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Impact of temperature changes on groundwater levels and irrigation costs in a groundwater-dependent agricultural region in Northwest Bangladesh

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Abstract:

Changes in hydrological processes due to rising temperatures and related effects on the socio-economy and people's livelihood are major concerns in Bangladesh. A study has been performed to assess the effects of increasing temperature on the groundwater levels and consequent changes in irrigation costs for groundwater-dependent irrigated agriculture in Northwest Bangladesh. A support vector machine (SVM) was used to model the temporal variations in groundwater level from rainfall, evapotranspiration, groundwater abstraction, and agricultural return flow. A multiple linear regression (MLR) model was developed to define the functional relationship between irrigation costs and groundwater levels. The model showed that average groundwater level during the major irrigation period (January–April) decreased by 0.15–2.01 m due to an increase in temperature of 1–5°C, which increased irrigation costs by 0.05–0.54 thousand Bangladesh Taka (BDT) per hector.

KEYWORDS temperature rise; groundwater level; irrigation cost; Northwest Bangladesh

INTRODUCTION

The Intergovernmental Panel on Climate Change (IPCC) has reported that the increased global average temperature will cause an increase in heavy rainfall events in most parts of the world. It has been projected that the global average air temperature will continue to increase by 1.1–6.4°C by 2099 (IPCC, 2007). The rising temperature will intensify the global water cycle and change precipitation patterns (Wang *et al.*, 2016a), which will affect surface runoff, evapotranspiration, groundwater recharge, and irrigation demand. Herrington (1996) estimated an irrigation demand increased of 12% in England because the temperature increased by 1.1°C. Similar studies in other parts of the world indicate that rising temperature due to global warming will increase irrigation demand in most climate regions (Peterson and Keller, 1990; Rosenberg *et al.*, 1990; Shahid 2011; Wang *et al.*, 2016a, b).

Groundwater is the major source of irrigation in many countries worldwide. Groundwater use in irrigation and food production continues increasing in both absolute terms and percentage of total irrigation, particularly in densely populated Asian countries (Shahid *et al.*, 2014). In China, 2.5×10^9 cubic meters of groundwater are abstracted annually to satisfy irrigation demands. In the Indian subcontinent, more than 85% of the abstracted groundwater is used for irrigation purposes (Mukherjee *et al.*, 2015). It has been projected that the world population will be more than 9.6 billion by 2050 (United Nations [UN], 2013). Food production will have to increase by 70% to feed the growing population, which will cause a vast expansion of global irrigated agriculture (Food and Agriculture Organization [FAO], 2009). The available surface water will be far less than the water required for increased food production (Watto and Mugera, 2015). Therefore, it can be anticipated that a major portion of increased water demand will be satisfied by groundwater abstraction. Higher air temperatures due to increased concentrations of atmospheric CO_2 increases evapotranspiration and makes the groundwater level deeper (Ranjan *et al.*, 2006; Gunawardhana and Kazama, 2012). Deeper groundwater may increase irrigation costs, which may seriously affect the livelihood of farmers, particularly in groundwater-dependent irrigated regions of developing countries, if proper adaptation measures are not taken (Dey *et al.*, 2013).

The major objective of the present study is to assess the effects of increasing temperature on groundwater levels and consequent changes in irrigation costs in a groundwater-dependent irrigated agriculture region in Northwest Bangladesh. Groundwater is the only sources of irrigation in this region. Therefore, a decrease in the groundwater table due to rising temperatures may seriously affect the agro-based economy in the region.

STUDY AREA

The study area in Northwest Bangladesh (latitude: 24.07°N to 24.43°N; longitude: 88.17°E to 88.58°E) is a part of the Ganges River basin (Figure 1a). The topography of the study area is extremely flat with some upland in the northwest. The surface geology of the area consists of sedimentary formations of alluvial sand, silt and clay of riverine

