adequately predict the weather and climate patterns for agricultural decision making. Furthermore, rainfall is the most important natural factor that determines agricultural production in Bangladesh as the variability of the rainfall and the pattern of extreme high or low precipitation are crucial for agriculture as well as the economy of the country [24]. Rainfall patterns, especially in the Bay of Bengal in coastal Bangladesh, are dominated by high spatial and temporal variability, and predictions indicate a high degree of uncertainty [1,25]. The erratic rainfall and associated extreme events impact ecosystems, land productivity, agriculture, food security, water availability and quality, as well as the livelihood of the farmers in Bangladesh. Therefore, there is a need for data-driven systems that will provide skillful weather and seasonal forecasting with a high spatio-temporal resolution, which is crucial for the farmers in the Lower Ganges Delta.

Related to this, the WATERAPPS project (http://www.waterapps.net/) was launched in 2016 aiming to improve food security and for sustainable agriculture in peri-urban areas in the Lower Ganges Delta through co-developing tailor-made weather and climate information services for farmers. The project follows a participatory approach by combining information technology with the latest insights on knowledge sharing and integrating scientific with local forecasting knowledge to improve weather predictability and subsequently farm decision making.

According to Kumar et al. [12], there are three cropping seasons in the Lower Ganges delta in the coastal region of Bangladesh: (1) kharif-I (pre-monsoon), (2) kharif-II (monsoon), which is mainly agricultural season, and (3) rabi (winter). Around 75–90% of the total rainfall occurs during the monsoon period and mainly during the months from June to September [26]. As a result, farmers face risks associated with severe waterlogging, salinity intrusion and drought conditions [27–31].

Skillful weather and climate information are thus crucial for farmers in the Lower Ganges Delta as it could improve farmers' decision making [32], and previous research has shown that skillful sub-seasonal and seasonal weather and climate prediction can provide meaningful information that can support farmers and decision-makers to make appropriate decisions in relation to agriculture [33–36]. This is especially valid in the Bay of Bengal in southeast Asia, where rainfed agriculture takes place and forecast uncertainties are related with the monsoon period. As an example, prediction of the monsoon onset provides highly significant information for agricultural planning [37].

Mani and Mukherjee [38] studied the accuracy of the weather forecast for the Hill zone of west Bengal for better agricultural management practices. They concluded that rainfall prediction during the monsoon period was very limited, whereas winter rainfall, although limited, could be predicted with very high accuracy. Debnath and Das [39] verified operational rainfall forecast over eastern India during the monsoon period and concluded that there is some gradual increase in performance. They found out that skill is still limited and there are differences amongst years with prediction performance. Mahmud et al. [40] developed an analysis of variance (ANOVA) method to forecast monthly rainfall for Bangladesh, and they found out that the developed model could predict monthly rainfall with a reasonable accuracy despite its nonlinear pattern.

Although in the recent decades considerable progress has been made in weather and climate forecasting [41–43], it is indisputable that because of its probabilistic nature, seasonal forecasting presents systematic errors and is a significant challenge around the globe [44,45]. Hence, much of the information that is generated by weather and climate predictions is limited for practical decision making either because it tends to focus on the average conditions rather than critical thresholds and/or because it does not adequately consider the model errors and uncertainties [46–53]. Therefore, forecast verification is an essential, necessary component of a forecasting system and an indispensable part of hydrometeorological research and operational forecasting activities. Verification results can provide crucial information and can effectively meet the needs of many diverse groups, including end-users of forecast information [54]. These end-users, such as the farmers in the Lower Ganges Delta, have the

possibility after receiving skillful forecast to deal with the increased hydro-climatic variability as a result of climate change and to manage their farms more successfully by making more sophisticated decisions with short- and long-term agricultural activities.

For this reason, the current study performs (1) a verification of the European Centre for Medium-Range Weather Forecasts' (ECMWF) latest seasonal prediction system, System 5 (SEAS5), against observed precipitation from the Bangladesh Meteorological Department for 22 stations in the coastal region of Bangladesh. Additionally, it (2) assesses the skill of the meteoblue hindcast that is provided within the scope of the WATERAPPS project to the peri-urban farmers in the rapidly urbanizing city of Khulna. Subsequently, (3) it characterizes trends and interannual variability of the onset and offset dates of the rainy season in Khulna, Bangladesh. The paper is organized as follows: in Section 2, we describe the datasets and the skills assessment metrics that were employed in the current study. Section 3 presents the results of the verification of SEAS5 and meteoblue hindcasts, as well as the results of the interannual variability and trend of onset/offset days from Khulna. In Section 4, we discuss the results of the skills assessment and what are the potential benefits of skillful forecasts for small livelihood farmers. We summarize and conclude in Section 5.

2. Data and Methods

2.1. Study Area and Background

The study area concerns the coastal region of Bangladesh in the Lower Ganges Delta. There, and specifically in the peri-urban area of Khulna, the third-largest metropolitan city of Bangladesh and the capital of the Khulna division the WATERAPPS project is active. It is co-developing with and for farmers tailor-made weather and climate information services for sustainable agriculture [32]. The city of Khulna is located in the southwest coastal region and is surrounded by the river of Rupsa, Bhairab, Pasur, Hatia and Mayur [55]. The area is characterized by a tropical savanna climate (*Aw*) [56,57]. During the summer (monsoon season), rainfall is plenty, while during the winter, there is very little. Following the climatological analysis that is mentioned in Kumar et al. [12], mean annual precipitation is 1752 mm and mean annual air temperature is 26.7 °C. Topography and climate provide ideal conditions for peri-urban agriculture and make Khulna a regional food production hub. Local farmers cultivate paddy, jute, sesame and vegetables, while small-scale aquaculture is also observed all year round. Additionally, farmers cultivate various short-term crops such as beans, gourds, eggplants and tomatoes in integrated agriculture–aquaculture farming systems.

Due to their location in the Lower Ganges Delta, the peri-urban communities in Khulna are highly influenced by tidal inundation and are consequently vulnerable to natural disasters as a result of climate change [17,58]. Besides that, in the last 15 years, farmers in the region have had to deal with the devastating socio-economic effects of the cyclones Sidr in 2007, Aila in 2009, Bulbul in 2019 and Amphan in May 2020 that had remarkable impacts in Bangladesh, costing lives and damages estimated to millions [18,59,60].

