Luo, Shuxin, and Ting Fong May Chui. "Annual variations in regional mangrove cover in southern China and potential macro-climatic and hydrological indicators." *Ecological Indicators* 110 (2020): 105927.

Annual variations in regional mangrove cover in southern China and potential macro-climatic and hydrological indicators

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Submitted to *Ecological Indicators* Mar 2019

Accepted 10 Nov 2019

Abstract

As previous studies often focus on single study site or only consider single climatic and hydrological factor, there is still a lack of regional studies that consider integrated effects from multiple climatic and hydrological factors on mangrove growth. Meanwhile, use of multi-year-averaged data can provide general relationships between mangrove growth and macro- climatic and hydrological conditions but often overlook the relationships at a finer temporal scale. Using data from 1990 to 2011, we extracted annual mangrove area from seven important mangrove nature reserves in Southern China. Annual and categorized variables of macro- climate and hydrology were also accordingly derived for each site (i.e., temperature, precipitation, solar radiation and evapotranspiration). Then we applied Kendall rank correlation and Bayesian regression to identify the relationships between mangrove variables and macro- climatic and hydrological variables. To investigate and validate the key factors that affect mangrove growth, we analyzed the changes in pattern of macro- climatic and hydrological conditions using Pettitt test and t test. We found that the tropical mangrove variables demonstrate very limited correlation, while the subtropical mangrove variables exhibit relatively strong correlation with precipitation and temperature. At a finer temporal scale (i.e., annual scale), the effects from precipitation show high dependence on the local salinity background and the salt tolerance of dominant species and are stronger not only in drier regions but also in drier periods. In subtropical regions, the increase in temperature is always positively correlated with mangrove expansion. The percentage of hot days (> 30 °C) in a year rather than cold days can better explain mangrove area variations. Our results indicate that it is reasonable to focus on subtropical regions when studying the effects from macro- climate and hydrology upon mangrove forests. Meanwhile, precipitation and temperature are the governing macro- climatic and hydrological factors on mangrove area variations. Although previous studies often found a positive relationship between precipitation and mangrove growth, the relationship is not necessarily positive at finer temporal resolution. While freezes are recognized as one of the main causes of mangrove die-back in many other parts of the world, indices based on hot weather may be more suitable in explaining and predicting mangrove area changes in warmer regions such as Southern China.

Key-words: mangrove forest cover; Southern China; remote-sensing; macro-climate; macro-hydrology.

1. Introduction

Mangroves grow in the intertidal zones in tropical and subtropical areas, and 42% of the global mangrove inventory is in Asia (Giri et al., 2011). They are capable of excluding salt, and thus can proliferate in saline and brackish water. They undertake high ecological values, improving the coastal water quality (MacDonnell, Zhang, Griffiths, & Mitsch, 2017), hosting various coastal species (Vo, Kuenzer, Vo, Moder, & Oppelt, 2012), and being used as fuel or furniture wood (Dinesh & Chaudhuri, 2013). However, there has been at least 35% of global mangrove loss from 1980 to 2000 (Valiela, Bowen, & York 2001) and a further loss of 192, 000 ha from 2001 to 2012, while Asia has the highest rate of loss (World Resources Institute, 2015). Anthropogenic effects such as deforestation (Richards & Friess, 2016), aquaculture development (Ilman, Dargusch & Dart 2016), urbanization (Tuholske, Tane, López-Carr, Roberts, & Cassels 2017), etc have been regarded as the main causes of mangrove loss. However, even in nature reserves with minimal direct human intervention, the growth of mangroves still fluctuates over time (Li, Mao, Shen, Liu, & Wei 2013) due to climatic and hydrological variations.

The growth of mangroves is largely influenced by climate and hydrology, particularly in subtropics in which there are seasonal changes. Climatic factors, such as temperature, precipitation and sunlight can alter mangrove composition and distribution in subtropical region (Chen, Peng, Li, Lin, & Zeng 2013; Eslami-Andargoli, Dale, Sipe, & Chaseling 2009; Lovelock, Clough, & Woodrow 1992; Osland et al., 2017; Saintilan, Wilson, Rogers, Rajkaran, & Krauss 2014). Hydrological process also is closely associated with climate and mangrove ecosystem. Hydrological processes, such as precipitation, evaporation, evapotransipiration and groundwater uptaken by mangroves (Teh, Koh, Deangelis, & Turtora 2013), are driven by climate, and they govern coastal hydrodynamics (e.g., surface water level, groundwater table depth and salinity) and influence the nutrient cycling for mangroves (Faridah-hanum et al., 2019).

Coastal wetlands such as mangrove ecosystems can be unstable, and their structures and functions could be largely altered by small changes in macro- climatic and hydrological conditions (Osland, Enwright, et al., 2016; Turner & Lewis, 1996). Some studies have confirmed that macroclimatic factors (e.g., temperature and precipitation) have nonlinear relationships with mangrove community transformation (Gabler et al., 2017). Other than climatic effects, Turner and Lewis (1996) found that hydrological changes due to declining freshwater supply brought about 40% loss of mangroves in Cienaga, Colombia. So far, previous studies have considered single climatic or hydrological factor (Osland et al., 2017; Quisthoudt et al., 2012) or have focused on single study site (Osland et al., 2017). Some studies have examined the responses of coastal wetland using mean values of decades, which provided useful implications that increasing temperature and precipitation can promote mangrove expansion at a long time scale (Eslami-Andargoli et al., 2009; Gabler et al., 2017). However, there is a strong need for an integrated study at regional scale with more detailed climatic and hydrological effects (e.g., category-based variables such as percentage of days with temperature above 15℃) and at finer temporal scale (e.g., annual scale) to further understand the effects from climate and hydrology on mangrove growth in a more comprehensive way. Based on the above knowledge, we hypothesized that climate and hydrology affect mangrove growth at a regional and also finer-temporal scale in subtropical region. We also expect stronger influence in subtropical region than in tropical region and site-specific responses from subtropical mangrove forests to macro- climatic and hydrological changes at a finer temporal scale.

Our study aimed to address the following questions: (1) in tropics or subtropics are the mangroves mostly influenced by macro- climatic and hydrological changes? (2) What are the key factors in macro- climate and hydrology affecting mangrove cover change? (3) How do these effects at a finer temporal scale differ from previous studies, especially the studies using mean values of decades? To address these questions, our investigation was conducted along the coastline of Southern China, where mangroves are distributed both in subtropics and tropics, rich in species diversity and regarded as a good choice for studying their responses to climatic and hydrological changes (Chen, Wang, Zhang, & Lin 2009). Similar to many other places in the world, the mangroves in China experienced dramatic decline due to rapid industrilization and urbanization last century. Apart from the most obvious and prominent cause, however, few studies considered the effects from climatic and hydrological changes on mangrove growth in China. This study aimed to develop comprehensive understanding of macro- climatic and hydrological effects on mangrove growth at regional scale in fine temporal resolution. The developed relationships shed light on the regional regulation of the macro- climate and hydrology on mangrove growth at annual scale. It can also be used to predict regional mangrove growth under assumed future macro- climatic and hydrological scenarios.

