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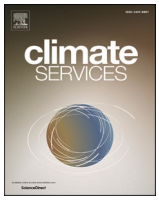

Developing a framework for an early warning system of seasonal temperature and rainfall tailored to aquaculture in Bangladesh

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ABSTRACT

The occurrence of high temperature and heavy rain events during the monsoon season are a major climate risk affecting aquaculture production in Bangladesh. Despite the advances in the seasonal forecasting, the development of operational tools remains a challenge. This work presents the development of a seasonal forecasting approach to predict the number of warm days (NWD) and number of heavy rain days (NHRD) tailored to aquaculture in two locations of Bangladesh (Sylhet and Khulna). The approach is based on the use of meteorological and pond temperature data to generate linear models of the relationship between three-monthly temperature and rainfall statistics and NWD and NHRD, and on the evaluation of the skill of three operational dynamical models from the North American Multi-Model Ensemble (NMME) project. The linear models were used to evaluate the forecasts for two seasons and 1-month lead time: May to July (MJJ), forecast generated in April, and August to October (ASO), forecast generated in July. Differences were observed in the skill of the models predicting maximum temperature and rainfall (Spearman correlation, Root Mean Square Error, Bias statistics, and Willmott's Index of Agreement,), in addition to NWD and NHRD from linear models, which also vary for the target seasons and location. In general, the models show higher predictive skill for NWD than NHRD, and for Sylhet than in Khulna. Among the three evaluated NMME models, CanSIPSv2 and GFDL-SPEAR exhibit the best performance, they show similar features in terms of error metrics, but CanSIPSv2 presents a lower interannual standard deviation.

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Practical implications

Mache Bhate Bangali. This adage translates as "fish and rice are what makes a Bengali". This expression is rather true since rice farming, fishing and aquaculture are a major source of livelihood in Bangladesh. This densely populated and low-lying deltaic country in the humid sub-tropics has landscape conditions permitting the production of a diversity of diverse aquacultural products, many of which are grown by small-scale and resource-poor farmers. Aquaculture is therefore important as an economic activity that sustains livelihoods and contributes to household nutrition. However, aquaculture production in Bangladesh is subject to the challenge of coping with adverse meteorological events associated with intense rains affecting operations and management decision and high temperatures that often induce physiological stress to fishes and affect oxygen solubility. We hypothesized that the availability of actionable climatic information generated and provided on an adequate time scale to allow effective decision-making by farmers could help mitigate the effects of adverse meteorological conditions through modifications aimed at more appropriate farm management. However, there is a gap in the availability and accessibility of tailored climate information for decision-making in the aquaculture sector. This paper aims to develop a seasonal-scale early warning system for high temperature and heavy rainfall events in two locations where aquaculture is an important activity in Bangladesh (Sylhet and Khulna districts), in order to generate actionable information for farm operations, and that can be easily implemented as an early warning system by agencies such as the Bangladesh Meteorological Department. As explained in this paper and a previous work by Hossain et al. (2021), events of high temperatures and intense rains were recognized by local farmers and experts as a priority when requesting climate information services.

The seasonal forecast developed in this research is based on a hybrid approach combining the use of state-of-the-art dynamic general circulation models (GCMs) and the empirical relationship between the number of high temperature and intense precipitation events above a fixed threshold and their seasonal averages over two locations in Bangladesh. The currently available seasonal forecasts from GCMs provide information on a monthly basis but the targeted events (relevant for aquaculture) occur on daily scales. On the other hand, multiple GCMs are currently available as part of the North American Multi-Model Ensemble (NMME) project and few of them provides operational and near real time forecasts. Consequently, in this work we focused on the evaluation of GCMs that can be potentially used to generate and deliver seasonal forecasts as climate services to aquaculture farmers in Bangladesh. In this way, the forecast of the number of warm days and rainy days from May to July and from August to October, the period of the year when important aquaculture operations decisions are taken, with one month of lead time for each period, was evaluated using outputs from three NMME GCMs and verified using ground observations of pond and air temperature and rainfall data.

The main practical implications of the results from this research are related both with the possibility of developing a seasonal early warning system for adverse events based on the assessment and use of GCMs climate predictions, and how this information should be transferred for decision-making, but also with regard to the aspects that must be taken with care, and that can be improved in future works. In this sense, the sequence of steps necessary to develop the proposed early warning system are explained so that it can be implemented flexibly. However, the pond temperature data used covers a limited time period (two seasons), and were considered as representative of the regional aquaculture. Certainly, the latter can be improved in the future by using longer time series and locations, in order to generate robust statistical models linking pond and air temperature, as well as daily events and seasonal averages. In addition, the results show that the CanSIPSv2 and GFDL-SPEAR GCMs show the best overall performance for the two locations and targeted variables. However, in practice GCMs are constantly modified in their structure, therefore any recommendation about the use of a specific model may not be valid in a scenario in which the ranking of their performance is altered or new models are incorporated to NMME, which implies that the development of a real-time seasonal forecast must be accompanied by a GCMs evaluation program, as well as the incorporation of quality observations. Although this work is mainly focused on the climate services generation stage, we have also provided information that can be used by stakeholders in the translation and transfer stages in order to build resilience in an economically relevant productive sector in a country highly exposed to the impacts of climate variability and change.

1. Introduction

Bangladesh, the densely populated sub-tropical country in South Asia, has favorable natural conditions for fish and shellfish production due to its long coastline, flat terrain, and its status as the primary delta of the regions' largest rivers. Among the three main fish and shellfish production categories found in Bangladesh, inland aquaculture contributes the most to total production (56% in 2016), followed by inland capture (28%) and marine fisheries (16%) (Shamsuzzaman et al., 2017). Aquaculture and fisheries are two of the fastest growing sectors in Bangladesh, where they have grown to be significant contributors to country's economy, food provision (as primary source of animal protein) and income source for rural households and for processing, transporting, and marketing industries. Recent statistics show that fish production increased by more than 2.3 times, from to 1,781 to 4,134 million metric tonnes, between 2000 and 2016, with an increasing share of production from aquaculture (Shamsuzzaman et al., 2020). Both fresh water and coastal aquaculture in Bangladesh is characterized by intensified production practices and growing use of technologies to cultivate carp and catfish species including Rui (*Labeo rohita*), Atla (*Catla catla*), Mrigal (*Cirrhinus cirrhosus*), Pangas (*Pangasius pangasius*) and Tilapia (*Oreochromis niloticus*) (Shamsuzzaman et al., 2017). Coastal aquaculture is conversely dominated by shrimp (*Penaeus monodon)* and prawn (*Macrobrachrium rosenbergii)*, which have become an export product of economic relevance (Paul and Vogl, 2011).

Aquaculture in Bangladesh can be seriously affected by adverse events associated with weather and climate variability, whose effects vary depending on the species grown and period of their development and reproductive cycle, affecting farm production and the livelihoods of small-scale farms. Adverse events include recurring extreme events such as flash floods, heavy rainfall episodes and heatwaves, each of which can inflict significant losses to production and aquacultural infrastructure (Islam et al., 2014b, Montes et al., 2021a). This is especially the case for inland freshwater farmers that have adopted fewer climatic adaptation measures compared to coastal areas (Islam et al., 2019). The latter is in turn enhanced by Bangladesh's high population density and low adaptation capacities (Shahid et al., 2016), which suggests that operational products for risk management with the potential of buffering the impacts of adverse weather events through informed decision making are necessary (Spillman et al., 2011; Bell et al., 2013). Furthermore, unfavorable long-term climatic projections highlight the importance of adapting farmers to both current and future possible risks (Ahmed and Diana, 2015). The lack of reliable, relevant and targeted weather forecasts and advisories remains a critical lacuna in aquaculture and fisheries that increases the vulnerability of the sector and reduces its growth potential (Islam et al., 2014a; Hossain et al., 2021). Progressive improvements of weather forecasting by the Bangladesh Meteorological Department (BMD) has made it possible to provide useful and actionable information (e.g. for high temperature events or tropical cyclones). BMD is also active in collaborative efforts to develop climate information

relevant to aquaculture, although they remain underdeveloped.

Recent advances and improvements in both dynamical and statistical modeling for weather and climate prediction have allowed the development of various products and services focused on the use of climate information and data in decision support systems. Numerous efforts have been carried out so that the scientific products can be transferred to users by extension institutions effectively and efficiently, with increased opportunities for feedback from users to iteratively improve products (Hewitt et al., 2013). In this way, dynamical and statistical seasonal forecasting have been implemented and delivered to aquaculture farmers as climate information services in other countries. Examples include forecasts of sea surface temperature (SST) and precipitation for marine farming operations in Australia (Hobday et al., 2016), rainfall and air temperature forecasts relevant to prawn aquaculture (Spillman et al., 2015), and pond water temperature to assist salmon farms, also in Australia (Spillman and Hobday, 2014). The skill in the seasonal forecasting of coastal SST by a set of dynamical models was also evaluated by Hervieux et al. (2019) in North America. Nevertheless, the benefits of targeted climate information lie in the possibility of improving decision-making at appropriate time-scales, including days, weeks or months, each of which should be aimed at reducing exposure to hazards and optimizing resource use efficiency (Spillman et al., 2015). While short-term decisions such as pond management or whether to fish or harvest can be aided by weather forecasting, medium-term planning in terms of mitigation options for high temperatures, feeding management, or species selection, to which seasonal climate anomalies are relevant can benefit from the availability of seasonal forecasts (Hobday et al., 2016; WorldFish, 2020). In a nutshell, a successful implementation of an early warning system advising pre-emptive and climate responsive aquacultural practices will depend on the appropriate choice of variables, timescales, lead times, along with a collaborative design co-design process between end-users and climate information producers (Buontempo et al., 2014; Stiller-Reeve et al., 2016).