Thus, farmers in the peri-urban area of Khulna are in need of skillful spatio-temporal information to improve their agricultural decision making [12]. Within the activities of the WATERAPPS project in peri-urban Khulna, Farmers' Field Schools (FFS) were organized at two farming communities to provide weather and climate information and to improve agricultural decision making. Following engagement and capacity building within the scope of the WATERAPPS project, local farmers have identified 7-day, 14-day and 3-month meteoblue rainfall forecasts, as well as the onset and offset dates of the rainy season as the most important variables in terms of forecast information for agricultural decision making [36]. The general location of the study area along with Khulna (highlighted) can be seen in Figure 1.
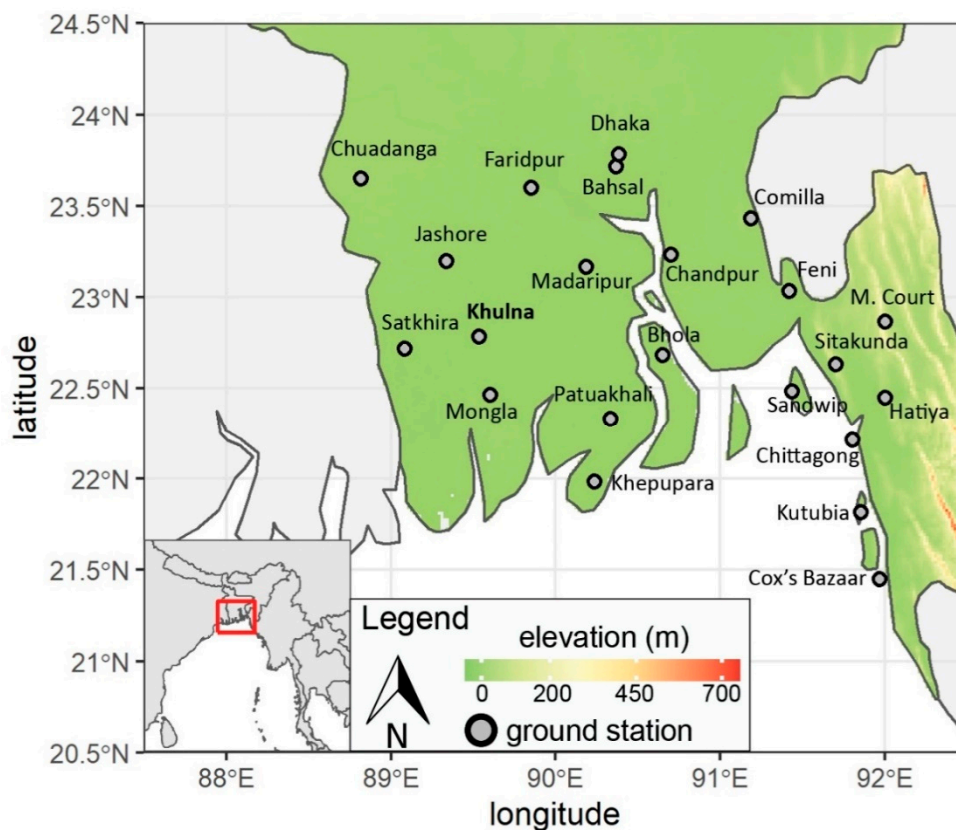
Figure 1. General location of the study area including the ground stations that were employed in the current study.

2.2. Datasets

2.2.1. ECMWF Seasonal Climate Hindcasts

The SEAS5 seasonal forecast system is ECMWF's fifth generation forecast system that became operational in November 2017 [61] and replaced System 4 (SEAS4, [62]) which had been operational since 2011. SEAS5 has a spatial resolution of ~35 km², and forecasts run up to 7 months. Hindcasts (also sometimes known as re-forecasts) start on the first of every month for years 1981 to 2016 and have 25 ensemble members. The current study verifies the hindcasts of SEAS5 for the period 1981–2016 focusing on forecasts with 0-month lead time, which refers to a hindcast, for example for June–August that is issued in May.

2.2.2. Meteoblue Weather Forecast

Meteoblue (https://www.meteoblue.com) historical weather simulation data in hourly resolution, aggregated in daily values for the period 1985–2016, were obtained for the city of Khulna, Bangladesh. The meteoblue weather provider provides local weather data developed through the NMN (Non-hydrostatic Meso-Scale Modeling) technology and the NEMS (NOAA Environmental Modeling System) framework, based on worldwide statistical experimental datasets. Additionally, meteoblue allows for the inclusion of detailed topography, ground and surface cover aspects [63].

2.2.3. Stations Observations

Thirty-five years of daily precipitation data were acquired for the period 1981–2016 from 22 stations from the Bangladesh Meteorological Department around the Lower Ganges Delta in the coastal region of Bangladesh (Figure 1). The ground observations were employed to: (1) serve as a reference

for the skills assessment of SEAS5 seasonal climate hindcast for the wider coastal region of Bangladesh, (2) to serve as a reference for the skills assessment of meteoblue historical weather simulation data in Khulna, Bangladesh, and (3) to characterize historical trend and interannual variability of the rainy season onset and offset in Khulna.

2.3. Methods

2.3.1. Agrometeorological Indices Definitions

Multiple definitions have been attributed to define onset and offset of the monsoon period for the South Asian Monsoon based on the different actors and sectors that are involved each time [64]. The current study follows Ahmed and Karmakar's [65] definition:

- Onset date: the first day of a period of three or more consecutive days in which rainfall is 5 mm or more. The analysis starts from the first of April to account for early onset monsoons.
- Offset date: the first day of a period of three or more consecutive days after the first of August in which rainfall is less than 1 mm.
- Total seasonal rainfall: the sum of rainfall over a season.

The seasons are defined as follows: (1) khariff-I or pre-monsoon period (March–May), (2) khariff-II or monsoon period (June–September) and (3) rabi or winter period (October–February).

To study the onset/offset trends of the observed dataset and to analyze whether there is a shift in the boundary conditions for the monsoon onset and offset periods, we applied linear trendlines through the 'ggplot' package in R software. Additionally, we divided the sample into two periods (first period: 1981–1996, second period: 2001–2016) for a more comprehensive comparison and we applied a t-test [66,67] to assess whether statistically significant changes in monsoon onset/offset have occurred over the reference analysis period.