2. Methodology

2.1 Study sites

Mangroves in China covered more than 50 000 ha in 1950s (Lin, 1999), but declined more than 50% from 1957 to 1986 owing to rapid industrialization and urbanization (Zheng, Zheng, Liao, & Li 1995). After 1980s, along the coastline of Southern China, over twenty mangrove nature reserves were established one after another, of which six has been entitled “Ramsar Wetlands of International Importance”. However, there are few attempts to systematically analyse the climatic and hydrological effects on the China’s mangrove ecosystem. The six Ramsar sites and one important nature reserve in Taiwan were selected as study sites (Fig. 1). The six Ramsar sites are distributed in five provinces or special administrative region, namely Zhangjiangkou (Fujian), Mai Po (Hong Kong), Zhanjiang (Guangdong), Shankou (Gunagxi), Beilun (Guangxi), Dongzhaigang (Hainan). Danshui (Taiwan) is the largest and most complete mangrove forest in Taiwan. Dongzhaigang is the only one among the seven sites located in tropical region and is used to test whether tropical mangrove ecosystem is less influenced by macro- climatic and hydrological variations. These sites were selected because nature reserves are less human impacted and are better choices for research with natural factors. Meanwhile, the seven sites ranging from 20° N to 26° N and 107° E to 122° E are geologically far away from each other and demonstrate an environmental gradient in soil salinity, temperature, precipitation, solar radiation and evapotranspiration, etc, which ensures the diversity of study sites. The dominant mangrove species and average soil salinity are documented in Table 1. *Kandelia obovata* is the most common dominant species followed by *Avicennia marina* in the seven study sites, while Danshui and Dongzhaigang have lowest soil salinity. Except Zhanjiang and Shankou, the regions that analysed for mangrove forest in each study site cover the entire mangrove natural forest (Fig. 1). In Zhanjiang, extensive *Sonneratia apetala* were planted in the nature reserve for afforestation since 1990 (Ren et al., 2008). Therefore, a small patch of natural forest was selected as study area to minimize the human disturbance. In Shankou, only the mangroves in Yingluo Habour were selected because the other area is severely invaded by *Spartina alterniflora* (Wan et al., 2014).

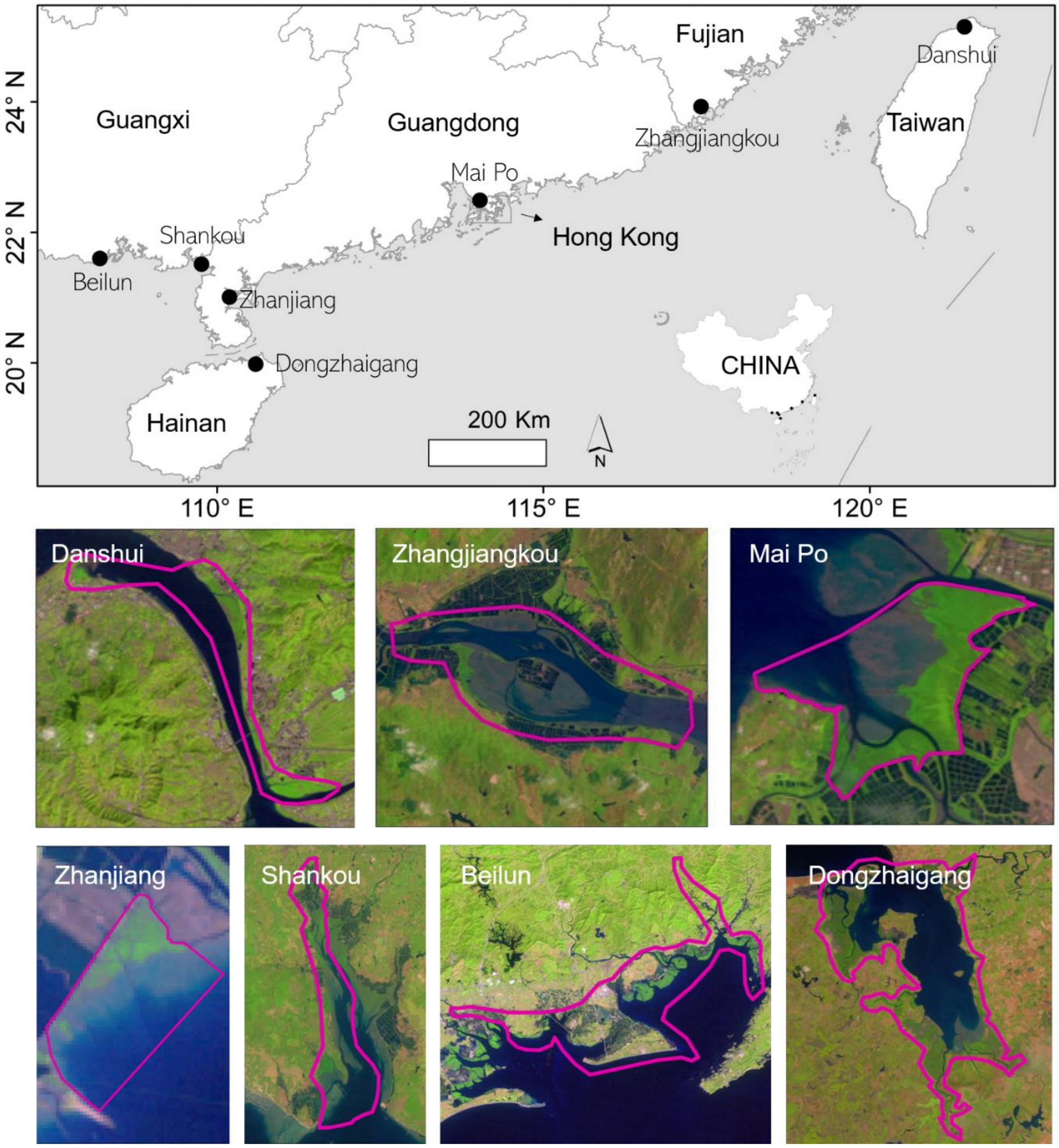

Fig. 1 Top: The distribution of selected mangrove nature reserves in Southern China. **Bottom:** the pink polygons highlight the regions analysed for mangrove cover.

Table 1 Dominant mangrove species and soil salinity of the seven study sites

Sites	Danshui	Zhangjiangkou	Mai Po	Zhanjiang	Shankou	Beilun	Dongzhaigang
Dominant mangrove species	*K. obovata* (Lee & Yeh, 2009)	*K. obovata; Aegiceras corniculatum* (Feng et al., 2017)	*K. obovata; A. marina* (AFCD, 2011)	*K. obovata; A. marina* (Ren et al., 2008)	*Rhizophora Stylosa; Bruguiera gymnorrhiza* (Wen, Liu, & Yuan 2002)	*A. corniculatum; A. marina* (Jia, Wang, Zhang, Ren, & Song 2015)	*R. stylosa; Bruguiera sexangular* (Huang et al., 2018)
Salinity (psu)	5 (Shiau, Dham, Tian, & Chiu 2016)	16 (Zhang et al., 2018)	10 (AFCD, 2011)	22 (Ren et al., 2008)	21 (Zheng, Chen, & Peng 1997)	9 (Luo, Su, Liu, Zhong, & Yang 2015)	5 (Li et al., 2016)

2.2 Data sets

Data used in this part mainly consist of mangrove area, climatic and hydrological data, which are listed in Table 2.