This paper responds by focusing on the preliminary steps needed to develop a framework for seasonal early warning system for high temperature and intense precipitation events that can assist pond aquaculture farmers in Bangladesh to take improved management decisions that safeguard production and protect their livelihoods. The performance evaluation of a set of operational General Circulation Models (dynamical models) belonging to the North American Multi-Model Ensemble (NMME) project (Kirtman et al., 2014) has been done for their skill in predicting these events. A simple approach has been adopted based on the linear relationship between the number of events of high temperatures and intense precipitation and monthly average values of temperature and rainfall. The manuscript is organized as follows: we describe the two study locations in Bangladesh in terms of climate, relevance of the aquaculture sector, and the definition of seasonal climate advisories. We then describe the ground-truth dataset and NMME models used, to later explain the way in which a set of customized forecasts relevant to aquaculture were developed and verified. Finally, we present forecasting results and discuss their potential use for an operational seasonal early warning system.

2. Study area, data used and forecasting approach

2.1. Study area and aquaculture in the Sylhet and Khulna divisions

The study was carried out in the Khulna and Sylhet divisions of Bangladesh (Fig. 1). These divisions are geographically contrasting in terms of climate (section 3.1), and aquacultural systems have been described as having moderate to high vulnerability to climate variability and change (Islam et al., 2019). Aquaculture in Sylhet and Khulna is a major source of nutrition, income, employment and livelihood for rural communities and the economies of both divisions. Aquaculture

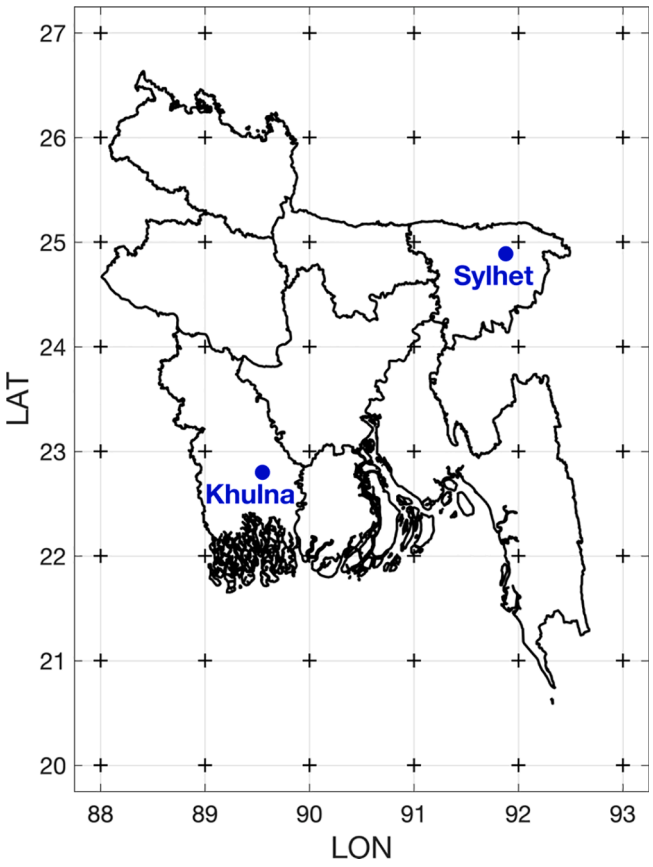

Fig. 1. Map of Bangladesh showing the location of BMD stations in the Khulna and Sylhet divisions (blue circles). Black lines are administrative divisions. Black *plus* sign corresponds to the NMME GCMs grid points.

production in ponds reaches 52% of the country's total (BBS, 2017), and north Khulna and Sylhet have 12% and 3% Bangladesh's pond fish production, respectively (BBS, 2017), indicating significant prospect in driving development and strengthening rural economy.

Khulna division has about 250,000 ha of high potential land for coastal pond aquaculture with an annual average catch of 3,5 tons/ha. In addition, a potential area of 180,000 ha is available for shrimp culture (Kashem et al., 2017). Currently, aquaculture is carried out over a total area of about 67,062 ha, which covers 65.28% of total inland water of Khulna (DoF, 2018). Major native culture species are bata (*Labeo bata*), mirigal (*Cirrhina mrigala*), tilapia (*Orechromis nilotica*), grass carp (*Ctenopharyngodon idealla*), silver carp (*Hypopthalmichthys nobilis*), pungus (*Pungassius suchi*), rui (*Labeo rohita*), catla (*Catla catla*) and thai koi (*Anabas testudineus*). Khulna is also known as a major shrimp producing district across the southern part of Bangladesh. Brackish water giant tiger shrimp (*Penaeus monodon*) and fresh water river prawn (*Macrobrachium rosenbergii*) are the main cultivated species (Azim et al., 2002), with a total production in 2014–2015 of 192,975 tons (BBS, 2017).

The Sylhet division is known as a depressed basin (*haor*) ecosystem and deeply flooded aquatic region covering 24,500 km^2 (Chakraborty, 2009), providing natural conditions for aquaculture. A number of *beels* (large lakes) and *haors* (large swamps) cover this saucer-shaped area. Currently, 17,009 ha are under aquaculture production in Sylhet (FRSS, 2017), with a culture fish production ranging from 25,000 to 50,000 tons (Shamsuzzaman et al., 2017). The most cultivated species in Sylhet are tilapia (*Oreochromis niloticus*), koi (*Anabas testudineus*) and carps such as rui (*Labeo rohita*), catla (*Catla catla*), kalibaush (*Labeo calbasu*), and mrigal (*Cirrhina mrigala*) (Hemal et al., 2017).

2.2. Defining warm and heavy rain days for aquaculture in Sylhet and Khulna

Along with the rapid expansion of intensive aquaculture farming, particularly tilapia and carps in Sylhet and shrimp in Khulna region, losses associated with climate variability are also a concern (Rahman et al., 2013; Matin et al., 2016). Flash floods and high temperature events are key climatic constraints for aquaculture (Siddiqua et al., 2019). During a recent dialogue on climate information services for aquaculture, a wide range of stakeholders identified extreme temperature and rainfall events as the most relevant climatic variables affecting operations and management decisions (WorldFish, 2020). Similarly, high temperatures and heavy rainfall events were found as the adverse climatic phenomena with highest economic damage in Khulna. Heavy rains can inundate up to 25% of the total land surface of this district (Rashid et al., 2014). Conversely, the Sylhet region corresponds to one of the rainiest areas in Bangladesh (Montes et al., 2021a).

In order to prioritize the relevant variables to be considered in a seasonal early warning system, we organized discussions with fish farmers and conducted formal interviews with aquaculture and meteorological experts as part of the CGIAR Capacitating Farmers and Fishers to Manage Climate Risks in South Asia (CaFFSA) project, which were complemented with literature review. The critical temperature and rainfall thresholds corresponding with the developmental phase of economically important and widely cultivated fish species in Khulna and Sylhet region were defined. Fish farmers typically start growing tilapia and rohu fingerlings in May and harvest in November. Hence, we have selected grow out phase of these two main species during this period. Water temperature directly affects fish physiology, and specifically breeding, spawning, and speed of growth, with high temperatures exceeding thresholds disrupting these processes (WorldFish, 2020). Temperature also affects management decisions including pond refill, feeding times, decisions on lime application, and pond fertilization. Aquaculture experts recognized that rohu and tiger shrimp can survive a water temperature of 30 °C, while tilapia fish can tolerate water temperature up to 32 °C, but physiological stress conditions occur when temperature exceeds those values (Hossain et al., 2021). In consequence, we defined 30 °C as a target maximum temperature threshold to define warm days for aquaculture in the study areas.

Similarly, precipitation can affect the growth environment for fish. Heavy rainfall can lower dissolved oxygen and pH levels, and can further imbalance water temperature (WorldFish, 2020). Experts from the Bangladesh Meteorological Department defined a rainfall intensity of 44 mm/day as a threshold for heavy rain events, and aquaculture experts agreed that when the rainfall exceeds a value in the range of 40 mm/day, can not only cause mortality of fingerlings, but also changes in water quality and damages to pond infrastructure. Therefore, we adopted 44 mm/day as rainfall threshold to define heavy rain days for aquaculture operations (Hossain et al., 2021). To our knowledge, no previous literature guidelines on rainfall thresholds for aquaculture operations in South Asia are available.