2.3.2. Bias-Correction and Lead-Time Selection of SEAS5 Hindcasts

The SEAS5 forecast products are generally corrected for mean biases in the forecast system, but no other corrections are applied. Thus, a first step before using them was to bias-correct them against reference observations from the ground network of the Bangladesh Meteorological Department (BMD) using the quantile mapping method [68] through the 'qmap' R-package [69]. For each given station, the method applies cumulative density functions (CDF) to match daily observed and forecasted (SEAS5) rainfall [70]. The quantile mapping method has been successfully used in multiple hydro-climatological and climate impact studies as well as medium-range or seasonal hindcasts verification [35,70–77].

2.3.3. Skill Assessment and Metrics

Multiple metrics were employed to assess the skill of the products that are used in the current study. To verify SEAS5 hindcast against BMD stations observations, we used the Relative Operating Characteristics (ROC) method, which is the most commonly used method to identify whether a set of forecasts is well-discriminated in relation to the different outcomes. ROC score originates from the signal detection theory and it is used to measure discrimination (i.e., the ability to discriminate hit rate and false alarms). ROC score has been used in many studies dealing with forecasts, in particular, to measure the discriminate ability between two outcomes [78,79]. The ROC curve gives the relation between the true-positive rate (sensitivity) and the false-positive rate (specificity). The area under the curve (AUC) was calculated to measure the accuracy of the forecast. The greater the area is, the more accurate the forecast. The AUC has a range from 0 to 1, where 1 is a perfect score [80,81]. Besides ROC, the Pearson correlation coefficient (PCC) (range: −1 to 1) and the Hanssen-Kuipers (H-K) discrimination skill score [82] (range: 0 to 1) were also used in the analysis. PCC measures how well the forecast anomalies correspond to the observed anomalies over the hindcast period 1981–2016 at each ground station. The H-K discriminant score is also used to verify (or better classify) events

and non-events and it is universally acceptable to provide the best estimate when evaluating binary (yes/no) forecasts for decision-making purposes [70,83]. The H-K metric has been employed by many scholars to verify precipitations forecasts against ground observations [84–89]. In general, all the skill metrics have been widely used to evaluate the skill of climate predictions [35,70,90–92]. The Pearson correlation coefficient and H-K skill score were calculated with base R. At the same time, the ROC and corresponding AUC were computed using the 'ROCR' R-package [93]. For further details about the specifics of the methods and equations used, we refer to the manuals of the software packages that were used in the current study.

To assess the skill for the different time-periods that the farmers around Khulna have identified (i.e., 7 days, 14 days and 3 months), the daily values were aggregated per respective time-period and analyzed separately per crop season (i.e., pre-monsoon, monsoon and winter). For the verification of the meteoblue forecast, the R^2 metric was applied for the period with commonly available data, i.e., 1985–2016.

3. Results

3.1. Verification of SEAS5 for Coastal Bangladesh

Figure 2 presents as an example the ensemble mean monthly climatology for the period 1981–2016 of the raw (SEAS5 raw) and the bias-corrected SEAS5 hindcasts (SEAS5 cor), along with the ground observations (observed) for Khulna station. After bias-correction is applied (Figure 2 and Appendix A), the bias-corrected SEAS5 product still cannot entirely capture the observed summer (monsoon) precipitation quantities and variability (see standard deviation in Appendix A, Table A1). Bias-corrected SEAS5 presents an overestimation of almost double the amount of precipitation, starting from May (the first monsoon month) and continuing into the month of June.
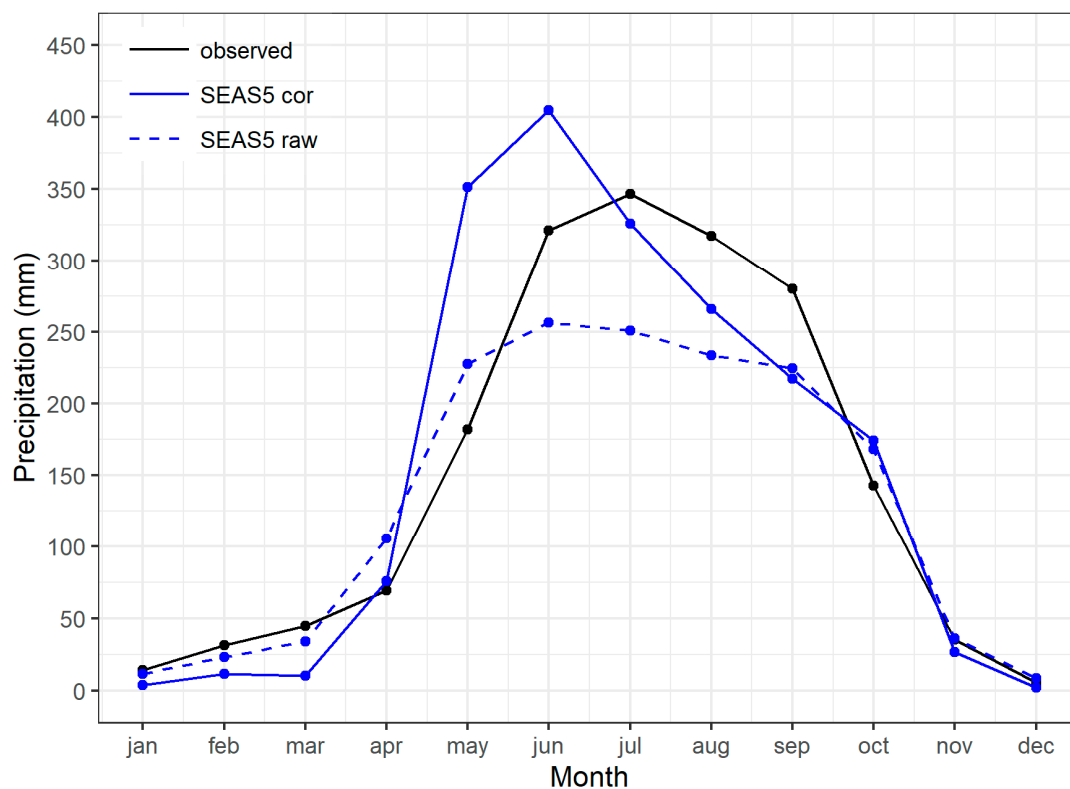

Figure 2. Mean monthly climatology for the period 1981–2016 of the raw and the bias-corrected SEAS5 hindcasts concerning observations for Khulna station.