2.2.1 Mangrove area

Remote-sensing data: Mangrove area is used to approximate the mangrove growth status. To extract the mangrove area, we used the Landsat TM and ETM + level 1 products (L1TP) of the seven nature reserves from the USGS EarthExplorer website (https://earthexplorer.usgs.gov/). LITP files used in this study are of highest quality among Landsat TM/ETM+ level 1 products and are suitable for pixel-level time series analysis (USGS, 2018). Landsat TM and ETM+ imageries have a moderate resolution (i.e., 30 m) for spectral bands 1-5 and 7, covering visible, near infrared and shortwave infrared bands. We chose the good-quality Landsat images with as less cloud cover as possible as the primary data for extracting mangrove area.

Land cover map: To assess the accuracy of the extracted mangrove area, one land cover map of MP was employed as reference. The reference image was provided by AFCD (2004) containing mangrove extent derived from high-resolution IKONOS satellite images (i.e., 1 m) in Feb 2000, which was used to validate the extracted mangrove area in Dec 1999.

2.2.2 Climatic and hydrological data

Climate data including temperature, precipitation and solar radiation were obtained from NOAA Physical Science Division (NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, https://www.esrl.noaa.gov/psd/). Both temperature and precipitation data have a resolution of 0.5 degree across the globe. Solar radiation data have a resolution of 2 degree. All the data on daily basis were used for climatic variable derivation.

Evapotranspiration data were provided by the MODIS Global Evapotranspiration Project (MOD16, http://www.ntsg.umt.edu/project/modis/mod16.php). The evapotranspiration datasets of MOD16 were derived using Mu, Zhao, and Running (2011)'s algorism based on Penman-Monteith equation (Monteith, 1965). The datasets have a variety of intervals (i.e., 8-day, monthly and annual) and we chose the 8-day interval data for deriving potential evapotranspiration.

Table 2 Data inventory

Data	**Time**	**Source**	**Temporal resolution**	**Spatial resolution**	**Format**
Landsat imagery	1990–2011	USGS	1 yr on average	30 m	tif

Land cover	2000	AFCD (2004)	_	vector	shp
Climate data	1990–2011	NOAA	1 d	0.5° x 0.5° or 2° x 2°	netCDF
Evapotranspiration	2000–2011	MODIS Global Evapotranspiration Project	8 d	500 m	hdf

2.3 Mangrove area extraction

The extraction of mangrove extent using supervised maximum likelihood method is standard (Giri, Pengra, Zhu, Singh, & Tieszen 2007). Compared to other objects, the digital number (DN) value of band 5 (shortwave infrared) in Landsat TM/ETM+ images is lower in mangrove forests, which is useful to discern mangroves from other objects (Alsaaideh, Al-Hanbali, Tateishi, Kobayashi, & Hoan 2013). Therefore, the false-colour composite of band 5, 4 (near infrared) and 3 (red) of the images were used for selection of training areas, where mangroves appear in dark green and can be easily distinguished from other classes (Fig. 2). As the mangroves in nature reserves consisting of mainly mangrove plants, four major classes in the analysis region were chosen: mangrove, barren lands, flooded and water bodies. For regions with vegetation other than mangrove such as Danshui, another class (non-mangrove) was also applied. Training areas of each class were carefully selected across the study sites. Then, supervised classification was performed using maximum likelihood rule. To assess the accuracy of the classification results, a total of 150 validation points were randomly selected from the land cover map of MP following stratified random sampling (Fig. 2). The accuracy of mangrove class (i.e., correct predictions/total predictions) is 90.0%. Through lack of reference images, the accuracies of other classification results were not validated. Detailed description of the classification and validation method can be found in Giri et al. (2007) and Mondal, Trzaska, and De Sherbinin (2018).

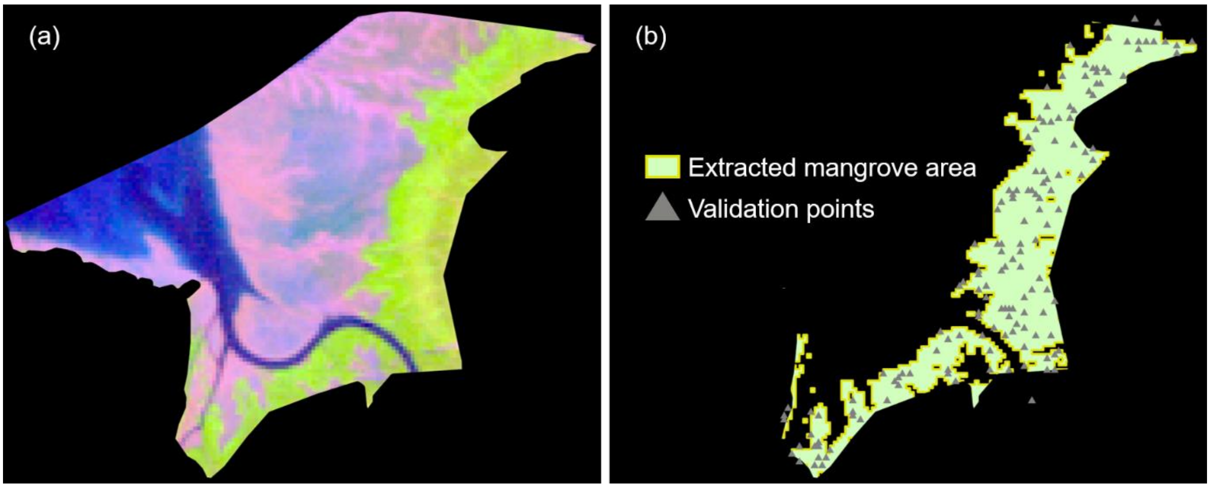

Fig. 2 Mangrove area extraction: (a) false color composite of Landsat TM bands 5, 4 and 3: mangroves appear in dark green; (b) the extracted mangrove area on 25 Dec 1999 and the validation points generated from reference image in Feb 2000 in Mai Po, Hong Kong.

To investigate the fine-temporal-resolution change, totally 154 images (1 image/year/site × 22 years × 7 sites) were processed for annual mangrove area in seven study sites from 1990 to 2011. The rate of change in mangrove area was also calculated by dividing the change over a year by area of previous year. The monthly distribution of images is shown in Fig. 3. Studies of extracting multi-decadal mangrove area often choose remote-sensing images acquired in winter or dry seasons, when the images with less clouds are mostly available across the years (Giri et al., 2007; Jia, Zhang, Wang, Song, & Ren 2014; Mondal et al., 2018)) and when the leaves of non-mangrove plants such as *S. alterniflora* turn yellow and can be easily discerned from mangrove plants (Zhang, Chen, & Wang 2015). During the entire study period, most images (~89%) of the study sites except Dongzhaigang and Danshui also come from Oct to Dec in dry seasons. However, in Dongzhaigang and Danshui, images available across the years mainly come from Jun to Aug in wet seasons (~68%). To further minimize the effects from clouds, different parts of images of close dates that are free of clouds were integrated together to produce one cloud free image. All the processing work was completed in ENVI 5.0.