2.3. Datasets

2.3.1. Daily pond temperature and meteorological data

Daily pond water temperature data from January 2018 through December 2019 were obtained from two farm fishery units belonging to the Bangladesh Rural Advancement Committee (BRAC). The fisheries are located in the Gutudia union (89.48°E, 22.82°N) of Dumuria Upazilla of Khulna district, and in the Motiganz union (91.71°E, 24.28°N) of Srimanagal Upazilla of Sylhet district. Data were collected over two ponds averaging a surface of 0.4 ha and 1.5 m depth. Temperatures were measured with a digital thermometer every day between 8:00 AM and 9:00 AM, and between 4:30 PM – 5:30 PM (local time) at approximately 15–25 cm below the pond surface. Temperatures are measured at those two times of the day given that they correspond to the hours in which minimum and maximum daily values typically occur, as it has been reported in previous studies (Losordo and Piedrahita, 1991).

In addition to pond temperatures, daily air temperature (maximum and minimum) and precipitation data from two synoptic weather stations provided by BMD were used (Fig. 1). These stations, located in Sylhet (91.88°E, 24.89°N) and Khulna (89.55°E, 22.80°N) divisions, spanned the period 1981 through 2019, but slightly shorter period was used in the analysis, as presented below.

Table 1
List of the three NMME models used, the responsible institutions, number of ensemble members, and reference.

Model acronym	Institution	Number of ensemble members	Reference
CanSIPSv2	Canadian Centre for Meteorological and Environmental Prediction (CCMEP)	20	Lin et al., 2020
NASA-GEOS-S2S-2	National Aeronautics and Space Administration (NASA), Goddard Space Flight Center	4	Borovikov et al., 2017
GFDL-SPEAR	Geophysical Fluid Dynamics Laboratory	15	Delworth and et al. (2020)

2.3.2. General circulation models for seasonal forecasting

Hindcasts (also referred to as retrospective forecasts) from three General Circulation Models (GCM) belonging to the North American Multi-Model Ensemble (NMME) project phase 2 (Kirtman et al., 2014) were studied to evaluate their skill in reproducing seasonal precipitation and maximum temperatures indices over the two study locations in Bangladesh. These models, listed in Table 1 (details can be found in the corresponding reference), were selected since they provide real-time operational forecasts which can be used for a framework to build an early warning system. Seasonal hindcasts data with spatial resolution of 1° × 1° (Fig. 1) were obtained from the Columbia University's International Research Institute (IRI) Data Library[1]. The models have different number of ensemble members representing different initialization methods, which were averaged to generate an ensemble mean. These three models include the Canadian Seasonal to Interannual Prediction System Version 2 (CanSIPSv2), the National Aeronautics and Space Administration (NASA) Global Modeling and Assimilation Office (GMAO) Subseasonal-To-Seasonal (S2S) forecasting system (NASA-GEOS-S2S-2), and Geophysical Fluid Dynamics Laboratory (GFDL) Seamless System for Prediction and EArth System Research (GFDL-SPEAR) (Table 1). Following the data availability from the three models, CanSIPSv2 and NASA-GEOS-S2S-2 data were obtained for years 1982 through 2016, and GFDL-SPEAR for years 1991 through 2016 for the lead-1 (initial conditions of April for predicting MJJ and July for ASO) hindcasts.

2.4. Forecasting approach

2.4.1. General methodology

As previously presented (section 2.2), the days above a selected threshold of 30 °C maximum temperature (warm days) and 44 mm day^{-1} rainfall intensity (heavy rain days) were selected as target variables to be predicted for aquaculture. However, since GCMs provide only monthly average of maximum temperature and total precipitation, a transformation function between the two variables was defined considering their linear relationship. In this way, linear regressions between MJJ and ASO maximum temperature and average precipitation (predictor variables) from BMD stations and total number of warms days

[1] https://iridl.ldeo.columbia.edu/SOURCES/.Models/.NMME/.

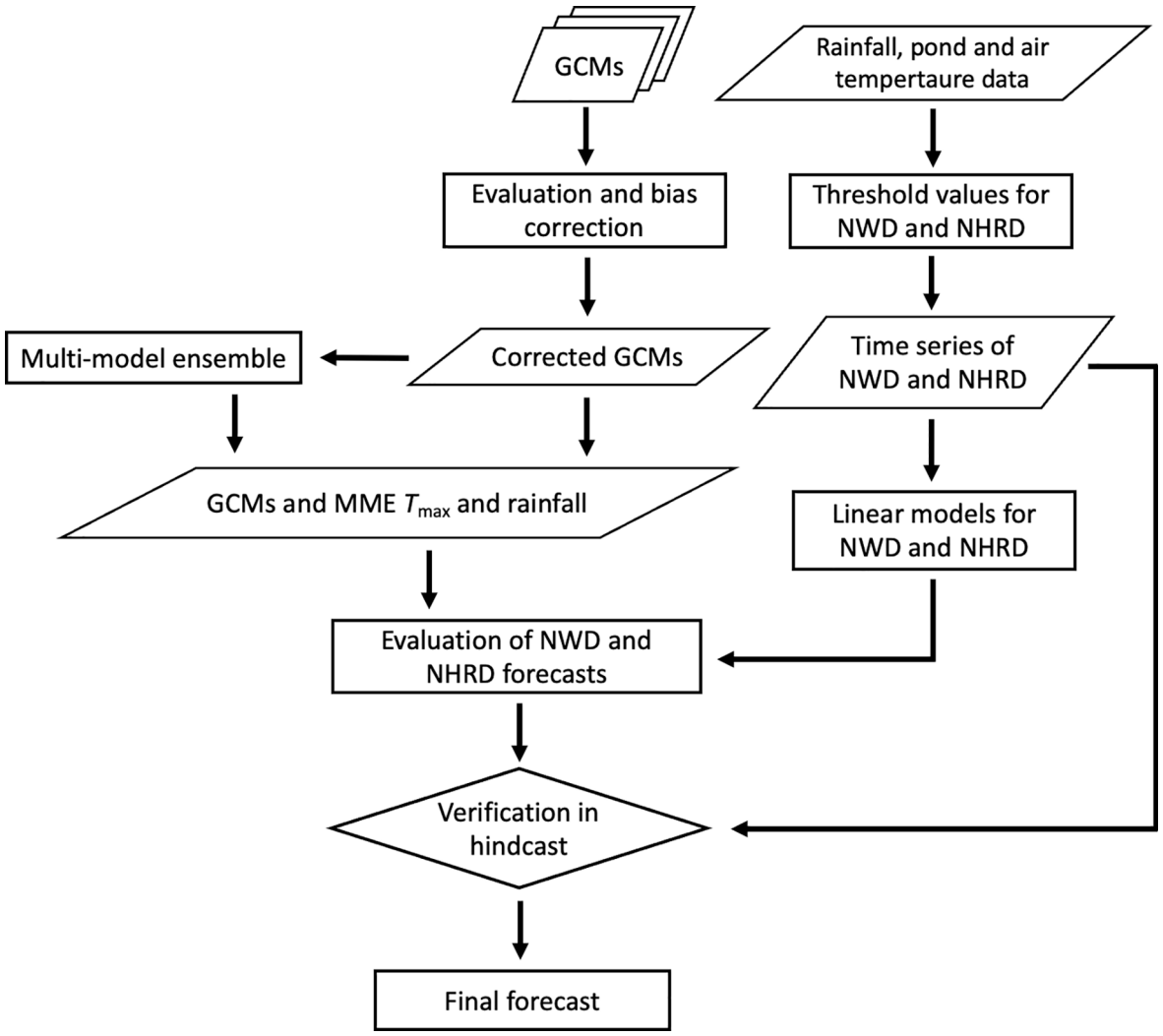

Fig. 2. Flow diagram of the proposed approach of seasonal forecasting of NWD and NHRD. See text for acronyms.

(NWD) and number of rainy days (NHRD) (predictand variables) were performed. Subsequently, the resulting linear models were used to generate a seasonal forecast of NWD and NHRD using the 3-month mean maximum temperature and precipitation from bias corrected NMME models' outputs (section 2.4.2). Finally, the overall performance of NMME models and the ensemble multi-model mean (MME) generated by averaging the three models was assessed in terms of predicted NWD and NHRD. Forecast skill was evaluated using Spearman rank correlation, the widely used Root Mean Square Error and Bias statistics, and the Index of Agreement, presented below. A flow diagram schematically describing the main steps of the forecasting approach is shown in Fig. 2.

The performance of the three NMME models, along with the MME, was assessed in terms of the seasonal forecasting of two 3-months target periods and 1-month lead time initialization for the closest GCM grid cell to the BMD weather stations (Sylhet and Khulna). The target periods are from May through July (MJJ), initialization in April, and from August through October (ASO), initialization in July. These two periods span the pre-monsoon, monsoon, and post-monsoon season. For every year (1982–2016 and 1991–2016 according to the model), two forecasts were evaluated for two variables (NWD and NHRD) and for 6 model forecasts (including MME).