Following that, the July bias-corrected SEAS5 product shows improvement for the monsoon months, which again presents a discrepancy for August and September during the offset of the monsoon period. Nevertheless, the bias-correction method that was applied in the raw SEAS5 dataset shows an overall improvement and the updated SEAS5 dataset is thus adopted and used hereafter.

The comparison of the products is not only for the value but also for the distribution since the values are aggregated, and this hides the distribution of rainfall on a daily basis. For example, it is different from having 10 mm in a month including 20 days with rain than 10 mm in two days of rain. For this reason, Figure 3 is introduced that presents a comparison of the number of wet days (rainfall > 1 mm).
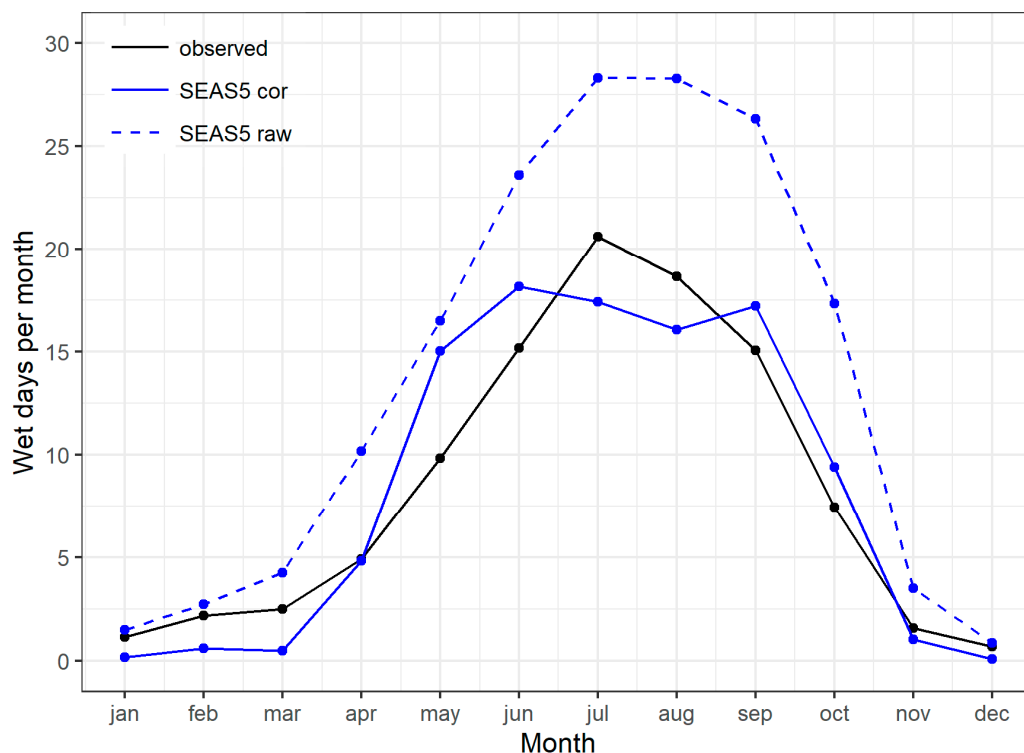

Figure 3. Mean monthly climatology of wet days per month for the period 1981–2016 of the raw and the bias-corrected SEAS5 hindcasts in relation to observations for Khulna station.

According to Figure 3, the raw SEAS5 product presents significant discrepancies, especially for the monsoon season as July and August are dominated by rainfall conditions almost the entire month. This is, however, not reflected in the observed data for Khulna. Nevertheless, the usefulness of bias-correction is undisputed as it corrects errors in the forecast product, and the corrected product presents a higher correlation concerning the ground observations, especially for the critical monsoon period.

Figure 4 depicts the skills assessment metrics for ROC, H-K and PCC for the coastal region of Bangladesh for each of the examined seasons (pre-monsoon, monsoon, winter) and stations. For each station and period, skills metrics were calculated for the ensemble to mean using lead-month 0. Khulna station is highlighted with a red circle. Additionally, Table 1 shows the skill metrics results for Khulna. The results for all scores and stations can be found in Appendix B, Table A3.

The results of the skills assessment for the SEAS5 hindcasts in relation to the observations from the stations in the coastal region of Bangladesh indicate that the skill is limited during the pre-monsoon and monsoon seasons, but considerable during the winter season. According to all metrics, skill is better in the east side of the Bay of Bengal compared to the upper west side where the skill is very limited. For the monsoon season, skill follows the same pattern and is relatively higher in the central and east side of the Bay of Bengal, whereas in the west side where Khulna is also located, the skill is