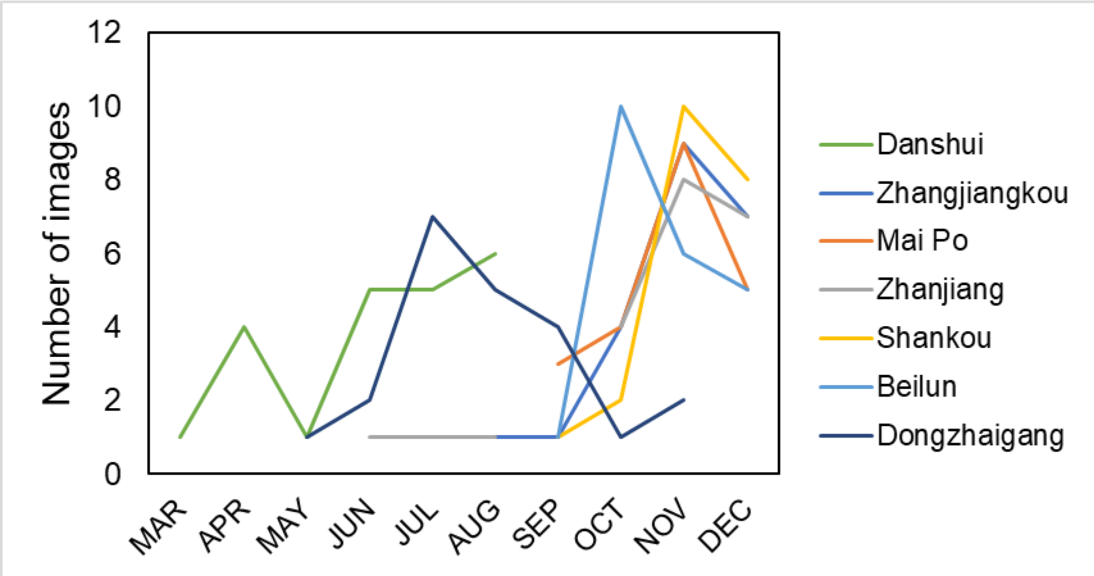

Fig. 3 Monthly distribution of Landsat TM/ETM+ images for seven study sites.

2.4 Macro- climatic and hydrological variables derivation

To examine the relationships between macro- climate and hydrology and mangrove cover, a total of 21 climatic and hydrological variables from four categories (i.e., temperature, precipitation, solar radiation and evapotranspiration) were derived in MATLAB 2016b and R software package. Annual indices were calculated for each category (i.e. annual mean air temperature (AT), annual total precipitation (AP), annual total solar radiation (AS), annual total evapotranspiration (AET) and annual total potential evapotranspiration (APET)). Based on prior studies in the literature (Eslami-Andargoli et al., 2009; Osland, Enwright, et al., 2016), we further classified the temperature and precipitation so that the derived variables can be used to better describe the patterns of the macro- temperature and precipitation in details. Temperature-based classified variables include percentage of days with temperature lower than 15 °C (tb15), minimum monthly mean temperature (minMT) and percentage of days with temperature higher than 30 °C (ta30) to describe the proportion of relatively cold/hot days for subtropical mangrove growth. Precipitation-based classified variables include percentage of days with precipitation higher than 10 mm (p10), percentage of days with precipitation higher than 25 mm (p25), percentage of days with precipitation lower than 1 mm (p01) to describe the proportion of wet/dry days. As climatic and hydrological data demonstrate high temporal variabilities, daily and monthly standard deviations of temperature (StdTd and StdTm), precipitation (StdPd and StdPm) and solar radiation (StdSd and StdSm) were also derived. 8-day standard deviations and means were used for evapotranspiration (StdETd and mET) and potential evapotranspiration (StdPETd and mPET) because MOD16's finest temporal resolution is 8-day. In this process, evapotranspiration data from MOD16 dataset with a spatial resolution of 500 m were resampled to the resolution the same as temperature and precipitation. Notably, to meet the acquiring dates of Landsat images, the annual periods of climatic and hydrological data do not necessarily follow calendar years. For example, the annual period of 1997 for Zhangjiangkou was from 1996-10-31 to 1997-11-18, which starts from the acquiring date of Landsat image in 1996 and ends on the day before the acquiring date in 1997.

2.5 Correlation test between mangrove area and macro- climatic and hydrological variables

Then, to test the concordance, Kendall rank correlations coefficient between mangrove area/rate of change in mangrove area and climatic and hydrological variables were determined. Kendall rank correlation coefficient, also known as Kendall's tau coefficient (τ), is a statistical parameter used to measure the ordinal association between two measured quantities (Eq. 1).

$$\tau = \frac{(number\ of\ concordant\ pairs) - (number\ of\ disconcordant\ pairs)}{\frac{n(n-1)}{2}} \tag{1}$$

where n denotes the total number of pairs to test the concordance. If the two rankings are perfectly matched, tau will be 1. If the two rankings are perfectly opposite, tau will be -1. Zero value of tau means no ordinal association between the two quantities. Considering the possible response time for the mangroves, the climatic and hydrological variables of the previous years were also examined. The more influential variables were identified and further tested using Pearson correlation coefficient for multicollinearity. Explanatory variables that are highly correlated with each other cause multicollinearity in multivariate regressions and should be carefully selected especially in complex ecological problems (Graham, 2003). To balance the regression performance and multicollinearity, among the highly correlated explanatory variable pairs ($r > 0.7$), the ones with lower correlation with mangrove cover were removed. Finally, at most five variables in the order of relevance to mangrove cover were chosen as candidate predictors in Bayesian regression analysis.

2.6 Key macro- climatic and hydrological factors identification

The causation of mangrove expansion or contraction can hardly be single. Therefore, based on correlation, we need more powerful tools to find the evidence of association from multiple causation (McElreath, 2016). To quantify the multiple associations between macroclimate and mangrove area in time sequence, we fitted a series of Bayesian models for each study site. Compared to simple linear regression models, Bayesian approach allows us to describe the uncertainty of the coefficient estimates, while the coefficients represent the level of influence from macro- climate and hydrology in this study. Meanwhile, Bayesian models help mitigate the common overfitting problem in time-series models by imposing a penalty on the posterior probability distribution via prior probability distribution of the variables (McElreath, 2016). The more influential macro- climatic and hydrological variables passing multicollinearity test were further organized and combined to form at most thirty-one (five variables can form 31 combinations: $C_5^1 + C_5^2 + C_5^3 + C_5^4 + C_5^5$) candidate Bayesian models for predicting mangrove cover. For sites that did not have five factors strongly correlated with mangrove cover and meanwhile less correlated with each other, less candidate Bayesian models were generated. Notably, the evapotranspiration data start from 2002, so they were not considered in the Bayesian model development.

Before model development, all the parameters were standardized by subtracting the mean and dividing by the standard deviation, so that the coefficient estimates can reflect the contribution of the variable on mangrove area. Rather than commonly used R square in simple linear models, Bayesian method uses the widely applicable information criterion (WAIC) to serve as the model selection criterion, which measures the relative model merit among all candidate models. The model with lowest WAIC was regarded as the best one that suits the subtropical mangrove ecosystem. The WAIC weight rescaling the WAIC values among all the candidate models was also calculated as in Eq. 2. The detailed method of selecting best models that suits the response variables can be found in Yang, Chui, Shen, Yang, and Gu (2018).

$$w_i = \frac{\exp\left(-\frac{1}{2}dWAIC_i\right)}{\sum_{j=1}^{m}\exp\left(-\frac{1}{2}dWAIC_j\right)} \tag{2}$$

where w_i denotes each WAIC weight; dWAIC denotes the difference between each WAIC and the lowest WAIC.