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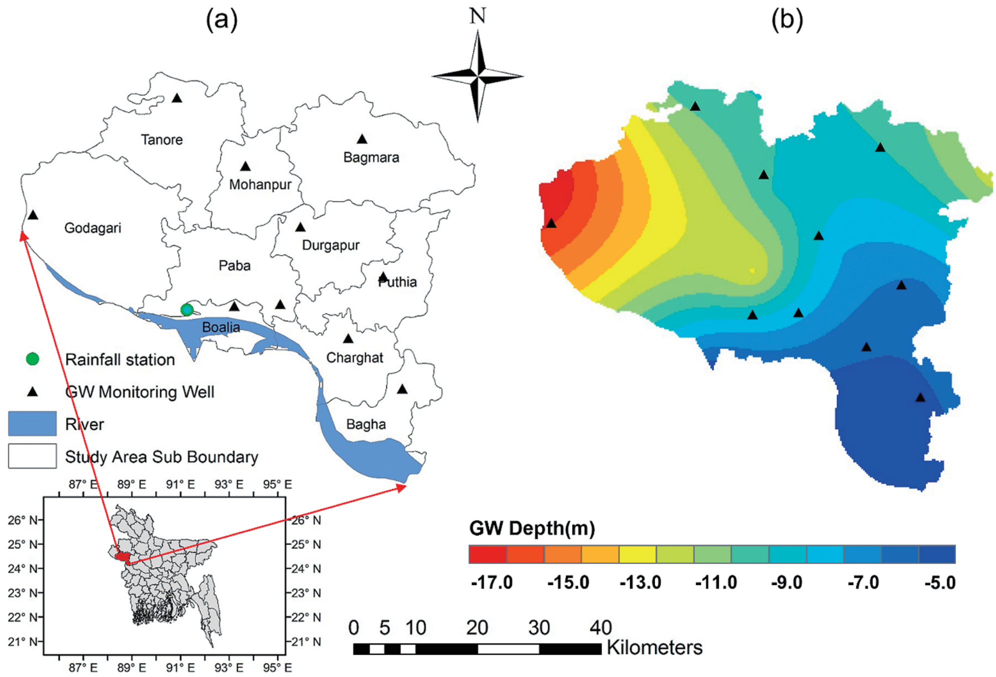

Figure 1. (a) Location of the study area and groundwater sampling points; (b) depth to groundwater table during the dry season irrigation period

origin (Shahid *et al.*, 2015; Sattar *et al.*, 2016). High-Yield Varity Boro rice is the major crop grown in the groundwater-based irrigation system and the lifeline of the economy of the area. The maximum depth to the groundwater table in the area is 5–17 m from the land surface (Figure 1b) during the irrigation season (January–April). The intensively irrigated agriculture in the area effectively contributes to ensuring the food security of Bangladesh. However, because of inappropriate anthropogenic intervention, the groundwater level during the irrigation period continues to decrease (Shahid and Behrawan, 2008; Shahid, 2011). Currently, the groundwater levels in most of the shallow tube-wells, which are widely used for irrigation, are below the suction lift capacity during the peak irrigation period.

METHODOLOGY AND DATA

Data and sources

Bi-monthly data on groundwater levels (the depth to groundwater table from the land surface) recorded at 10 observation wells across the study area during 1991–2009 were obtained from the Bangladesh Water Development Board (BWDB). Daily rainfall and air temperature at 2 meters above the ground surface, which were recorded at Rajshahi station in the study area between 1961–2010, were obtained from the Bangladesh Meteorological Department (BMD). Data related to the irrigation cost, irrigation area, and groundwater level in 116 irrigated paddy fields were obtained from the Bangladesh Rural Advancement Committee (BRAC) Research Centre.

Methodology

The steps to estimate the effect of increasing temperature on the groundwater level and irrigation cost were as follows:

1. A support vector machine (SVM) model was calibrated and validated to simulate the monthly average depth to groundwater level from the monthly total of rainfall, evapotranspiration, groundwater withdrawal, and irrigation return flow.
2. The calibrated SVM model was used to simulate the changes in depth to groundwater level due to changes in temperature.
3. A multiple linear regression (MLR) model was developed to simulate the irrigation cost from the depth of groundwater level and irrigated area.
4. The MLR model was used to estimate the changes in irrigation cost that result from the changes in the depth of groundwater level due to temperature rise.

In the present study, the actual crop evapotranspiration was obtained by multiplying the crop coefficient with the reference evapotranspiration value, which was estimated using the modified Penman formula (Doorenbos and Pruitt, 1977). The crop coefficient values for different growing stages of rice, provided by FAO, were used for this purpose (Brouwer and Heibloen, 1986).