lower. On the other hand, the winter season is presented with significant skill, especially on the central and west side of the Bay. The Pearson Correlation Coefficient is the highest in Khulna amongst all examined stations (PCC = 0.73) according to the results from Table 1 and in relation to Appendix B. In the winter season, the skill was lower but still substantial in the east side of the Bay of Bengal.
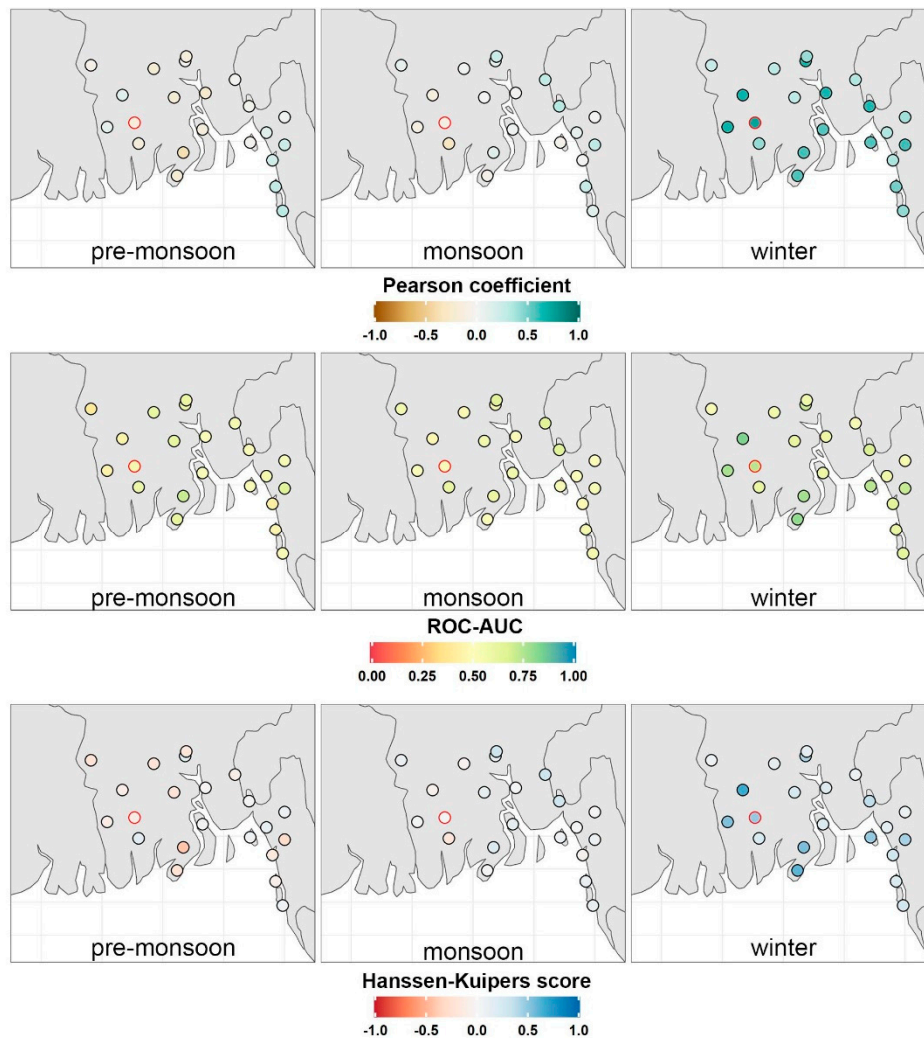

Figure 4. Skills assessment metrics (ROC, H-K and PCC) for the coastal region of Bangladesh for SEAS5 hindcasts for each of the examined seasons (pre-monsoon, monsoon, winter) and stations for the period 1981–2016. Khulna station is highlighted with a red circle.

Table 1. Skills assessment metrics (Relative Operating Characteristics (ROC), Hanssen-Kuipers (H-K) and Pearson correlation coefficient (PCC)) of SEAS5 forecast in relation to the observations for Khulna station under lead time 0-months.

Skills Metrics	ROC	H-K	PCC	ROC	H-K	PCC	ROC	H-K	PCC
Period	Pre-Monsoon			Monsoon			Winter		
Khulna	0.55	−0.10	−0.16	0.5	0.01	−0.11	0.74	0.47	0.73

3.2. Verification of Meteoblue Forecast for Khulna

Figure 5 presents the mean monthly climatology meteoblue hindcast along with ground observations for Khulna station. Note that the observed dataset presents differences compared

to Figure 2 since it accounts for a different time period. According to Figure 5, it is evident that although meteoblue hindcast follow the climatology for the winter season where rainfall is negligible, it fails to capture the climatology and variability (Appendix A, Table A2) of the observed datasets during the monsoon period. More specifically, starting in May during the onset of the rainy season, meteoblue hindcast is underestimating the amount of rainfall compared to the observed rainfall by half. Moreover, during the monsoon season for all months, meteoblue hindcast underestimates total rainfall by almost 200 mm per month, which is a considerable amount in terms of total annual precipitation.
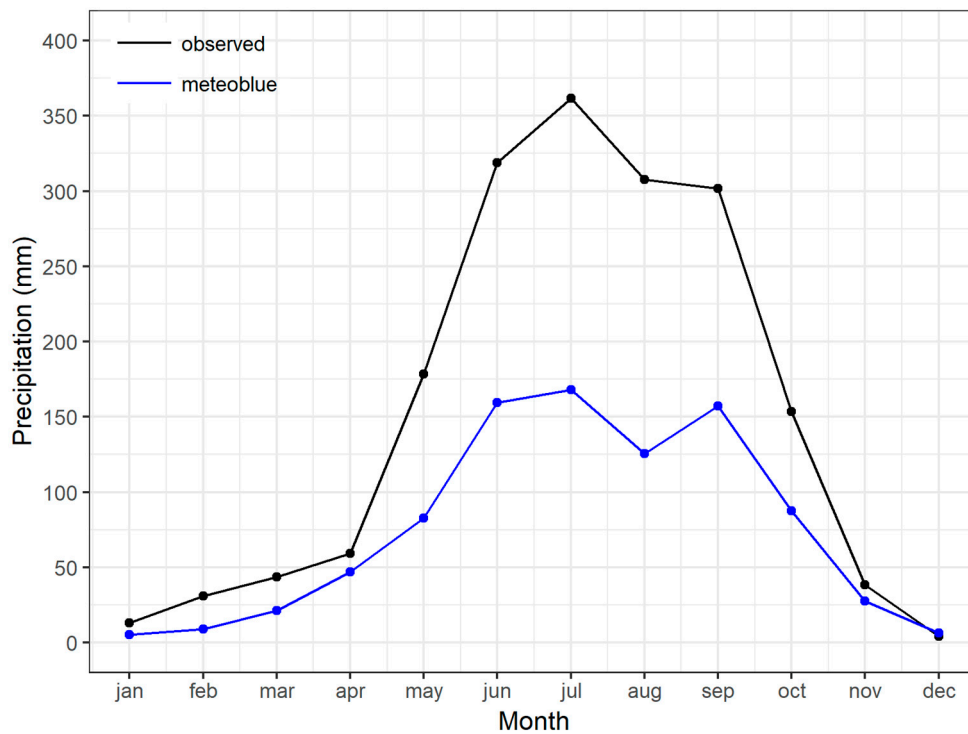
Figure 5. Mean monthly climatology for the period 1981–2016 of the meteoblue hindcast with observations for Khulna station.