To further investigate and validate the effects from the key factors in Bayesian model, Pettitt test was performed to analyze the changes in pattern of macro- climatic and hydrological factors. Pettitt test is a non-parametric approach and often used to detect the change point in climatic or hydrological time-series data (Pettitt, 1979). As soon as a change point was detected, t test was used to compare the means of the relevant variables before and after the change point.

After confirmation of the change point through t test, the relationships between mangrove area and macro- climatic and hydrological variables were analysed separately using Bayesian regression in different climatic or hydrological patterns.

3. Results

3.1 Evolution of mangrove area in Southern China

The evolution of mangrove area from 1991 to 2011 of the seven study sites in Southern China is shown in Fig. 4. As illustrated in this figure, the average area of each site is of different size, ranging from tens to hundreds of hectares. The mangrove area in Zhangjiangkou decreased for the first 5 years and finally increased by about 37.0% compared to the area in 1991. The mangrove area in Mai Po demonstrated a general increase during the study period, but the inter-annual variation of mangrove area was very different at the first and last half of the period. Before 2003, the rate of change in mangrove area varied significantly, indicating an unsteady increment or reduction year by year, while after 2003, the change in mangrove area started to stabilize. This is also seen in Dongzhaigang, though Dongzhaigang ended up with the largest increase in area of about 438.8 ha (i.e., 38.2%) based on its largest extent of all time. Shankou went through a modest increase in the two decades with obvious inter-annual fluctuations. The biggest increase in percentage occurred in Beilun, whose mangrove area increased to more than twice of that 21 years ago. By contrast, the area of natural mangrove forest in Zhanjiang and Danshui underwent frequent ups and downs around a value slightly above the initial area during the 21 years, except that Danshui showed an upward trend in the last three years. Although the mangrove area in all the study sites increased from 1991 to 2011 as a whole, it should be noted that all sites experienced evidently interannual fluctuations in mangrove area during the entire study period, especially obvious from the rate of change. Danshui even experienced a 26.1%

decrease in 1993. These results indicate that even in nature reserves with minimum human interference, the mangrove cover still fluctuates over time, which is most possibly because of the effects from natural factors.

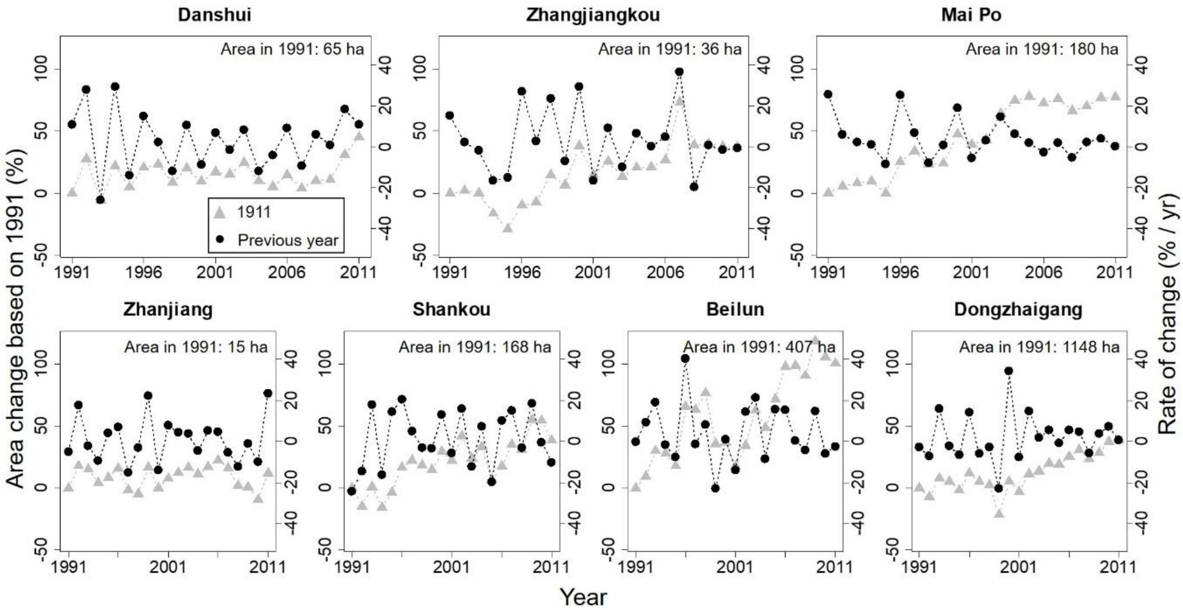

Fig. 4 The evolution of mangrove area from 1991 to 2011 in Southern China. The left axes describe mangrove area change based on the area in 1991 and the right axes describe rate of change in mangrove area based on the area of previous year.

3.2 Macro- climatic and hydrological features

In this study, we used macro- climatic and hydrological variables at a finer temporal scale. We further averaged and summarized the derived annual variables for each site as described in Sec 2.4, and these averaged values are shown in Table 3. As expected, the seven study sites showed an environmental gradient in temperature, precipitation, solar radiation, evapotranspiration and potential evapotranspiration. Temperature, precipitation and solar radiation were generally higher in more southern regions, with ranges of 21.7 to 25.1 °C, 1372.3 to 1804.1 mm, 46.5 to 70.4 × 10^3 kw/m^2, respectively. However, evapotranspiration and potential evapotranspiration ranging from 751.8 to 1008.7 mm and 1451.4 to 1622.7 mm, respectively, did not follow a latitude-based distribution, mainly because they are also affected by other atmospheric and terrestrial factors such as wind, vegetation type and land fertility, etc (Allen, Pereira, Raes, & Smith 1998). Zhangjiangkou is located in the driest region among the seven study sites, for its lowest aridity index (i.e., annual precipitation / potential evapotranspiration ratio) in the two decades (UNEP, 1992).

Table 3 The macro- climatic and hydrological properties of the seven study sites.

Sites	T (°C)	P (mm)	S (× 10^3 kw/m^2)	ET (mm)	PET (mm)
Zhangjiangkou	21.7	1372.3	46.5	975.6	1622.7
Mai Po	23.6	1451.6	55.9	1008.7	1567.1
Zhanjiang	24.1	1469.6	66.3	756.1	1451.4
Shankou	23.9	1502.5	69.9	751.8	1495.4
Beilun	22.9	1526.3	70.4	964.4	1453.0
Danshui	23.3	1804.1	58.4	978.7	1524.0
Dongzhaigang	25.1	1740.9	69.8	984.8	1517.8

* T denotes temperature; P denotes precipitation; S denotes solar radiation; ET denotes evapotranspiration and PET denotes potential evapotranspiration. All the data are multidecadal averages, and the annual periods for the years do not necessarily follow calendar years in order to meet the acquiring dates of Landsat images.

3.3 Kendall correlation with macro- climatic and hydrological variables

Dongzhaigang demonstrates very limited correlation among the variables, while the mangrove variables of other sites exhibit relatively strong correlation with variables from the four categories (i.e., temperature, precipitation, solar radiation and evapotranspiration) (Fig. 5). It therefore is concluded that tropical mangrove ecosystem is less influenced by macro- climatic and hydrological variations, and it is reasonable to focus on subtropical regions when studying the effects from macro- climate and hydrology upon mangrove forests.

