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A salinity projection model for determining impacts of climate change on river ecosystems in Taiwan

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SUMMARY

Climate change would impact ecosystems in many different ways, including alteration of hydrological conditions. The purpose of the research described in this paper is to determine the potential impacts of climate change on river ecosystems by mathematically simulating changes in salinity. Salinity, which is highly related to the relative abundance of particular organisms in the river and estuary wetland ecosystems, is a good indicator for impacts of climate change. The salinity projection model described in this research uses back-propagation neural networks, a robust method to simulate water quality conditions, to simulate salinity changes at several locations in a Taiwanese river. The results show the increase of salinity among all study sites under all climate change scenarios. We relate this to aquatic organism population effects by noting the threats of increased salinity on blockages or competition in some areas among species. Riparian mangroves and wetland plants near the river mouth may face increased stress due to the increased salinity concentrations. This tool allows a potential threat caused by salinity change to be analyzed as precautionary information for water resources and river ecosystem management.

1. Introduction

The impacts of climate change on air temperature, precipitation rates, and overland runoff has been well-documented globally, including in Taiwan (Daufresne et al., 2003; Dudgeon, 2011; Meyer et al., 1999; Suen, 2010; Wrona et al., 2006). The changing climate is expected to continue into the foreseeable future, increasing the vulnerability of river ecosystems (Arthington et al., 2010; Palmer et al., 2008). In Taiwan, the surface temperature has increased approximately 1.0–1.4 °C over the last 100 years (Hsu and Chen, 2002). The annual precipitation has increased in northern Taiwan, and declined in central and southern Taiwan during the past 80 years (Yu et al., 2006). The changing climate also has shown some impacts on river ecosystems in Taiwan. More-frequent habitat disturbances of higher magnitudes have caused shift in aquatic organism distributions and population decline (Chiu, 2009; Han et al., 2007).

Future climate change may cause further damage to river ecosystems, though the response of organisms varies depending on their sensitivity, vulnerability, and adaptive capacity to the environmental changes (IPCC, 2007). In assessing future climate change impacts on river ecosystems, much attention has been paid by some researchers to increasing temperature trends, whereas others discuss extreme streamflow events (Meyer et al., 1999; Palmer et al., 2009). While water quality (e.g. dissolved oxygen, nitrogen and phosphorus concentrations, etc.) impairments due to future streamflow variations could potentially affect aquatic ecosystems (Poff et al., 1996; Mimikou et al., 2000; Holmberg et al., 2006; Rehana and Mujumdar, 2011; Astaraie-Imani et al., 2012), very little research focuses on direct effects of salinity changes. Although salinity variation imposes a natural stress on river ecosystems, anthropogenic or climate change related influences may exacerbate these stresses to the aquatic organisms (Gilman et al., 2008; Horrigan et al., 2005; James et al., 2003).

Natural variation of the salinity gradient from river mouth to upstream areas changes daily and seasonally in response to streamflow and tidal influences and interactions, but the physical mechanism is not easy to model. Several hydrodynamic models have been developed to simulate salinity variation and applied to mangrove spreading (Azevedo et al., 2010; Liu et al., 2007; Shih et al., 2011; Teh et al., 2008). At the same time, artificial neural network (ANN) models have also been used to simulate salinity gradient along the rivers. Because ANN models can perform well with limited inputs and data sets, recently some researchers have used such models to simulate water quality or salinity to predict future trends under climate change scenarios (Bowden et al., 2005b; He et al., 2011). These water quality/salinity models are then used to assess the impacts on river ecosystems (Herricks and Suen, 2006; Horrigan et al., 2005; Liu et al., 2007; Shih et al., 2011; Teh et al., 2008).

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This study develops an artificial neural network model to project future salinity concentration in a river under assumed climate change influences. Fig. 1 shows the flowchart of this study. Five inputs are used for the simulation. Precipitation data sets from seven general circulation models resulting in change of hydrological conditions comprise the probability distribution for understanding the future salinity range and the resulting impacts on river ecosystems. The model may identify precautionary measures for riparian land-use planning and water resources management.

2. Materials and methods

2.1. Study area and data set

The study area is the Puzih River, located in southwestern Taiwan (Fig. 2). The river originates on Mt. Ali and flows for 76 km with an average slope of less than 2% to the Taiwan Strait on the west side of Taiwan. The Puzih River has a drainage area of 426 km^2. It provides water for agriculture, aquaculture, and municipal and industrial consumption. The average annual precipitation in this part of Taiwan is 1855 mm, but the monsoon-type weather patterns concentrate rainfall to May through October. On average, there are approximately 122 days of precipitation per year.

The Puzih River was one of the most polluted rivers in Taiwan in the early 1990s. In response, the Taiwan Environmental Protection Agency (EPA) started the Puzih River Basin Pollution Control Project in 2002. The project resulted in the addition of several wastewater treatment facilities in efforts not only to improve water quality but also to provide ecological recreation areas to serve as habitat for mangroves and other wetland and riparian plants.