2.4.2. *Bias correction of GCMs: The standardized-reconstruction technique*

Outputs from dynamical climate models are often biased given the inherent complexity of simulating the climate system (Acharya et al., 2014). As a way to mitigate this problem, multiple statistical methods for model bias corrections have been developed, for instance Quantile Mapping, Principal Component Regression, or regression-based methods. We used the Standardized-reconstruction technique (Pan and van den Dool, 1998) to correct systematic biases in maximum temperature and precipitation from NMME models. We selected this method as it has been previously reported as more skillful than others in correcting GCM outputs over the Indian subcontinent (Acharya et al., 2013a).

We implemented the method to correct biases in each of the three NMME raw maximum temperature and precipitation seasonal datasets, taking BMD stations data as an observational reference. The method consists of two steps. The first step corresponds to the standardization of the model annual (MJJ and ASO) time series to be corrected, which is applied for every i year as:

$$SF_i = \left(\frac{M_i - \overline{M}_j}{\sigma_{M_j}}\right) \quad (1)$$

where M_i is the model maximum temperature or precipitation value of year i, $\overline{M}_j$ the mean of the remaining j years (removing i), σ_{M_j} the standard deviation of the remaining j years, and SF_i the standardization factor for year i. Secondly, the bias corrected value for year i is obtained by adjusting the systematic error of the model by projecting the long-term observed climatology and standard deviation to the model value as:

$$Z_i = SF_i \times \sigma_{O_j} + \overline{O}_j \quad (2)$$

where Z_i corrected model value for year i, σ_{O_j} the standard deviation of observations for the remaining j years, and $\overline{O_j}$ the mean of observations for the remaining j years (removing i). Correcting the value of year i using statistics from the remaining j years ('training' dataset) is a form of leave-one-out cross-validation that can be used when applying the bias correction method.

2.4.3. Verification metrics for evaluation of GCMs

We employed a set of verification metrics for GMCs evaluation: Spearman rank correlation, the Root Mean Square Error (RMSE), the Bias statistics, and the Willmott's Index of Agreement, in order to examine the performance of the models and the MME. Spearman rank correlation measures the association between ranked values of two variables. Given that correlations are insensitive to biases, we also used the RMSE and the Bias statistics. In addition, we used the skill metric proposed by Willmott (1982) called Index of Agreement (d) to evaluate the performance bias corrected NMME seasonal forecasting. This index, which has the advantage of being bounded between 0 and 1, combines both the difference (error) and correlation forecast and observations, and is calculated as:

$$d = 1 - \left[\frac{\sum_i (f_i - O_i)^2}{\sum_i (|f_i - \overline{O}| + |O_i - \overline{O}|)^2}\right] \quad (3)$$

where f_i and O_i are the forecast and observations of year i, respectively, and $\overline{O}$ is the observations climatology. The closer d is to 1, the higher the efficiency of the model in producing the forecast. We calculated d both for the set of three models and for the ensemble mean MME, which was calculated for the common period 1991–2016. The efficacy of Index of Agreement in assessing GCM outputs over the Indian subcontinent has been discussed in previous studies (Acharya et al., 2013a; Acharya et al., 2013c).

3. Results

3.1. Climatology of temperature and precipitation in Khulna and Sylhet

Time series of annual rainfall and temperatures are displayed in Fig. 3, along with their mean annual cycles. Total rainfall differs considerably between Sylhet and Khulna (Fig. 3a). Sylhet and Khulna average 4,125 mm year^{-1} and 1,830 mm year^{-1}, respectively. As seen in

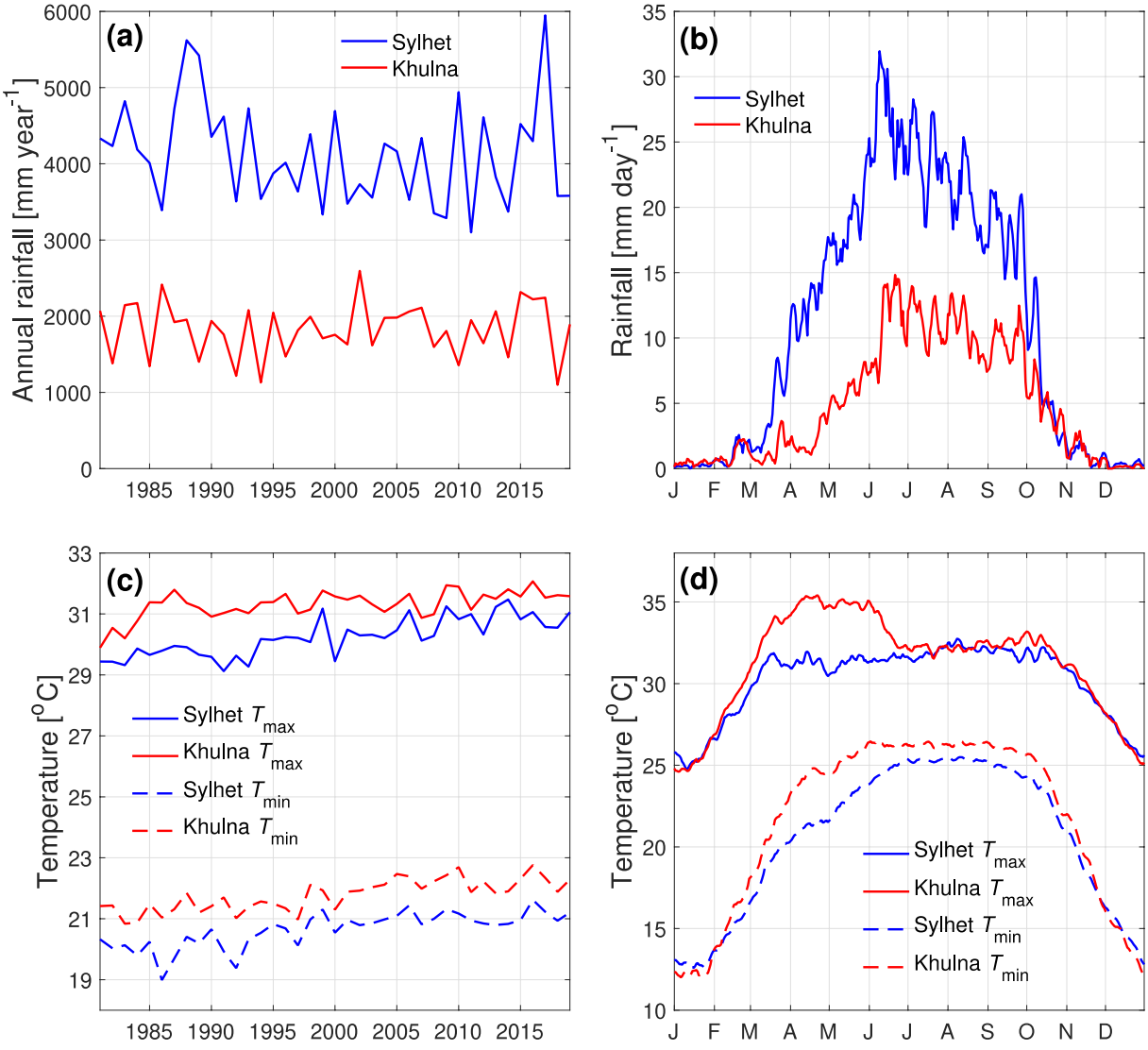

Fig. 3. Climatology of precipitation and air temperature in Sylhet and Khulna from BMD stations data: (a) time series of total annual rainfall (1981–2019), (b) 5-day moving average of the mean rainfall annual cycle, (c) mean annual minimum (T_{min}) and maximum (T_{max}) temperature, and (d) 5-day moving average of the mean annual cycle of minimum (T_{min}) and maximum (T_{max}) temperature.

the annual cycle of precipitation (Fig. 3b), the two stations show a strong seasonality, with an increasing rate around March, which is significantly higher in Sylhet, with a peak around June, and a declining rate in October associated with the monsoon demise. Both the higher total rainfall and the significantly higher rate of increase in Sylhet are the result of factors such as the occurrence of intense pre-monsoon precipitation originated by local rainstorms (Basher et al., 2018), both an earlier monsoon onset and later withdrawal (Stiller-Reeve et al., 2015; Montes et al., 2021b), and also by interactions between low-level moisture transport and topography (Ahmed et al., 2020). On the other hand, Fig. 3c shows that annual mean maximum (T_{max}) and minimum (T_{min}) air temperatures are slightly higher in Khulna, with an interannual average T_{max} (T_{min}) in Khulna of 31.3 °C (21.8 °C) and in Sylhet of 30.2 °C (20.6 °C). These differences are likely associated with the lower seasonal rainfall of Khulna. In fact, the mean annual cycle of the T_{max} (Fig. 3d) shows a seasonal warming regulated by the increasing rainfall rates (Fig. 3b), effect that is more pronounced in Sylhet. T_{max} is especially higher in Khulna from March to June before the establishment of the monsoon. T_{min} is systematically higher in Khulna maybe due to other factors such as elevation or sea proximity.