From the correlation results with mangrove area, we found that solar-radiation- and evapotranspiration- based variables barely show correlations with mangrove area. Daily standard deviation of solar radiation and mean 8-day evapotranspiration solely show a positive effect on mangrove growth in Danshui (tau = 0.40, $p < 0.05$) and Shankou (tau = 0.72, $p < 0.01$), respectively. Meanwhile, precipitation-based variables were found to have most impact on mangrove growth followed by temperature-based variables. From the correlation results of Mai Po, Zhanjiang and Beilun, the increase in precipitation, as well as the variation of precipitation may hinder the mangrove growth of both the same year and the following year. Especially for Mai Po, where a strongly negative correlation with annual precipitation (tau = -0.62, $p < 0.001$) is noted, and Beilun, where a significantly positive correlation with the percentage of dry days (tau = 0.53, $p < 0.001$) is also noted. Even in Dongzhaigang, we observed a slightly positive correlation with percentage of dry days of previous year (tau = 0.32, $p < 0.05$). On the other hand, the increase in precipitation, as well as the variation of precipitation in Zhangjiangkou and Shankou was found to possibly facilitate the mangrove growth of both the same year and the following year. It should also be noted that there are no correlations in Danshui between mangrove area and the precipitation variables. The correlations between mangrove area and temperature related variables are rather consistent that increase in temperature tends to favour mangrove expansion.

In contrast, the correlations with rate of change are much weaker than those with mangrove area and appear to be random, indicating rate of change per se may not be a good choice of mangrove variable in time-series regression analysis.

Fig. 5 Kendall correlation results. AT – Annual average of air temperature (°C); AP –Annual total precipitation; AS – Annual total solar radiation (kw/m^2); AET – Annual total evapotranspiration (mm/yr); APET – Annual total potential evapotranspiration (mm/yr); StdT, StdP, StdS – Standard deviation of average temperature (°C), total precipitation (mm) and total solar radiation (kw/m^2), respectively. The suffixes "-d" and "-m" represent daily and monthly, respectively; StdETd, StdPETd - 8-day standard deviation of total evapotranspiration (mm/8d) and total potential evapotranspiration (mm/8d), respectively; tb15 – Percentage of days with temperature below 15 °C (%); ta30 – Percentage of days with temperature above 30 °C (%); minMT – Lowest monthly average of temperature (°C); p10 – Percentage of days with precipitation higher than 10 mm (%); p25 – Percentage of days with precipitation higher than 25 mm (%); p01 – Percentage of days with precipitation lower than 1 mm (%). The suffix "-p" means variables from previous year.

3.4 Bayesian regression models for mangrove area

To further investigate the joint effects from high-impact variables and to identify the key macro- climatic and hydrological factors, we developed Bayesian models for each subtropical study site and selected the best ones according to the WAIC weight for explaining the mangrove area variation. The numbers of candidate models developed for Danshui, Zhangjiangkou, Mai Po, Zhanjiang, Shankou and Beilun are 7, 31, 31, 31, 3 and 15, respectively. Higher WAIC weight indicates that the model has the highest possibility to be the best one among all the candidate models. The models, parameters and WAIC weights are listed in Table 4. It should be noted that the WAIC weights are the weights among the candidate models in each site, so the WAIC weights of different sites cannot be compared together. All the parameters have been scaled before model development, so that the coefficient of each parameter can reflect the contribution of the variable on mangrove area. Among a number of variables passing Kendall and Pearson tests, only one to three variables, referred to as predictors in Table 4, were eventually selected as key factors and combined together to form the best model for each study site in Bayesian regression. These selected factors are all either precipitation- or temperature-based. Of the six subtropical sites, four sites show that temperature-based variables are the key factors influencing mangrove area. The absolute value of scaled effects (i.e., the coefficients) from temperature-based variables ranges from 0.04 to 0.08, where the percentage of temperature above 30 °C in a year shows highest impact. Similarly as in the correlation tests, these equations also show that the increase in temperature favours the mangrove area expansion. For all study sites except Danshui, precipitation-based variables are regarded as key factors in explaining mangrove area variations. The absolute value of scaled effects (i.e., the coefficients) from precipitation is generally higher than that from temperature, ranging from 0.05 to 0.11. Besides, the Bayesian analysis confirmed that the effects from precipitation differ in study sites. In Mai Po, Zhanjiang and Beilun, the increase in precipitation would result in an increase in mangrove area, while the opposite is observed in Zhangjiangkou.

Table 4 Bayesian regression models with best performance in each subtropical site. The meaning of the predictors can be found in the caption of Fig. 5.

Study Site	Predictor	Equation	a1	a2	a3	c	No. of candidate models	WAIC weight
Danshui	ta30	log (Area) = a1* ta30+c	0.068	-	-	4.280	7	0.29
Zhangjiangkou	APp, tb15p, ta30p	log (Area) = a1*APp+a2*tb15p+ a3*ta30p+c	0.084	-0.079	0.085	3.737	31	0.34

Mai Po	p10p, AP	log (Area) = a1*p10p+a2*APp+c	-0.076	-0.103	-	5.553	31	0.23
Zhanjiang	p10, ATp	log (Area) = a1*p10+a2*ATp+c	-0.048	0.040	-	2.805	31	0.38
Shankou	StdPdp	log (Area) = a1*StdPdp+c	0.096	-	-	5.306	3	0.66
Beilun	p01, ta30	log (Area) = a1*p01+a2*ta30+c	0.108	0.084	-	6.460	15	0.36

In Fig. 6, the comparison between estimated and extracted mangrove area is shown. The general trends of extracted mangrove area for the six subtropical sites are well captured by the Bayesian models. Most of the extracted area data fall within the 95% confidence interval of estimated mangrove area. Several points of extracted mangrove area are lower than the estimated values and even fall outside the uncertainty intervals, such as the data in 1995 in Zhangjiangkou and in 1994 in Danshui. This is most possibly because some environmental factors that were not considered in the equations impeded the mangrove expansion, such as oil spill, pollution and super typhoon, etc (Fan, 2008). For example, oil leakage from vessels or other sources may lead to tree mortality, leaf defoliation and seedling deformation, etc in nearby mangrove forests (Getter, Scott, & Michel 1981). Excessive heavy metals in industrial effluent are also harmful for mangrove growth (MacFarlane & Burchett, 2002). Supper typhoon can even destroy 30% of the mangrove trees in a short amount of time (Kauffman & Cole, 2010). Other extreme environmental events resulting in mangrove contraction can be found in Fan (2008).