The radar charts that are presented in Figure 6 and Table 2 depict the R^2 of the meteoblue hindcast for 7-, 14-day and 3-month periods, separated per crop season for Khulna station.
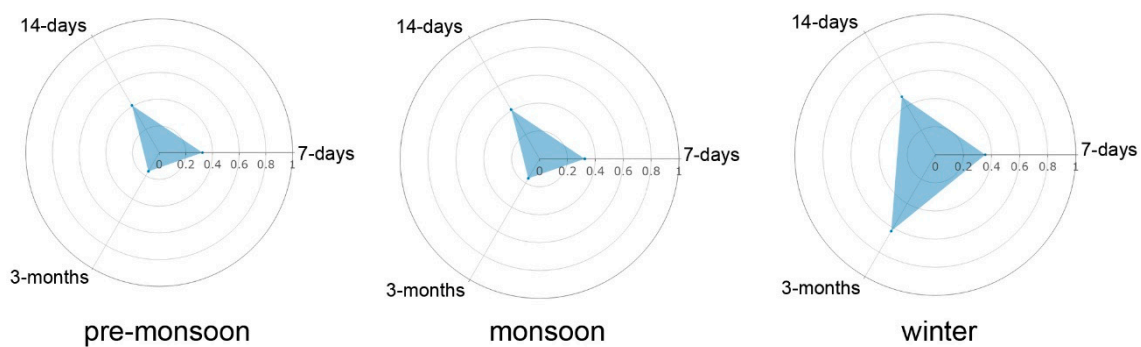

Figure 6. Radar charts of correlation for 7-, 14-day and 3-month meteoblue hindcasts with the observations for Khulna station.

Table 2. R^2 for 7-, 14-days and 3 months of meteoblue forecast with the observations for Khulna station. Results of R^2 are expressed in % to indicate the variability explained by the forecasts.

Forecast Interval	7 Days	14 Days	3 Months	7 Days	14 Days	3 Months	7 Days	14 Days	3 Months
Period	Pre-monsoon			Monsoon			Winter		
R^2	32%	41%	16%	35%	44%	31%	35%	47%	63%

According to the results of Figure 6 and Table 2, meteoblue hindcasts are not able to capture the total amount of precipitation during the year. However, there is some skill in the hindcast to predict rainfall occurrence, mainly during winter and especially for 3 months (R^2: 63%), followed by 14 days (R^2: 47%), respectively. For the monsoon period, which is the rainfed season, skill is limited for 7 days (R^2: 35%). However, there is some skill in the 14-day hindcast (R^2: 44%). Conversely, the comparison between meteoblue hindcasts and observations for the pre-monsoon season, besides the 14-day time period where there is some correlation (R^2: 41%), indicates that there is a low statistical correlation, especially for the 3-month time-period. In general, the 14-day meteoblue hindcast has a fair correlation against observations for Khulna for all examined seasons and could be used by farmers for medium-range agricultural planning.

3.3. Trend and Variability of Onset/Offset Days

Based on observed data from Khulna station for the period 1981–2016, Figure 7 depicts the interannual variability of onset and offset dates as well as the historical trend. Additionally, Table 3 presents some statistics on the onset/offset days for Khulna station. Regarding the onset of the rainy season, it follows a significant upward trend. At the beginning of the analysis period in 1981, the onset occurred around the beginning of May, while by 2016, the onset had shifted towards mid-June. This indicates that the start of the rainy season occurs more than a month later in recent years. According to Table 3, where two distinct time periods were analyzed, the monsoon onset date shifted significantly ($t(30) = 2.502$, $p = 0.002$) between these periods from around the 25th of May in the 1981–1996 period to around the 11th of June in the 2001–2016 period. Concerning the offset of the rainy season, on the other hand, it shows a slight downward trend since the beginning of the analysis period. It has shifted from mid-September towards the beginning of September for the whole analysis period. Specifically, during the first examined period, offset is placed around the 13th of September, while during the second analysis period, offset is shifted towards the 10th of September. This shift was not found to be statistically significant ($t(30) = 0.704$, $p = 0.0487$). Altogether this indicates that the length of the monsoon season has almost decreased by a month. Nevertheless, from the interannual analysis of rainfall, the total rainfall amount from the monsoon season (not shown in the text) has slightly increased for the analysis period 1981–2016. This indicates that in the future, the farmers need to deal with more extreme rainfall during the monsoon season, which will put further pressure on the already challenging situation they are experiencing.

Table 3. Onset/offset days analysis statistics of the two examined periods for Khulna station. SD = standard deviation. Asterisk (*) indicates significance at 95% confidence level.

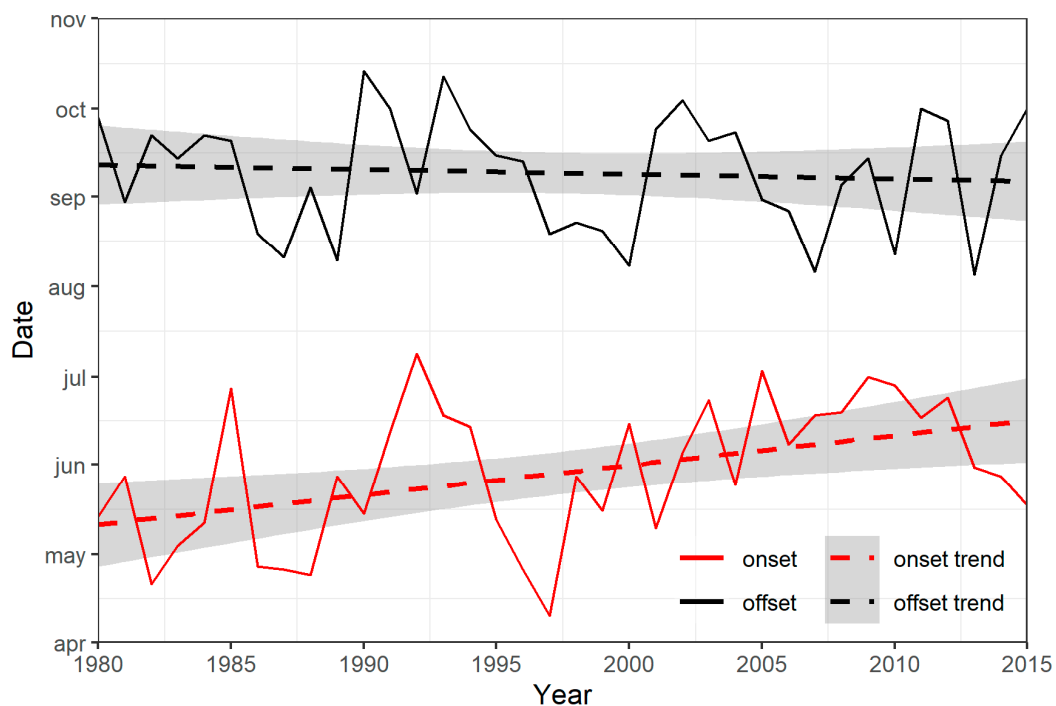| Type	Period 1: 1981–1996		Period 2: 2001–2016				
	Mean (Day)	SD (Days)	Mean (Day)	SD (Days)	*t* Value	Degrees of Freedom	*p*-Value
Onset	25/05	25	11/06	17	2.5021	30	0.0197 *
Offset	13/09	21	10/09	21	0.70386	30	0.4871

Figure 7. Interannual variability and trend of onset (in red) and offset (in black) days in Bangladesh Meteorological Department (BMD) observations for Khulna station.