Since groundwater is the only source of irrigation in the study area, the monthly amount of groundwater abstraction was considered equal to the net irrigation water required for a paddy field. The irrigation requirement in a paddy field was calculated using the FAO-56 model (Brouwer and Heibloen, 1986):

$$W_n = ET_c + W_{rs} - P_e \quad (1)$$

where W_n is the net irrigation water requirements (mm d^{-1}), ET_c is the crop evapotranspiration from the paddy field (mm d^{-1}), W_{rs} is the total amount of water required for land preparation and seepage loss from the paddy field (mm d^{-1}), and P_e is the effective precipitation (mm month^{-1}). Details of the irrigation requirement estimation are provided in Shahid (2011).

The irrigation return flow to groundwater or the water loss through percolation from the rice field was calculated from soil data. Following Brouwer and Heibloem (1986), the percolation loss for sandy, clayey and loam soils is 8, 4 and 6 mm d^{-1}, respectively.

Various conceptual and process-based modeling techniques have been developed and successfully used to simulate groundwater levels in various hydrogeological settings (Coppola *et al.*, 2003, 2005; Coulibaly *et al.*, 2001; Uddameri, 2007). However, physically based models are highly data intensive, which hinders their application in data-scarce regions (Nikolos *et al.*, 2008). Therefore, empirical models are often suggested for hydrological modeling in data-poor regions (Shortridge *et al.*, 2016). Recent studies have reported the impressive predictive accuracy of empirical models based on machine learning methods in groundwater level simulation (Behzad *et al.*, 2010; Mohanty *et al.*, 2010; Shortridge *et al.*, 2016). Among the machine learning methods, SVM performs better in groundwater level simulations because it can model highly non-linear relationships (Behzad *et al.*, 2010; Sudheer *et al.*, 2011; Raghavendra and Deka, 2015; Tapak *et al.*, 2014). Therefore, SVM was used to model the functional (f) dependence of groundwater level (y) on different independent variables (x_i),

$$y = f(x_i) = \boldsymbol{w}\phi(x_i) + b \tag{2}$$

where $\boldsymbol{w}$ and b are the weight vector and bias, respectively; ϕ is a nonlinear transfer function that maps the input vectors into a high-dimensional feature space, where a simple linear regression can theoretically cope with the complex non-linear regression of the input space. The SVM solves the nonlinear regression function using an optimization problem with an ε insensitivity loss function,

$$\frac{1}{2}(\boldsymbol{w}^T\boldsymbol{w}) + C\sum_{i=1}^{N}\xi_i + C\sum_{i=1}^{N}\xi_i^* = 0 \tag{3}$$

The function can be minimized using the following criteria:

$$\boldsymbol{w}^T\phi(x_i) + b - y_i \le \varepsilon + \xi_i^* \tag{4}$$

$$y_i - \boldsymbol{w}^T\phi(x_i) - b \le \varepsilon + \xi_i \tag{5}$$

$$\xi_i\xi_i^* \ge 0,\ i = 1,\ 2,\cdots\cdots N \tag{6}$$

where ξ_i and ξ_i^* are slack variables, which are the distance of the training data set points from the region to an error tolerance ε. The trade-off between the flatness of $f(x_i)$ and deviations greater than ε is depicted by $C > 0$, where C is a positive constant that indicates the degree of penalized loss when there are errors during training.

In the present study, the monthly total rainfall, crop evapotranspiration, groundwater abstraction and irrigation return period from the paddy field were used as input variables to predict the groundwater level using the SVM. The SVM model was developed using the *e1071* package of the statistical software program R. Separate SVM models were developed to predict the depth to groundwater table at different locations. The models were calibrated and validated with the observed data for the period of 1991–2009. Seventy percent of the observed data was used for the model calibration, and the remaining thirty percent was used for the validation. The accuracy of the SVM model principally depends on the selection of the model parameters such as the kernel type (γ), regularization parameter (C) and epsilon value (ε). In the present study, the grid search algorithm available in the R software was used with a K-fold cross-validation to find the optimal parameters using the error computed from the training data. The radial bias function (RBF) kernel was found most suitable at all locations, and the optimal values of C and ε were 91–102 and 0.09–0.15, respectively. The calibrated and validated SVM models were used to project the depth to groundwater level due to the changes in evapotranspiration under different temperature increase scenarios.