3.2. Number of warm days and rainy days: climatology and linear models

As explained in section 2.4.1, the adopted approach seeks to generate seasonal predictions of NWD and NHRD from NMME 3-monthly T_{max} and precipitation. The first step consisted of the analysis of the relationship between daily maximum pond temperature (T_{pond}) and T_{max} in order to establish a threshold T_{max} value when T_{pond} is above the previously identified 30 °C. Fig. 4 shows T_{max} and T_{pond} recorded in Sylhet and Khulna in 2018 and 2019. Days when T_{pond} exceeded 30 °C and the corresponding T_{max} during those days are also displayed. The number of days above 30 °C, and in general T_{pond}, is higher in Sylhet (Fig. 4a-4b) than in Khulna (Fig. 4d-4e); they typically occur between May and October, and differences between temperatures are higher in Khulna. The temperature range is wider in Sylhet, with T_{pond} (T_{max}) values ranging between 21 °C and 37 °C (25 °C and 38 °C), and from 26 °C to 33 °C (28 °C and 39 °C) in Khulna. According to the linear relationship between T_{pond} and T_{max}, a T_{max} value of 33 °C and 32 °C in Sylhet and Khulna, respectively, as a threshold for air temperature would be reasonable choice to define NWD considering that the corresponding percentiles 35% and 13% of those threshold temperatures would allow removing values that might be too low, considering the longer length of the time series to be analyzed in the following steps.

In a similar way, the daily precipitation threshold of 44 mm/day identified through expert interviews as heavy rainfall that can cause fingerlings mortality and unfavorable water conditions problems in pond aquaculture was analyzed in the context of the climatological precipitation values in Sylhet and Khulna. Fig. 5 shows the resulting histograms of daily rainfall (≥1 mm/day) and the corresponding percentiles 95%, 99% and of 44 mm/day. As expected, the threshold value of 44 mm/day equates to a lower percentile in Sylhet (82%) than in Khulna (92%). Based on these results, the selected threshold of 44 mm/day allows most of the rainfall events that can be statistically identified as extreme events to be considered in the forecasting, so that the threshold of 44 mm/day was subsequently used to determine NHRD.

The linear relationship between observed 3-month average T_{max} and NWD, and 3-month average precipitation and NHRD is displayed in Fig. 6 for both MJJ and ASO. Linear models generated from linear regression are presented in Table 2. For the case of NWD (Fig. 6a and 6b), our results show a good linear fit between T_{max} and NWD, with R^2 values that vary between 0.71 and 0.9 and Spearman correlations from 0.84 to 0.94, all statistically significant ($\alpha = 0.05$). The linear relationship between 3-month average rainfall and the NHRD of Fig. 6c-6d shows a linear regression fit that is similarly statistically significant but at a slightly lower level, with R^2 values ranging between 0.6 and 0.79 and Spearman correlation from 0.81 to 0.9, indicating a better fit for NWD than for NHRD. Finally, previous analysis resulted in a set of linear equations, displayed in Fig. 6, which will be used for the seasonal forecast in MJJ and ASO, using the predictor X (3-month T_{max} and precipitation) to obtain the predictand Y (NWD, NHRD), as shown below.

3.3. The skill of NMME seasonal forecasting of T_{max}, rainfall, NWD and NHRD

NMME models were evaluated in terms of their performance predicting T_{max}, rainfall, NWD and NHRD, for the two target periods MJJ and ASO, and 1-month (April and July, respectively) lead time. We report in Table 3 the biases in raw (not bias-corrected) and bias-corrected NMME models' predictions of T_{max} and rainfall. It can be

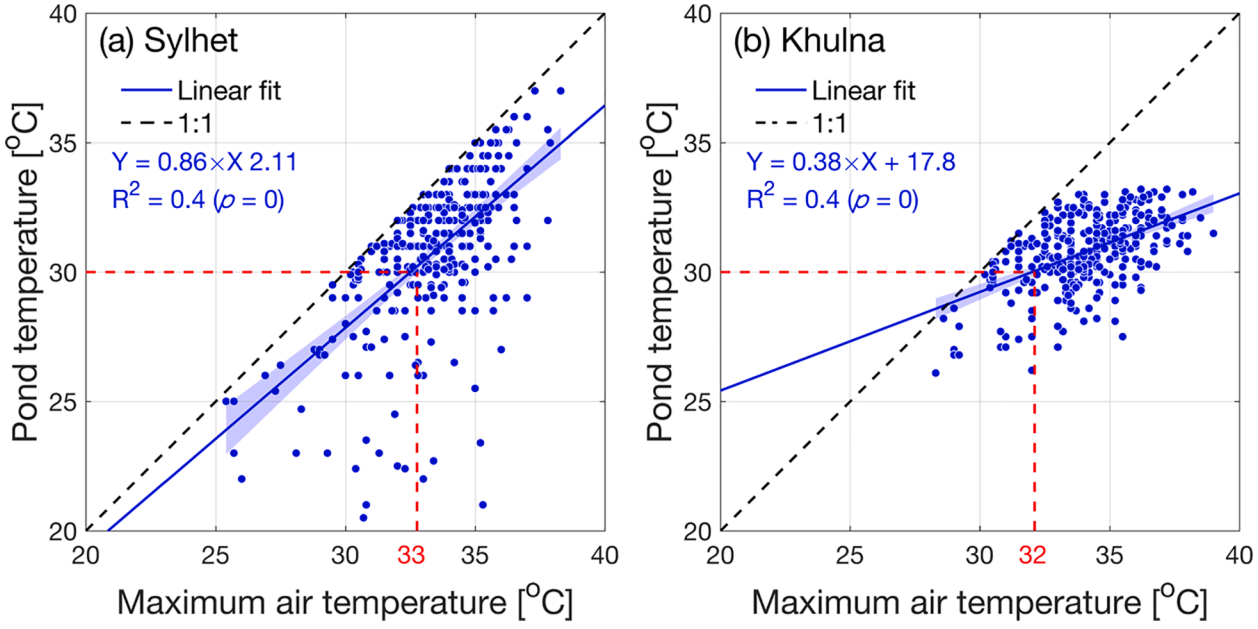

Fig. 4. Scatter plot between daily maximum pond and air temperature for (a) Sylhet and (b) Khulna. The corresponding air temperature when pond temperature equals 30 °C according to the linear fit is shown in red. The shaded area corresponds to the 95% confidence interval.

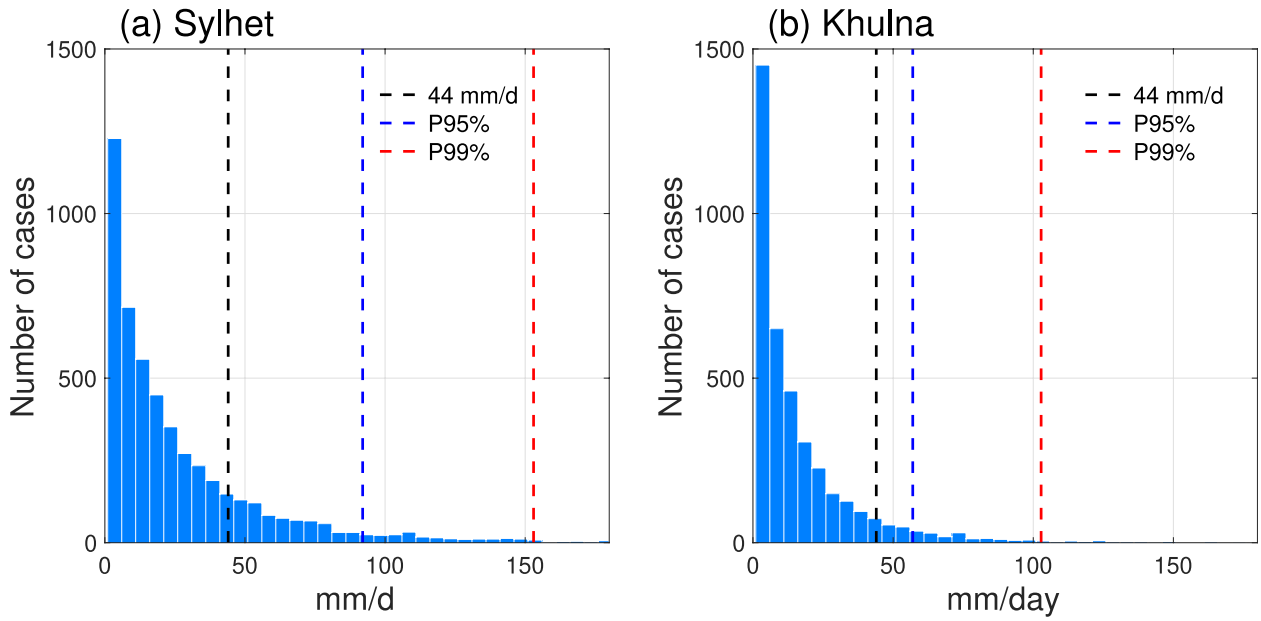

Fig. 5. Histograms of daily precipitation (≥1 mm/day; 1982–2016) in (a) Sylhet and (b) Khulna from May through October. Vertical lines represent the selected threshold of 44 mm/day and percentiles 95% and 99%.

seen that biases are highly variable for temperature and precipitation and the selected models, exhibiting a performance that range from −0.4 °C to 6.8 °C in the case of raw T_{max} predictions, and from 1 mm to −534 mm in the case of not bias-corrected rainfall. In general, these results suggest that the use of a bias correction method is necessary to improve the skill of the predictions, which is observed in Table 4, and presented below.