4. Discussion

4.1. Ability of Hindcasts to Capture the Prevailing Conditions

In general, the overall skill and performance of the hindcast products that were examined in the current study are limited. Specifically, the SEAS5 and meteoblue hindcasts present limited skill for the pre-monsoon and especially during the monsoon period. Although they capture the climatology, they do not capture the total precipitation amount. Especially for SEAS5, the hindcasts overestimate the amount of rainfall during the onset of the rainy season in May–June. In contrast, they underestimate the amount during the offset period. Concerning the SEAS5 hindcasts, the results of the current study come in comparison to the results of Ratri et al. [94], as in a comparative verification study of raw and bias-corrected SEAS5 hindcasts for Java, Indonesia, they found some skill and potential economic value of SEAS5 raw and bias-corrected precipitation hindcasts for July–September in Java. This can be attributed to the fact that Ratri's study used as the observational dataset a gridded dataset for the Southeast Asia-Observations (SA-OBS, [95]) which is based on a Kriging variogram. Additionally, Gubler et al. [96] performed verification of SEAS5 over South America, and when comparing it with a previous study of Weisheimer and Palmer [44] that was verifying SEAS4, they concluded that higher reliabilities could be attributed to the improvement of the predictions due to spatial aggregation. However, improving performance by spatio-temporal aggregation limits their potential use only by large-scale farmers. It excludes small livelihood farmers from potential opportunities due to loss of information. The use of large-scale gridded data may result in the loss of information on local variations due to micro-scale processes according to multiple scholars [35,90,97,98]. Besides, according to Ehsan et al. [99], who also employed SEAS5 to predict peak summer monsoon precipitation over Pakistan, forecasting summer seasonal monsoon precipitation even 1 month in advance is extremely challenging in Southeast Asia and currently, seasonal prediction models have low potential predictability and skill. Hence, a recommendation of the current study is that to achieve skillful and meaningful forecasts, integration of forecast information with ground observations is needed, especially in areas where rainfall patterns are very local, which is precisely the case in Southeast

Asia and the Bay of Bengal. Regarding the winter period, both hindcasts deliver the highest skills in terms of the current analysis, which indicates that although rainfall amount is negligible, it has, however, the ability to provide skillful information. Considering the fact that in the Ganges during the winter season irrigated agriculture or rainfed agriculture on irrigated land agriculture is extensive, along with the water demand [100], a skillful forecast on the rainfall amount could have potential socio-economic benefits concerning irrigation planning and/or the selection of water-demanding crops.

4.2. Potential Benefits of Skillful Forecasts in Agricultural Decision Making

Considering the ability of seasonal forecasts to predict at least up to some extent the weather patterns in the coastal area of Bangladesh in the Lower Ganges Delta, there is obvious potential in socio-economic benefits with seasonal prediction in this region. Also, a study by Paparrizos et al. [32] investigated the potential benefit of sub-seasonal and seasonal forecasts for smallholder farmers by providing participatory Weather and Climate Information Services and subsequently assessing their willingness to pay. More than 75% of the farmers are willing to pay for Weather and Climate Information Services to receive weather and forecast information that could assist them in agricultural planning and decision making. This fact indicates that farmers consider this information as crucial and they are willing to invest in it, regardless of the associated uncertainties.

Skillful seasonal forecasts could provide crucial information for effective planning and management of agricultural practices such as cultivar selection since farmers can decide based on the seasonal forecast whether to invest in more or less water-demanding cultivars if they have been informed in advance about the water availability. Additionally, the skillful seasonal forecast could provide information to the local farmers regarding the availability of irrigation water as well as the timing of high/low river system flows. Moreover, seasonal weather outlook could assist farmers in the Lower Ganges Delta with irrigation planning and sowing dates for sensitive cultivars as well as harvesting [101]. Especially for the peri-urban farmers in Khulna that produce paddy, skillful seasonal rainfall forecast is a critical input for predicting the planting date and the type of the rice crop that will be planted, based on the expected duration of the rainy (monsoon) season or the forecast amount of rainfall in the dry (winter) season.

Alongside this, sub-seasonal weather information in short and medium ranges could greatly contribute towards tactical planning, for example, when it comes to fertilizer application or labor hiring, the knowledge of which helps minimize losses resulting from adverse weather conditions and improve the quality and quantity of their agricultural production. Moreover, indications and subsequently warnings about seasonal extreme weather phenomena such as floods and droughts are also crucial for local farmers' planning and decision-making. An example was the 'Amphan' Super Cyclone that hit southwest Bangladesh in May 2020 that caused severe socio-economic and environmental damages and left thousands of people homeless during the COVID-19 pandemic. During past cyclone events, local farmers in the peri-urban area of Khulna have reported that they experienced severe damages due to a lack of timely information which was only 1–2 days in advance and left no time for the farmers to prepare themselves and secure their agricultural livelihoods [36]. For the Super Cyclone 'Amphan', the WATERAPPS team disseminated an initial warning about signals of an upcoming cyclone at the study villages in peri-urban Khulna where the project is active around mid-April, long before the 'Amphan' hit. Additionally, it followed up with periodical updates regarding the latest developments as the cyclone was approaching. Based on the provided information, all farmers in the study site harvested their paddy before the cyclone hit, and, in general, were able to secure their livelihoods by trusting the forecast information and reported negligible damages.

Overall, to ensure that forecasts are trusted and applied by farmers, the performance of the forecast and the forecast's relevance for decision making at the local scale are crucial [102]. Therefore, fine-tuning of the existing weather prediction models with an adequate network of ground observations is a prerequisite to achieve skillful forecasts that would be used by farmers for operational decision making. Additionally, assessing farmers' needs [36] as well as building farmers' capacity is also of

great importance for them to trust and accept weather forecasts since successful weather and climate information services are developed through a bottom-up approach, with strong involvement of farmers and interested stakeholders in the supply chain in a co-production model to better understand the priorities and practical requirements of the users.