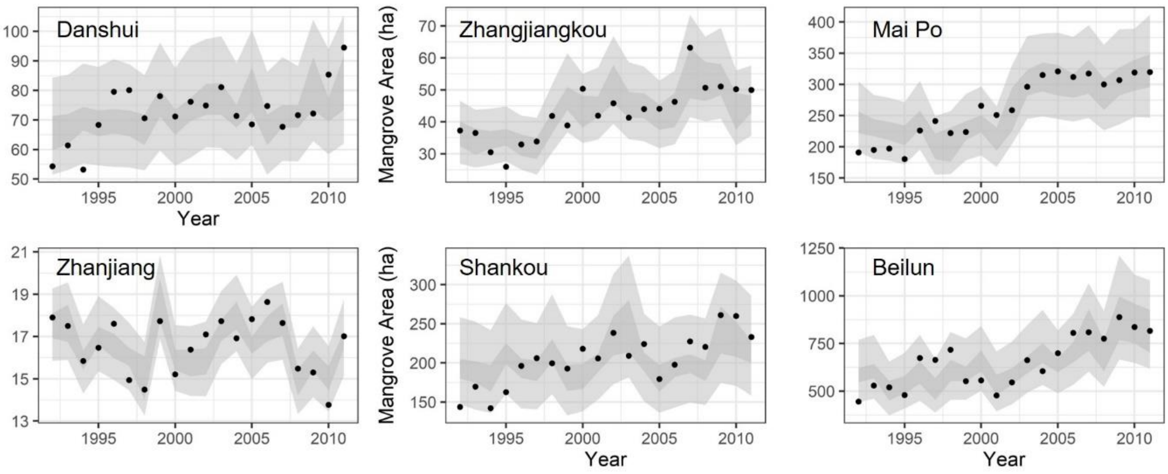

Fig. 6 Bayesian models depicting time-series mangrove cover. The points are extracted mangrove cover from Landsat satellite images; the narrower shaded regions are distributions of the means of estimated mangrove area (within 95% confidence interval); and the wider shaded regions are the estimated mangrove area (within 95% confidence interval).

3.5 Change in precipitation pattern and the effects on mangrove growth

As precipitation shows the distinct effects on mangrove growth, we analysed the precipitation patterns to identify if abrupt changes occurred and the possible effects on the above established relationships. The precipitation pattern of Danshui was not analysed because the precipitation-based variables were not chosen as key factors in explaining the mangrove growth. We found that precipitation pattern remained consistent for the macro- climatic regions containing Zhangjiangkou, Zhanjiang and Shankou, for no change point was detected in these sites in Pettitt test with a p-value of 1.0, 0.3 and 0.5, respectively. Therefore, the mangrove variations for the entire study period can be explained by one equation for each site. The developed equations in terms of precipitation are thus reliable, confirming the validity of the key role of precipitation for these sites. However, the pattern of precipitation was divided into two parts in regions containing Mai Po ($p < 0.001$) and Beilun ($p < 0.01$) by 2001, which was found as the change point for the two sites (Fig. 7 Top). The means of precipitation-based variables for the different patterns in the two sites are also documented in Table 5. Apart from the dramatical decline in the multi-year average of annual precipitation (MAP), the means of all the classified precipitation variables also differ in the two periods of statistical significance. MAP dropped by 1256.6 mm and 633.9 mm in regions containing Mai Po and Beilun, respectively. For the classified variables, we also observed a notable decrease in wet days and increase in dry days. It should also be noted that the regional distribution of rainfall changed significantly, and the surrounding areas of Mai Po and Beilun became comparatively drier in the second period (Fig 7).

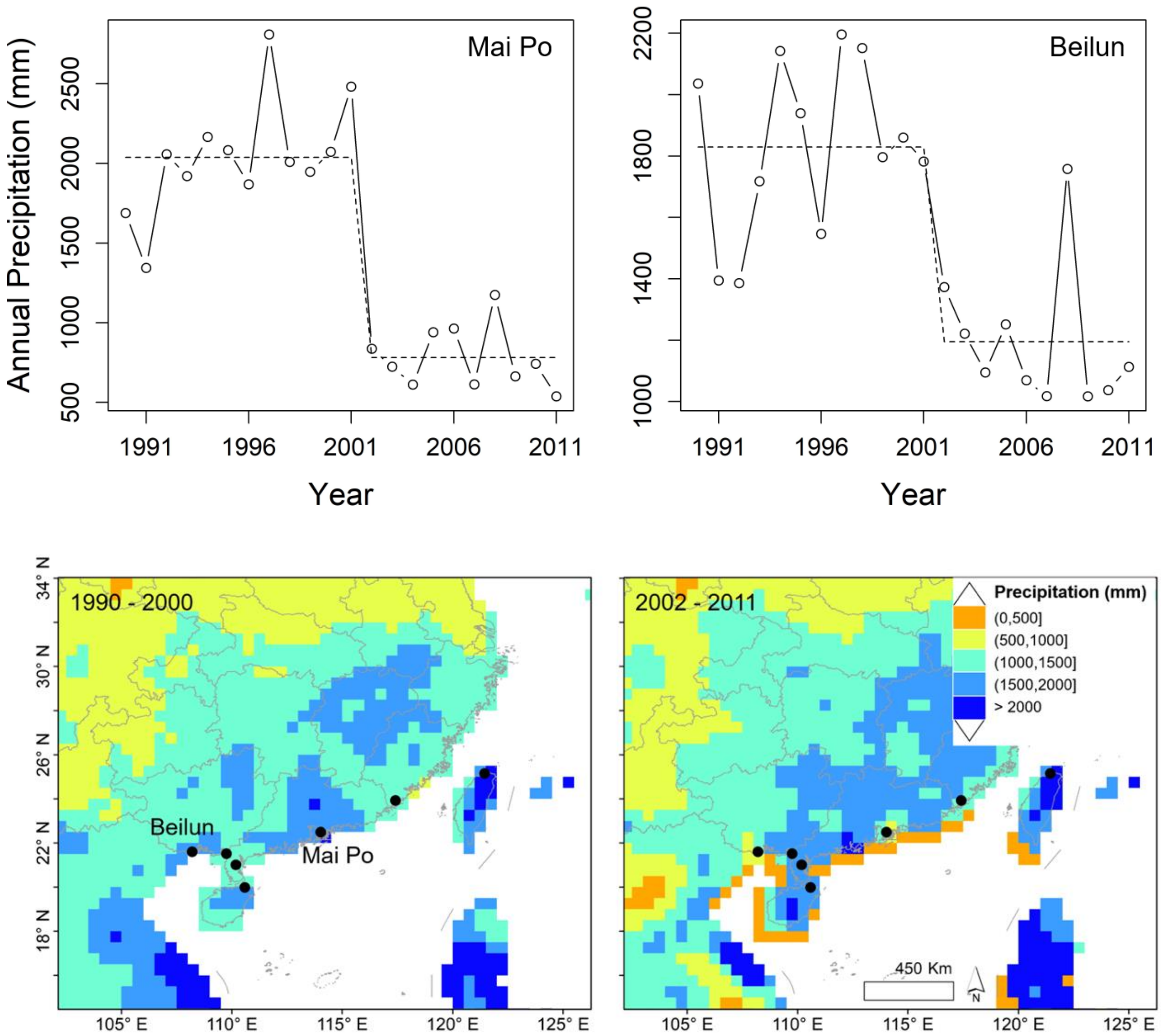

Fig. 7 **Top:** Pettitt test for change point detection in Mai Po and Beilun. **Bottom:** Distribution of multi-year average of annual precipitation before and after the change point. The black dots represent the seven mangrove nature reserves.