The forecast skill of bias corrected NMME models and MME using the standardized-reconstruction technique and in terms of Spearman rank correlation and RMSE is presented in Table 4 and Fig. 7, respectively, which shows the corresponding matrices of skill metrics. The bias is not presented here since after applying the correction method, resulting biases reached values close to zero. As described in previous studies in Bangladesh (e.g. Kelley et al., 2020), Spearman rank correlation varies widely among models and for T_{max} and rainfall. Table 4 shows that correlations are mostly positive for both T_{max} and rainfall, except for NASA-GEOS-S2S-2 rainfall, where negative correlations are observed. Although these correlations are within the range of previous assessments of NMME models' outputs (e.g. Slater et al., 2019), results show varying skill for each variable and model, and also a higher skill for T_{max} than for rainfall. The latter is not unexpected given the higher difficulties of predicting precipitation than temperature. Moreover, and although the heterogeneous performance of NMME models, Table 4 shows that CanSIPSv2 and GFDL-SPEAR present the higher and more consistent skill in terms of Spearman correlation for both T_{max} and rainfall. On the other hand, RMSE (Fig. 7a and 7b) after bias correction varies widely according to the predicted variable and model used. In general, variables such as T_{max} and rainfall ASO in Khulna seem to be consistently well represented by the models, and models such as NASA-GEOS-S2S-2 exhibit a divergent skill predicting temperature and rainfall. Similar, lower consistency between models is observed for variables such as T_{max} MJJ in Khulna.

The skill of NMME models predicting NWD and NHRD was assessed by using the Willmott's Index of Agreement (d). However, a slightly different approach that for T_{max} and rainfall was used in the current study. Performance evaluation was carried out by comparing outputs using the linear models generated from BMD stations' temperature and precipitation data and presented in Fig. 6. In this way, NWD and NHRD obtained by the linear models using BMD data were considered as observations in the calculation of d. The matrix of d values for all three NMME models and MME and variables is presented in Fig. 8a, where values closer to 1 suggest higher mean skill (Acharya et al., 2013b). A wide range of d values can be observed in Fig. 8a, which range from 0.25 to 0.78, with a median of 0.53. In terms of variables, it is observed that NWD has in general higher values of d than NHRD. Also, the lowest skill was obtained for NHRD MJJ in Khulna, with an among-models average d of 0.33. On the other hand, NWD ASO in Sylhet exhibits a higher skill in its predictability when models are compared, with an among-models average d of 0.7. Regarding the models, GFDL-GFDL-SPEAR shows the higher individual skill, with a d of 0.76 predicting NWD ASO in Sylhet. It is worth noting that ASO rainfall prediction in Sylhet has both relatively higher positive Spearman correlation and lower RMSE (Table 4), metrics that are captured by the Index of Agreement d.

The implementation of a seasonal early warning system of NWD and NHRD should be carried out in an effective and organized manner. The above results imply that although the poorer and better performance in terms of d were obtained for NWD ASO in Sylhet and NHRD MJJ in Khulna, respectively, an appropriate option might be the selection of the model (or MME) that performs better predicting NWD and NHRD both for Sylhet and Khulna, and for the two target periods MJJ and ASO. For this, the overall skill is presented in Fig. 8b, where boxplots of d were calculated for each model, including MME, taking the 8 individual values presented in Fig. 8a, represented by rows. Among the 3 NMME models and MME, CanSIPSv2 and GFLD-SPEAR provide similar skill for both NWD and NHRD, with a median (mean) of 0.58 (0.61) and 0.57 (0.65), respectively, followed by MME and NASA-GEOS-S2S-2, which provides poorer overall performance. However, a lower amplitude (interannual variability) is observed for CanSIPSv2 than GFDL-SPEAR, with a standard deviation of 0.09 and 0.19 in d, respectively, which can be corroborated in the first row of Fig. 8a, which shows more homogeneous d values for both NWD and NHRD. The latter implies that it would be expected a higher consistency in the forecast generated by CanSIPSv2 over time compared to GFDL-SPEAR.

In order to illustrate the performance of the proposed approach predicting NWD and NHRD, Fig. 9 shows the time series of NWD and NHRD for Khulna and Sylhet and for MJJ and ASO obtained by the corresponding linear model using CanSIPSv2 and observations as an example. The predictands can be highly variable in time and for both locations, and the time series of both NWD observations and models show an increasing trend in MJJ and ASO, and an interannual variability

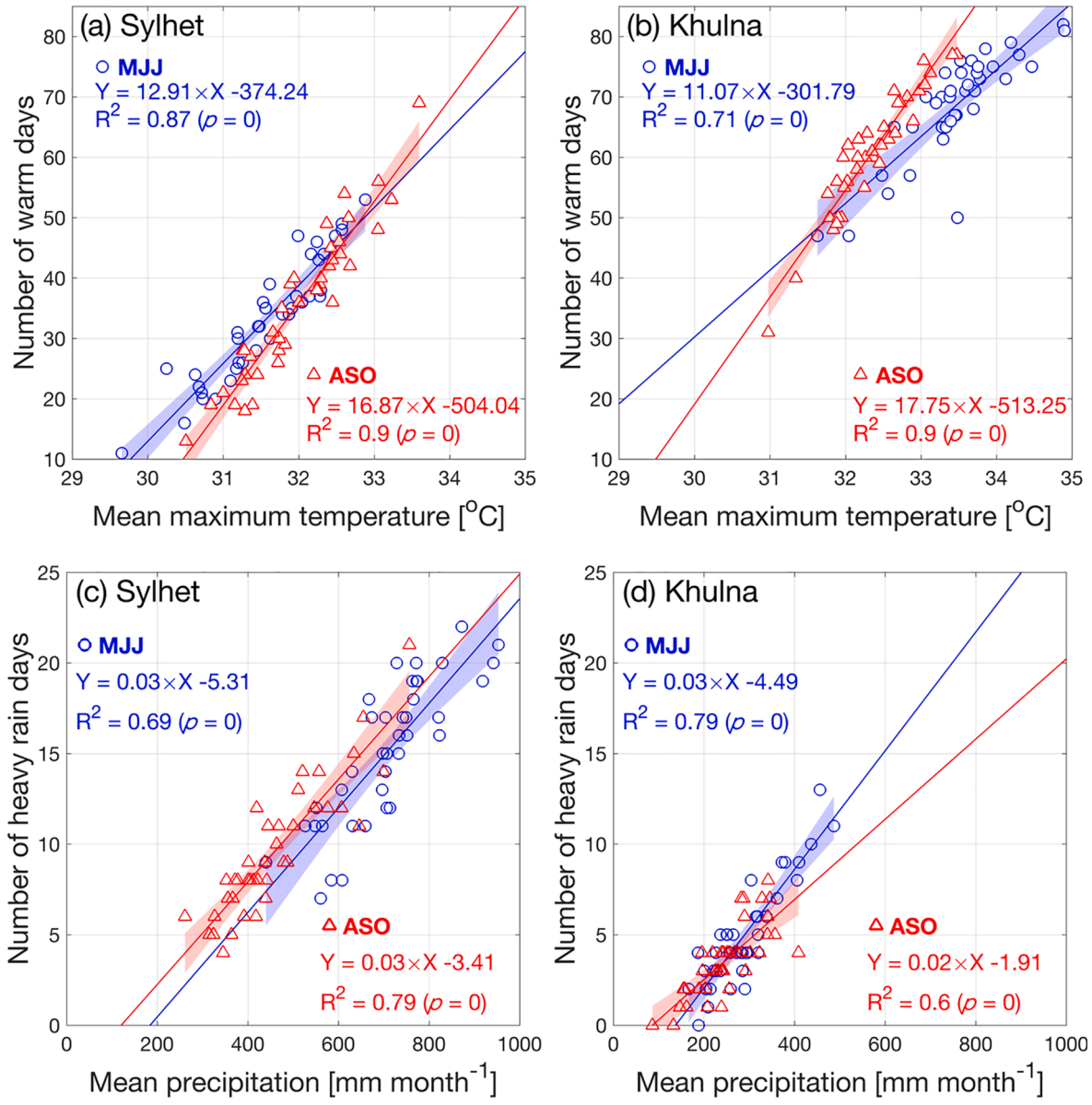

Fig. 6. Linear relationship (1981–2019) between (a)-(b) seasonal mean maximum temperature and total number of warm days, and (c)-(d) mean seasonal precipitation and total number of heavy rain days during May through July (MJJ) and August to October (ASO) for Sylhet and Khulna. Lines are the fit generated by the corresponding linear model. The shaded area corresponds to the 95% confidence interval.

Table 2
Linear models generated to estimate NWD and NHRD from 3-month average maximum temperature (MT_{max}) and rainfall (*Rain*) in Sylhet and Khulna. MJJ: May to July, ASO: August to October.