An MLR model was developed to relate the irrigation cost with the irrigated area and depth to groundwater table. The model was calibrated and validated with the irrigation cost data from 116 irrigation paddy fields in the study area.

RESULTS AND DISCUSSION

SVM model calibration and validation

Figure 2 shows the relationship between the observed and simulated groundwater levels during the calibration and validation of the SVM model at representative locations in the study area. Figure 2 shows that the observed and simulated groundwater levels are consistent for the entire period. Table I shows the estimated statistical indices from the observed and simulated groundwater levels at all locations. The root mean square error (RMSE) values between the observed and simulated groundwater levels (0.96–2.56) were less than 50% of the standard deviation of the groundwater level; coefficient of determination R^2 (0.58–0.70) and Nash-Sutcliff efficiency (NSE) (0.55–0.70) were greater than 0.5 in all cases. Moriasi *et al.* (2007) reported that an NSE greater than 0.5 and an RMSE less than 50% of the standard

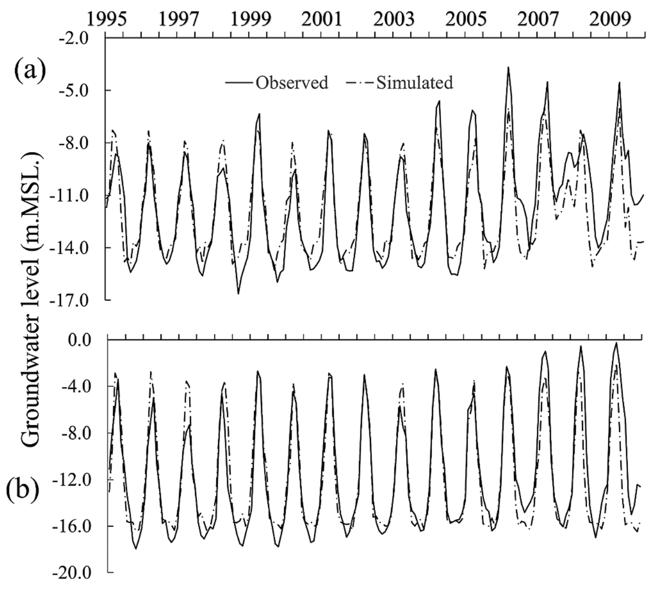

Figure 2. Observed and simulated groundwater levels above the mean sea level (MSL) during the model calibration and validation at two locations: (a) Bagmara; (b) Durgapur

Table I. Root Mean Square Error, Coefficient of Determination and Nash-Sutcliff Efficiency values during model calibration and validation

Station Name	Calibration			Validation		
	RMSE	NSE	R^2	RMSE	NSE	R^2
Bagha	0.96	0.59	0.59	0.94	0.58	0.59
Tanore	1.29	0.63	0.64	1.31	0.62	0.63
Bagmara	2.56	0.69	0.70	2.55	0.70	0.72
Godagari	2.11	0.57	0.58	2.16	0.56	0.58
Paba	2.36	0.55	0.56	2.39	0.55	0.56
Mohonpur	2.01	0.62	0.63	2.05	0.60	0.62
Charghat	1.17	0.70	0.70	1.15	0.69	0.70
Durgapur	1.74	0.63	0.65	1.74	0.62	0.64
Puthia	1.59	0.68	0.69	1.57	0.68	0.69
Boalia	0.96	0.59	0.59	0.94	0.58	0.59

deviation of the dependent variable indicate an acceptable performance of the model. Therefore, the SVM effectively simulated the groundwater level, and it can be used for future projections of groundwater tables due to the increase in temperature.

Sensitivity analysis using the SVM model

The calibrated and validated SVM model was used to assess the sensitivity of the groundwater level to rainfall and evapotranspiration. A sensitivity analysis was performed by measuring the variation in model output due to the variations in model inputs such as the rainfall and evapotranspiration. Thus, the rainfall and evapotranspiration values in the model were separately varied, while all other parameters remained constant. It was observed that an increase in evapotranspiration in the reference period (1991–2009) due to 1°C increase in temperature decreased the groundwater level during the irrigation period by 1.02%. Furthermore, a 1% increase in rainfall from the same reference period increases the groundwater table by 0.05%. This result indicates that the groundwater level in the study area is more sensitive to temperature than to rainfall.