5. Conclusions

The current study performed verification of forecast information concerning the farmers' needs in the Lower Ganges Delta. It verified the skill of ECMWF's latest seasonal prediction system, SEAS5, for coastal Bangladesh, as well as the 7-, 14-day and 3-month meteoblue forecast for Khulna, Bangladesh, concerning ground observations, following the local farmers' needs in forecast information. Additionally, it used the ground observations from Khulna station to characterize the interannual variability and trend of onset and offset dates which are another agro-meteorological indicator that the local farmers identified as crucial for agricultural decision making. The results of the skills assessment metrics indicated that ECMWF's latest seasonal prediction system, SEAS5, presents limited skill during the pre-monsoon and monsoon periods in the coastal region of Bangladesh, especially on the west side of the Bay of Bengal. On the other hand, skill is higher during the winter season; however, rainfall during this period is negligible. For the meteoblue examined hindcast, results indicated that 14-day skills are fair and could provide some indication about the prevailing conditions in the medium-range future.

Regarding the onset/offset of the monsoon season, results indicated that this would be shortened by more than one month. In contrast, the total amount of precipitation during the monsoon season will be slightly increased. These existing and upcoming pressures that occur from the limited skill of the provisioned forecast, as well as the evident increase in extreme weather phenomena during the monsoon season, will demand the development and implementation of appropriate methods to address issues of vulnerability to weather and climate. To this direction, well-defined, tailor-made and skillful weather and climate information services have the potential to become an adequate risk assessment tool for the rural-farm households in the Lower Ganges Delta around the Bay of Bengal. These services could be subsidized by governmental institutions and will help create a market that will boost social entrepreneurship and will attract private entities that are willing to invest in these services, as well as their refinement concerning the provided information. These will be needed to assist farmers to further develop their adaptive capacity with improved planning and management decisions. More effective approaches to delivering skillful forecast information to farmers should be carried out through participatory, cross-disciplinary approaches through enhancing awareness of user groups that would contribute towards unlocking Bangladesh's agriculture potential.

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Appendix A

Table A1. Comparison of observed and SEAS5 monthly mean precipitation and standard deviation (in mm) for Khulna station.

	Mean Precipitation			Standard Deviation		
	Observed	Modelled	Modelled-Bias Corrected	Observed	Modelled	Modelled-Bias Corrected
JAN	14	12	4	22	12	17
FEB	31	23	12	42	25	27
MAR	45	34	10	66	21	38
APR	69	105	76	62	42	80
MAY	182	228	351	85	73	258
JUN	321	257	405	162	69	279
JUL	347	251	326	144	60	215
AUG	317	234	266	131	59	213
SEP	280	225	217	157	30	110
OCT	143	168	174	102	47	128
NOV	35	36	27	54	37	63
DEC	6	8	2	14	9	8

Table A2. Comparison of observed and meteoblue monthly mean precipitation and standard deviation (in mm) for Khulna station.

	Mean Precipitation		Standard Deviation	
	Observed	Modelled	Observed	Modelled
JAN	13	5	22	13
FEB	31	9	43	12
MAR	44	21	62	19
APR	59	47	37	31
MAY	178	83	73	57
JUN	319	160	155	121
JUL	362	168	146	94
AUG	308	125	127	44
SEP	302	157	165	75
OCT	153	88	102	57
NOV	38	28	57	47
DEC	4	6	10	15

Appendix B

Table A3, following Table 1 from the text, presents the skill metrics results for all examined stations in coastal Bangladesh.

Table A3. Skills assessment metrics (ROC, H-K and PCC) for all stations under lead time 0-months.

Skills Metrics	ROC	H-K	PCC	ROC	H-K	PCC	ROC	H-K	PCC
Period	Pre-Monsoon			Monsoon			Winter		
Barisal	0.6	0.19	−0.02	0.57	0.14	0.11	0.72	0.43	0.66
Bhola	0.52	0.03	−0.16	0.57	0.13	0.04	0.59	0.18	0.56
Chandpur	0.51	−0.02	−0.25	0.51	0.13	−0.02	0.59	0.18	0.64
Chittagong (AP)	0.42	−0.15	0.2	0.47	−0.05	−0.01	0.64	0.27	0.36
Chuadanga	0.39	−0.21	−0.08	0.55	0.11	0.09	0.53	0.06	0.24
Comilla	0.55	−0.09	−0.03	0.65	0.3	0.27	0.53	0.07	0.35
Cox's Bazar	0.53	0.05	0.31	0.56	0.12	0.13	0.62	0.25	0.43
Dhaka	0.6	−0.19	−0.16	0.65	0.3	0.24	0.57	0.14	0.41
Faridpur	0.61	−0.21	−0.21	0.48	−0.05	0.04	0.57	0.14	0.31
Feni	0.49	−0.02	−0.05	0.64	0.28	0.32	0.68	0.36	0.63
Hatiya	0.65	−0.30	0.23	0.53	0.07	0.29	0.71	0.43	0.59
Jashore	0.45	−0.10	0.12	0.47	−0.06	−0.14	0.83	0.66	0.66
Khepupara	0.62	−0.23	−0.02	0.51	0.02	−0.07	0.8	0.6	0.57
Khulna	0.55	−0.10	−0.16	0.5	0.01	−0.11	0.74	0.47	0.73
Kutubdia	0.45	−0.09	0.28	0.56	0.11	0.24	0.6	0.21	0.49
Madaripur	0.61	−0.21	−0.20	0.56	0.12	0.01	0.62	0.24	0.29
M. court	0.53	0.07	0.04	0.49	−0.01	−0.02	0.54	0.08	0.39
Mongla	0.58	0.17	−0.17	0.6	−0.20	−0.33	0.61	0.21	0.42
Patuakhali	0.71	−0.42	−0.38	0.6	0.2	0.13	0.77	0.54	0.58
Sandwip	0.53	0.06	−0.04	0.54	0.07	−0.06	0.74	0.48	0.56
Satkhira	0.45	−0.11	0.08	0.51	0.02	−0.12	0.77	0.53	0.67
Sitakunda	0.56	0.12	0.13	0.51	0.02	0.1	0.58	0.16	0.35

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