	NWD		NHRD	
	MJJ	ASO	MJJ	ASO
Sylhet	$NWD = 12.91 \times MT_{max} - 374.24$	$NWD = 16.87 \times MT_{max} - 504.04$	$NHRD = 0.03 \times Rain - 5.31$	$NHRD = 0.03 \times Rain - 3.41$
Khulna	$NWD = 11.07 \times MT_{max} - 301.79$	$NWD = 17.75 \times MT_{max} - 513.25$	$NHRD = 0.03 \times Rain - 4.49$	$NHRD = 0.02 \times Rain - 1.91$

that is better captured by CanSIPSv2 in Sylhet than in Khulna. On the other hand, no trend is observed in NHRD, but in this case CanSIPSv2 is able to reproduce the regional and seasonal differences. It is also observed that CanSIPSv2 reproduces better NHRD in Sylhet during the MJJ season, during ASO in Khulna. In addition, the model is able to reproduce the interannual variability, with an average difference in standard deviation between observations and hindcasts that is lower than one event per year for both NWD and NHRD (results not shown). However, and despite the fact that the correlations between observations and forecasts are mostly statistically significant, in some cases they can be considered as low.

4. Discussion and conclusions

The main goal of this work was to develop a framework for the seasonal forecasting of high temperatures and intense precipitation events that can affect aquaculture in two locations in Bangladesh and validating the method using NMME models' outputs to facilitate the

Table 3
Bias in T_{max} and rainfall, and for the two target periods May-June-July (MJJ) and August-September-October (ASO), for not bias-corrected and bias-corrected NMME models seasonal forecasting.

		CanSIPSv2		NASA-GEOS-S2S-2		GFDL-SPEAR		Ensemble mean	
		Not bias-corrected	Bias-corrected	Not bias-corrected	Bias-corrected	Not bias-corrected	Bias-corrected	Not bias-corrected	Bias-corrected
T_{max} (°C)	Khulna MJJ	−0.8	0	6.8	0	1.5	−0.1	1.4	−0.1
	Sylhet MJJ	−2.6	0	6.3	0	−0.7	−0.1	0.9	−0.2
	Khulna ASO	−1.9	0	−0.4	0	−0.4	−0.2	−1.0	−0.1
	Sylhet ASO	−4.7	0	−0.7	0	−1.2	−0.3	−2.3	−0.2
Rainfall (mm/month)	Khulna MJJ	−6	0	−534	0	−181	8	−231	15
	Sylhet MJJ	392	1.5	−409	1	−3	9	1	14
	Khulna ASO	166	1	58	1	87	35	124	29
	Sylhet ASO	126	1	130	1	265	37	196	35

Table 4
Spearman rank correlation for T_{max} and rainfall, and for the two target periods May-June-July (MJJ) and August-September-October (ASO), between NMME models, including MME, and observations in Khulna and Sylhet.

		CanSIPSv2	NASA-GEOS-S2S-2	GFDL-SPEAR	Ensemble mean
T_{max} (°C)	Khulna MJJ	0.42	0.22	0.51	0.33
	Sylhet MJJ	0.43	0.00	0.62	0.37
	Khulna ASO	0.44	0.01	0.49	0.18
	Sylhet ASO	0.55	0.31	0.68	0.67
Rainfall (mm/month)	Khulna MJJ	0.24	−0.21	0.04	0.02
	Sylhet MJJ	0.22	0.04	0.46	0.26
	Khulna ASO	0.38	−0.04	0.14	0.08
	Sylhet ASO	0.16	−0.03	−0.05	−0.04

implementation of an early warning system for farmers and stakeholders. The seasonal forecasts are expected to improve aquacultural management decisions based on the information provided. Although significant additional work is needed to develop systems that 'translate' seasonal forecast information into advisories that can easily be understood and applied by fish farmers, this work presents an important first step towards this goal.

Hindcast monthly runs (lead 1 for MJJ and ASO, 1982–2016 and 1991–2016) from three NMME dynamical models along with the multi-model ensemble were evaluated in their performance using a simple approach to predict NWD and NHRD based on linear models. Skillful seasonal predictions of NWD and NHRD were obtained for 1-month lead time and two target seasons (MJJ and ASO). Although linear models generated based on meteorological observations of 3-month average maximum temperature and precipitation exhibit a statistically significant fit, multiple sources of error can make the forecast of estimated NWD and NHRD not perfect. For instance, threshold values for the definition of NWD and NHRD were taken from expert opinions and no empirical evidence on the impact of the NWD and NHRD criteria on aquaculture activities over Khulna and Sylhet was considered as a criterion. In this way, a long-term observational assessment of the impact of high temperatures and heavy rain events on the physiology of

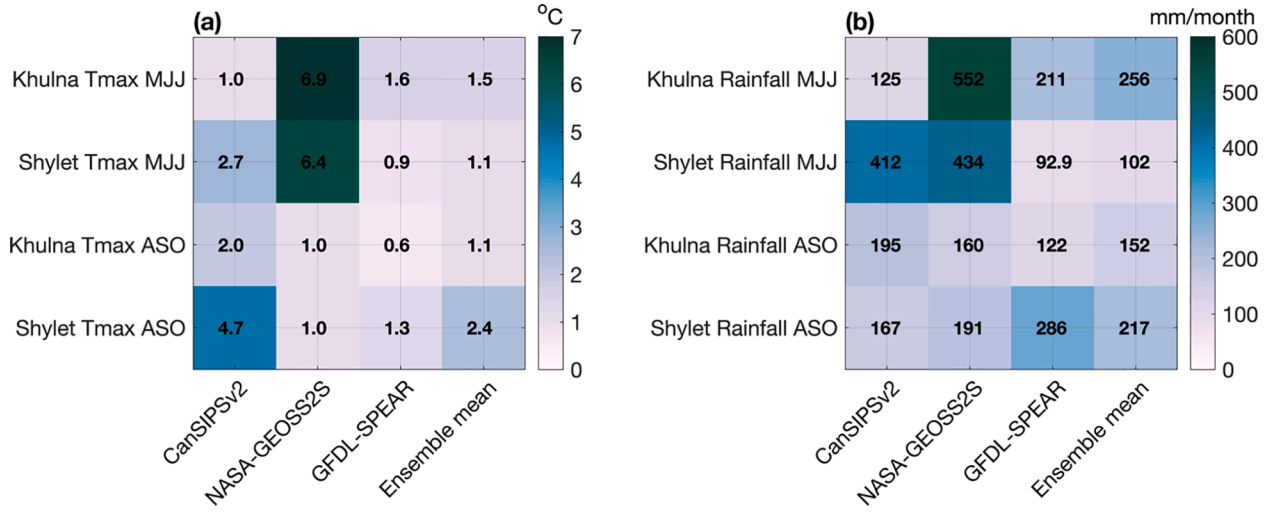

Fig. 7. Matrices of RMSE for (a) T_{max} and (b) rainfall, and for the two target periods MJJ and ASO, between NMME models, including MME, and observations in Khulna and Sylhet.

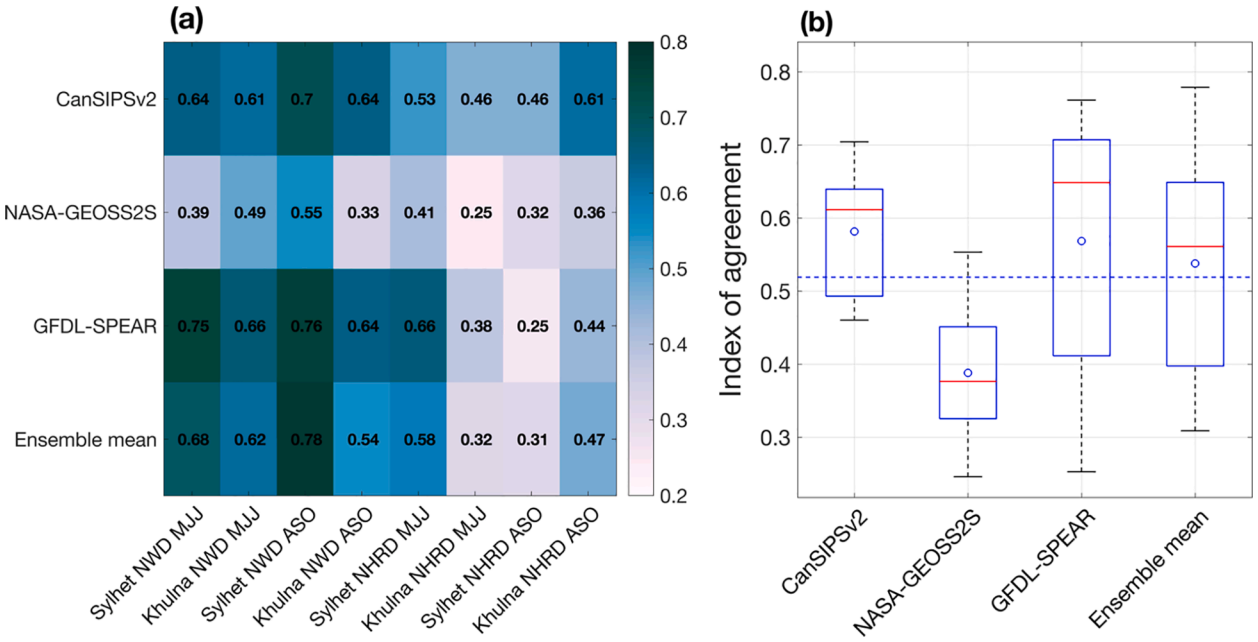

Fig. 8. (a) Matrix of Index of Agreement (*d*) between NWD and NHRD for NMME models. (b) Boxplot of global *d* obtained from NMME models for NWD and NHRD and for the two locations and target periods (MJJ, ASO). In (b), central red line shows the median and circle the mean, box edges are the 25th and 75th percentiles, and dashed lines extend to the most extreme values not considered outliers. Horizontal dashed line in (b) corresponds to the global among-model mean *d*.