Rainfall during the irrigation period mainly occurs in March and April as thunderstorms. The short and intense rainfall produces more runoff than groundwater recharge. Therefore, the increase in pre-monsoon rainfall does not significantly affect the groundwater recharge. IPCC (2007) also reported that a 9% increase in runoff due to short intense rainfalls increases groundwater recharge by only 2%. Furthermore, the rainfall interception by leaves in vegetated paddy significantly reduces the groundwater recharge. On the other hand, the temperature is higher in March and April than in other months, which causes more evapotranspiration from paddy fields. Because evapotranspiration is directly related to the temperature, higher evapotranspiration decreases the soil moisture, groundwater recharge, and consequently groundwater level. Therefore, the groundwater level in the study area is more sensitive to temperature than to rainfall. Chen *et al.* (2004) also reported that the sensitivity of groundwater to temperature increased for higher temperature.

Effect of the increasing temperature on the groundwater level

The temperature values were changed in the SVM model to estimate the effect of increasing temperature on the groundwater level. The groundwater withdrawal for irrigation and the return flow from the irrigated crop field were assumed unchanged in the future. Furthermore, the rainfall was considered identical to the historical rainfall to assess the effect of temperature only. Changes in groundwater level under five temperature rise scenarios were considered: 1°C, 2°C, 3°C, 4°C and 5°C rise compared to the historical period (1991–2009).

The capability of predicting future climate changes by a model calibrated with historical climate is often doubtful. The model in the present study was calibrated using the K-fold cross-validation procedure, which provides a mechanism to evaluate the generalization of a model to an unseen dataset (Elshorbagy *et al.*, 2010; Shortridge *et al.*, 2016). Therefore, the model can be used to predict the groundwater level at unseen temperature levels. Furthermore, the model output was used to provide a general trend in the change in groundwater level under different temperature increase scenarios, instead of predicting a particular event.

The changes in groundwater level under the five temperature rise scenarios are shown in Figure 3. The results show that the groundwater level decreases by 0.15–2.01 m, with an average of 1.04 m, during the irrigation months (January to April) under different temperature change scenarios. However, the changes in groundwater level are statistically significant at the 95% confidence level only for a temperature increase of at least 2°C.

The MLR model was developed to relate the irrigation cost with the irrigated area and depth to groundwater table. The coefficients of the MLR model parameters, which are the irrigation area and groundwater table depth, are 1.12 and 0.27, respectively. Both coefficients were found significant at $p < 0.01$. The scatter plot of the observed irrigation cost and simulated irrigation cost obtained using the MLR model is shown in Figure 4a. The figure shows that most points are aligned along the diagonal line, which indicates the good

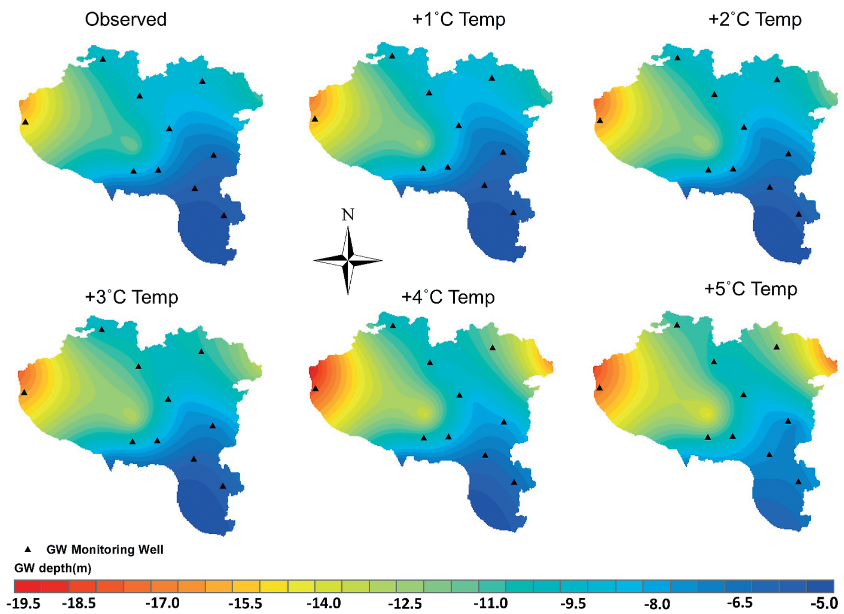

Figure 3. Changes in groundwater table depth during the irrigation period (January to April) under different temperature change scenarios