Water quality monitoring data throughout the river are usually collected by Taiwan EPA once per month. Data from six of these water quality monitoring stations were used in this study. The selected stations span the length of the river. Because the tidal influence extends approximately 26 km upstream from river mouth, three of the stations are in the tidal reach section (Table 1). The longitudinal salinity gradient along the Puzih River exponentially decreases with upstream location; the other three stations are located in this gradient zone. For each station, an artificial neural network model was developed to project future salinity concentrations and determine the potential impacts on river ecosystems.

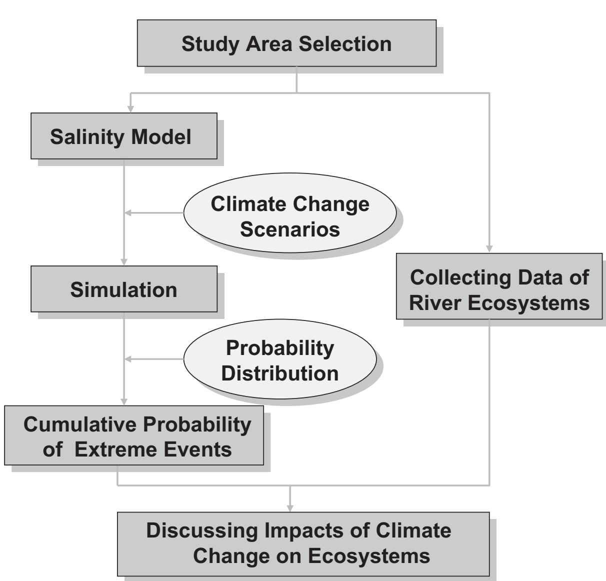

Fig. 1. Research flowchart.

Several wetlands are situated along the Puzih River. Some plants in these wetlands, including mangroves, are sensitive to the salinity concentrations. Such stenohaline species have evolved over time to tolerate an optimal range of salinity conditions; anything beyond the ideal range is essentially lethal. Fig. 3 shows the relationship between the species population survival and salinity gradient levels. The wetland and riparian areas of the Puzih River are populated by *Kandelia obovata* Sheue, Liu, & Yong., *Avicennia marina* (Forsk.) Vierh., *Lumnitzera racemosa* Willd., *Phragmites communis* (Cav.) Trin ex Steud., and *Typha angustifolia* L., all of which are stenohaline organisms. Table 2 shows the optimal and tolerable salinity ranges for these mangrove and wetland plant species.

2.2. Artificial neural network salinity model

This study uses an artificial neural network model for projecting salinity changes under different climate change scenarios. The ANN research of recent years has attempted to mimic natural neural networks to attain the advantages of their flexible and powerful calculating abilities. ANN models are well developed and have been applied widely in various hydrologic contexts (Maier et al., 2010). A critical step in developing an ANN model is the selection of appropriate model inputs (Bowden et al., 2005a). Because this salinity model is going to be used for projecting future salinity concentration gradients, all the model inputs require estimated values of future conditions. For this reason, five model input parameters – two precipitation factors, sea level, tidal height, and Julian date number – are considered in this study. The model output variable is the salinity concentration at the monitoring station.

2.2.1. Precipitation

Future daily precipitation data are generated by statistically downscaling results from seven general circulation models (GCMs): CGCM3.1, CSIRO-Mk3.5, ECHAM5, GFDL-CM2.0, GFDL-CM2.1, MRI-CGCM2.3.2, and MIROC3.2 (Chu and Yu, 2010). These seven GCMs could reasonably project the future weather conditions in East Asia and Taiwan (Chu and Yu, 2010). For each GCM, two time periods (2010–2045 and 2080–2100) are considered and 200 years of daily precipitation are generated for each period to represent the statistical characteristics of future climate.

High precipitation generally increases streamflow, resulting in rapidly decreased salinity concentrations in rivers. Accordingly, long periods of no precipitation and associated low streamflow causes gradually increasing salinity concentration. In order to capture the characteristics of rapidly decreasing and gradually increasing salinity concentration change, two precipitation inputs, *cumulative precipitation factor* (CPF) and *cumulative non-precipitation factor* (CNPF), are considered. The CPF is defined as:

$$\mathrm{CFP} = \sum_{i=0}^{n-1} w_i \times r_i \tag{1}$$

where n is the number of the cumulative days of precipitation; r_i is ith day's precipitation prior to the sampling day and r_0 is the sampling day's precipitation; w is the influence factor and $w_i = n - i$. The CNPF is defined as:

$$\begin{cases} d_i = 0, r_i > 0 \\ d_i = x, r_i = 0 \end{cases} i = 0, \ldots, n-1$$

$$\mathrm{CNFP} = \sum_{i=0}^{n-1} w_i \times d_i \tag{2}$$

where x is the number of consecutive precipitation days. These two factors are the major manifestations of possible future climatic change. In this research, n is set to 60, because the correlation