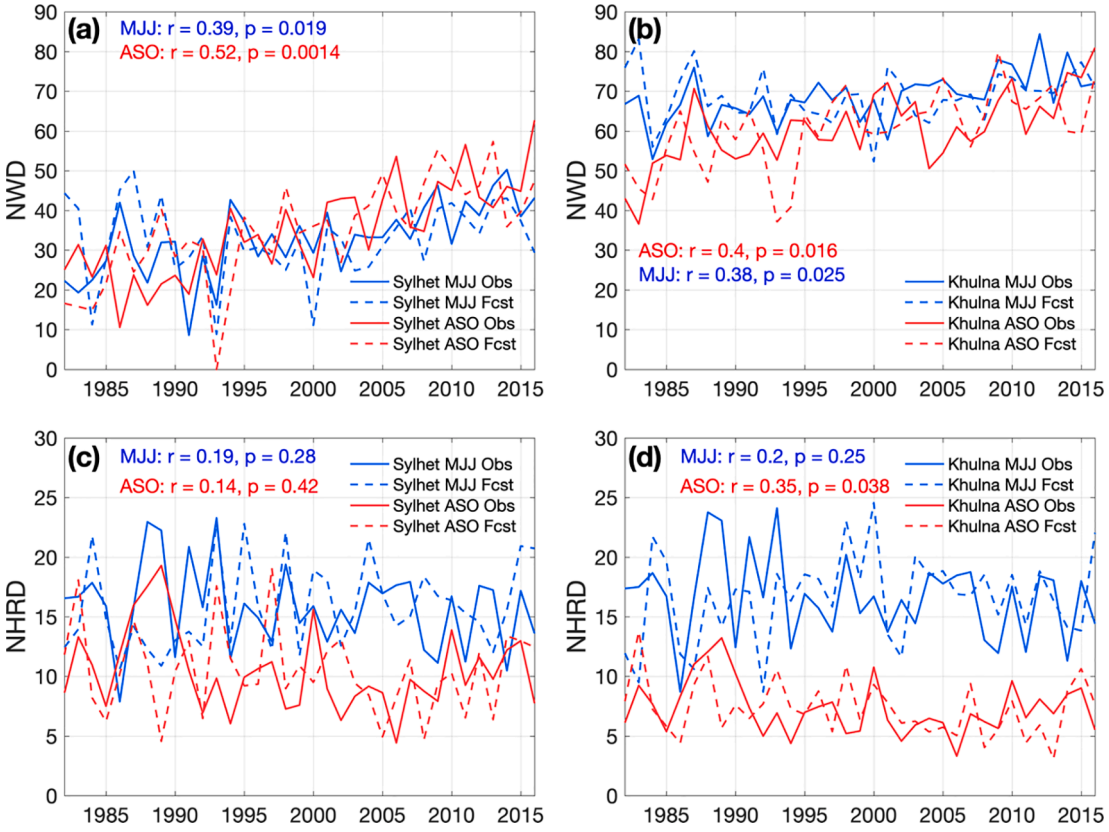

Fig. 9. Time series (1982–2016) of (a) NWD and (b) NHRD obtained with the linear models using station observations (Obs) and outputs from the CanSIPSv2 model (Fcst). Spearman correlations between observations and forecast (*r*) and *p* value for statistical significance are also displayed.

cultivated species and infrastructure, for example, seems to be highly necessary to be able to understand more appropriately the relationship between climate risks and aquaculture production in Bangladesh. The foregoing should be accompanied by research that allows establishing threshold values of NWD leading to stress conditions for each species of aquaculture interest and for different stages of their growth cycle, and the NHRD that can act as a hydrometeorological hazard damaging infrastructure and consequently generating stress conditions. Regarding

the use of climate information, we selected the closest model grid to the weather station from models of $1^\circ \times 1^\circ$ resolution, which of course can be translated into a smoothing effect of local variability in climate. The foregoing corresponds to a recurring source of error when working with GCMs, since these models are not able of well capture the variability induced especially by topography (e.g. orographic precipitation), for which statistical and dynamical downscaling is often used (Ménégoz et al., 2013). Although the above might not be a major issue in Bangladesh's flat terrain conditions, a product of higher grid resolution could certainly reduce the uncertainty associated with the coarse resolution of the GCMs. At the same time, linear models allow the estimation of daily NWD and NHRD from monthly data with a variable reliability. However, the differences among GCMs in terms of physical schemes, parameterizations, and forcing, are a major source of differences determining the accuracy of the forecasting, beyond the complexity of predicting the climate system at seasonal scales.

Despite the above, results show that it is possible to statistically link the occurrence of weather events on a daily scale to monthly climate in the context of the development of practical applications, aquaculture farming in the present case. In this sense, after statistically removing the strong bias of the models, the evaluation of seasonal forecasts of NWD and NHRD showed, on the one hand, high differences in the performance of the models, but at the same time it was possible to identify the models (CanSIPSv2 and GFDL-SPEAR) providing the most reliable global results for Khulna and Sylhet. The latter can be valuable in the context of developing an operational early warning system, where both the most reliable model or the ensemble mean could be selected to deliver a final forecast product, as it has been previously done for the prediction of other variables (e.g. Kelley et al., 2020), considering also that the prediction skill can be improved when the ensemble mean is used (Acharya et al., 2013b). However, the use of a previously identified best fit model (or MME) should be an ongoing activity by climate services providers, since GCMs such as the ones used in this work are constantly evaluated and modified by the corresponding institutions.

The present work focuses on the evaluation of the NMME models, which is part of the climate information services generation stage. In this sense, it is important to consider that the development and maintenance of GCMs as such as those evaluated in this work is a continuous process in search of improvements in the representation of the climate system. This is of relevance at the moment of implementing an operational early warning system based on dynamical models since the configuration of a particular selected model may change over time which makes a continuous evaluation of its performance necessary (Kirtman et al., 2014). In the present case, whatever method used to present and deliver forecasts to decision makers, the first step corresponds to bias correction of the new forecast generated in April and July for the upcoming three months (MJJ and ASO) using the forecasts of previous years. In addition to the generation of climate information, effective translation and transfer (delivery) of generated information are crucial additional next-steps (Spillman and Hobday, 2014). Furthermore, a scaling plan should also be considered in future work in order to reach more aquaculture producing areas and species, involving relevant actors and facilitators to improve the services provided (e.g. Blundo-Canto et al., 2021).

As stated, in addition to the continuous review of the generation stage associated with the above, the translation and delivery of the forecast in an adequate form that is easy to understand and use by stakeholders is of great relevance. For instance, Spillman *et al.* (2014) suggest that probability distributions of both forecast and observed climatologies can be used for experienced forecast users for salmon farmers in Australia. The same authors and Spillman et al. (2015) translated seasonal temperature forecasts into terciles-based probabilistic pie charts. In addition, the generated information can also be tailored to specific actions in aquaculture in the target area. Properly planned advisories can mitigate the inaccuracies inherent in climate forecasts and substantially improve decision making in aquaculture avoiding larger economic damage and enhance productivity. In Bangladesh, an actionable seasonal forecasting can provide information on adverse events that can be used by aquaculture producers for operations planning regarding unsuitable climate conditions (e.g. Hobday et al., 2018). Information about adverse meteorological events can assist fish-farmers make decisions on pond preparation, fingerling stocking, production volume, maintenance and harvesting schedule. These climate-sensitive management decisions are crucial for aquaculture operations in managing climate risks, reducing costs and ensuring business profit (Hossain et al., 2021). In any case, the above must be conceived as a co-production process that requires the interaction with farmers and relevant local research and development institutions and individuals such as aquaculture extensionists in order to find the best fit between targeted forecasts and users' possibilities, which is a subsequent stage of iterative work. Climate services for aquaculture in developing countries are in a stage of infancy and no major efforts are reported so far in South Asia. As such, the current efforts are expected to provide an initial momentum for such efforts in the region.

CRediT authorship contribution statement

Carlo Montes: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Nachiketa Acharya:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Peerzadi Rumana Hossain:** Writing – original draft, Writing – review & editing. **T.S. Amjath Babu:** Writing – original draft, Writing – review & editing. **Timothy J. Krupnik:** Writing – original draft, Writing – review & editing. **S.M. Quamrul Hassan:** Writing – original draft, Writing – review & editing.

Declaration of Competing 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.

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