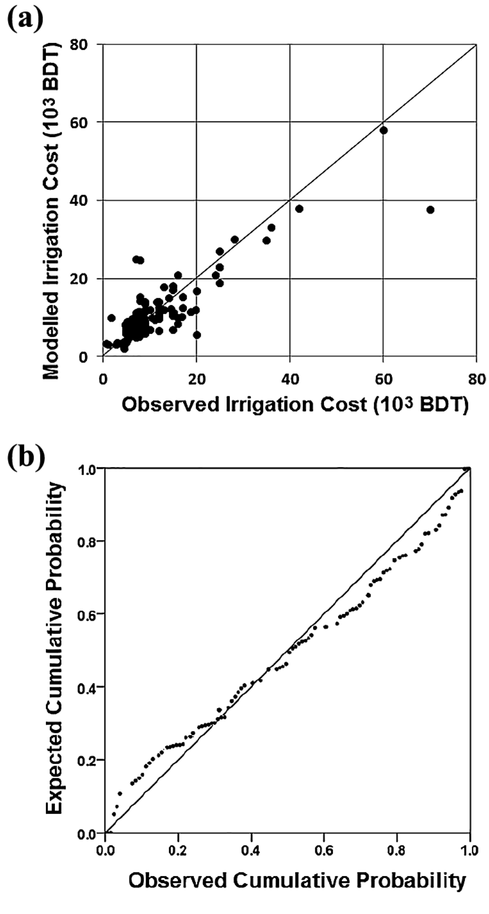

Figure 4. (a) Scatter plot of the observed irrigation cost and simulated irrigation cost obtained using the MLR model; (b) probability (P-P) plot of model residuals against a theoretical normal distribution

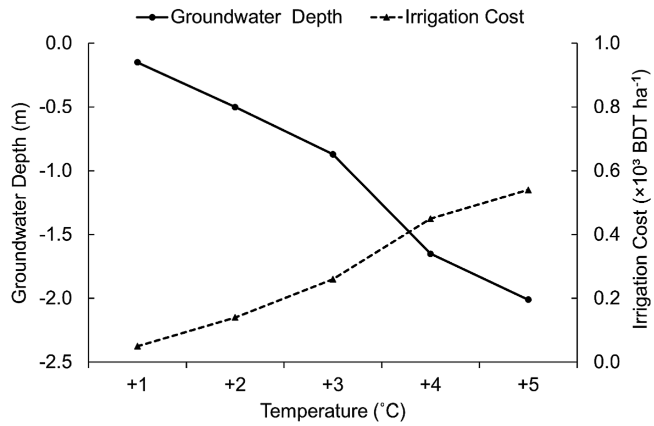

Figure 5. Changes in irrigation cost due to the changes in depth to groundwater table during the irrigation period (January to April) under different temperature change scenarios

prediction capability of the model. The distribution of model residuals also shows a normal distribution (Figure 4b). Therefore, the MLR model can be used to reliably predict the irrigation cost.

The simulated groundwater table depth values were used in the MLR model to estimate the effect of the decrease in groundwater level on the irrigation cost under different scenarios of temperature increase. The obtained results are shown in Figure 5. The results show that a decrease in groundwater level by 0.15–2.01 m caused an increase in irrigation cost of 0.05–0.54 thousand BDT ha^{-1}. Therefore, climate change will directly affect the crop production cost and farmer profits in the study area. However, the changes in irrigation cost due to the decrease in groundwater level were not statistically significant.

CONCLUSIONS

This paper assesses the effects of increasing temperature on groundwater levels and irrigation costs in a groundwater-dependent irrigated region in Northwest Bangladesh. The results show that the average groundwater level during the major irrigation period (January-April) decreased by 0.15–2.01 m because of an increase in temperature of 1–5°C, which increased irrigation costs by 0.05–0.54 thousand BDT ha^{-1}. The findings of the study are expected to be helpful for adaptation studies and adoption of necessary mitigation measures.

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