Table 5 t test of precipitation-based variables in two precipitation patterns

	Mai Po			Beilun		
	Pre-2001	Post-2001	p-value	Pre-2001	Post-2001	p-value
Annual precipitation (mm)	2037.6	781.0	< 0.001	1829.1	1195.2	< 0.001
Percentage of rainy days>=10 mm	14.7	6.0	< 0.001	14.6	9.2	< 0.001
Percentage of rainy days>=25 mm	6.9	1.9	< 0.001	5.3	2.9	< 0.001
Percentage of rainy days<=1 mm	49.1	62.1	< 0.001	39.1	51.2	< 0.001

To understand effects other than the prominent effects from precipitation, we further performed Bayesian regression analysis in separate periods in Mai Po and Beilun. Fig. 8 shows the relationships between key macro- climatic and hydrological factors and mangrove area in the two periods. The extracted mangrove area in each site agrees well with the estimated ones along the gradient of the variables, which illustrates the good performance of the Bayesian models in identifying the important effects from macro- climatic and hydrological variables on mangrove area. In both periods in Mai Po, the key factors are restricted to temperature-based variables. Before 2001, the increase in annual average temperature contributes to mangrove area expansion, while after 2001, the daily variations in temperature also facilitate mangrove growth. After change point analysis, the mangrove area in the first period can no longer be explained by macro- climatic and hydrological variables in Beilun, while the mangrove area in the second period can still be explained by precipitation. The increase in percentage of dry days (< 1 mm) in a year tends to favour mangrove expansion. These results indicate that the mangrove variation needs to be explained by separate relationships in different macro- climatic patterns, which highlights the importance of studies at finer temporal scales.

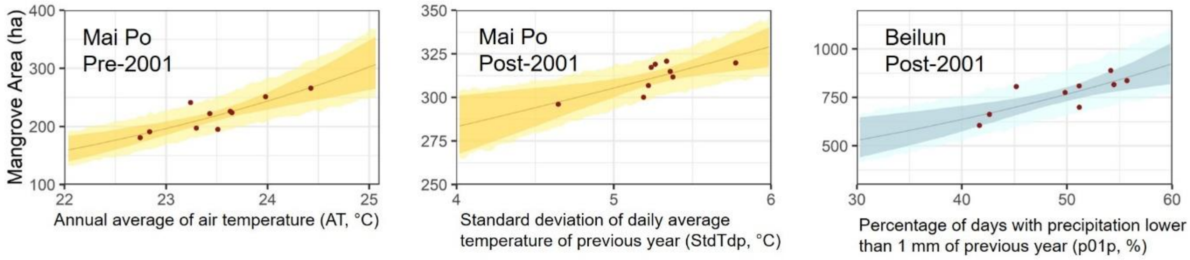

Fig. 8 Variations of mangrove cover along the gradient of key macro- climatic and hydrological factors. The points are extracted mangrove cover from Landsat satellite images; the narrower shaded regions are distributions of the means of estimated mangrove area (within 95% confidence interval); and the wider shaded regions are the estimated mangrove area (within 95% confidence interval). Temperature-based variables are shaded in yellow and precipitation-based variables are shaded in blue.

4. Discussion

4.1 Effects from precipitation are not necessarily positive

Based on mean values of decades, other researchers often found that precipitation decrease would result in decrease in seedling survival rate and net primary productivity of mangrove plants and eventually would lead to shrinkage of mangrove area (Eslami-Andargoli et al., 2009; Gabler et al., 2017; Gilman, Ellison, Duke, & Field 2008). The possible reasons are mainly attributed to salinity increase through less freshwater inputs from precipitation because sufficient freshwater inputs are essential for creating a brackish condition for mangrove growth (Gilman et al., 2008; Xia & Li, 2012). Although these studies found the general relationships between precipitation and mangrove growth using mean values of decades, precipitation effects on mangrove forests are site-dependent at a finer temporal scale. The site-dependent features such as the dominant mangrove species and local salinity can be overlooked when analyzing the influence from multi-year-averaged climatic and hydrological data. In our study, precipitation has a positive effect in Zhangjiangkou and Shankou, but has a negative effect in Zhanjiang and Beilun. As documented in Table 1, the soil salinity of Zhanjiang and Beilun are all lower than 25 psu. Meanwhile, the dominant species in these sites include mainly *A. marina*, which is more salt-tolerant than other species and grows better in conditions with a salinity of $17.5 \sim 26.3$ psu than fresh or less saline water (Fan, 2008; Nguyen, Stanton, Schmitz, Farquhar, & Ball 2015). The lower background salinity and also the more salt-tolerant properties of dominant species likely reduce the freshwater demand so that less precipitation appears to promote mangrove expansion at these sites. In contrast, the background salinity in Shankou is comparatively higher than other subtropical sites except Zhanjiang. It should also be noted that the dominant mangrove species in Shankou are *Rhizophora stylosa* and *Bruguiera gymnorrhiza. B. gymnorrhiza* is a well-studied non-secreting mangrove (Liang, Zhou, Dong, & Shi 2008), the growth of which is slightly stressed and severely stunted in a salinity of about 14.4 and 28.4 psu, respectively (Takemura et al., 2000). *R. stylosa* is found to be less salt-tolerant than the dominant species of other study sites, *A. marina* (Clough, 1984). In Zhangjiangkou, the dominant mangrove species is similar as in Zhanjiang and Beilun, which should have indicated an expectation of lower precipitation for mangrove thriving. However, as mentioned before, Zhangjiankou is located in the driest region where annual precipitation / potential evapotranspiration ratio is the lowest. In addition, high potential evapotranspiration can inhibit mangrove above-ground biomass accumulation (Rovai et al., 2016). These probably can explain the positive effects of precipitation on mangrove expansion in Zhangjiankou. These findings overall indicate that the effects from precipitation are not necessarily positive on mangrove growth and still depend on the local salinity background, the salt tolerance of dominant species and the aridity at a finer temporal scale. Therefore, the highly interannual variability of precipitation and the corresponding effects on mangrove growth should not be overlooked.

4.2 Future precipitation change is expected to shift the mangrove distribution latitudinally and longitudinally

Precipitation is known to exhibit latitudinal effects on mangrove growth. Mangrove trees often appear more sparse and shorter in lower-rainfall regions such as subtropical regions and appear more diverse, denser and taller in higher-rainfall regions such as equatorial and tropical regions mainly because of the increasing nutrient supply coming along with abundant rainfall (Duke, Ball, & Ellison 1998; Ellison, 2000). Except the latitudinal effects, the relationship between precipitation and longitudinal distribution of mangroves is still unclear. Compared to tropical regions, subtropical regions often exhibit lower amount of rainfall with higher variability, producing a highly variable environmental condition. For example, groundwater level that is of vital importance for mangroves also experiences the parallel variations with rainfall (Dowling & McDonald, 1982). In such a variable condition with limited rainfall, the altered average precipitation is more probably to cause environmental changes such as groundwater level and further influence mangrove growth. In our study, the results from change point analysis revealed that subtropical precipitation shows stronger effects on mangrove growth not only in drier regions but also in drier periods. In relatively drier regions, the subtropical sites all exhibited very strong correlation with precipitation, but Danshui with the most abundant rainfall did not exhibit any correlation with precipitation-based variables. This also corresponds to the findings in Gabler et al. (2017) that precipitation has the strongest effects at coastal regions with limited rainfall. Through pattern analysis, we further found that in wetter period such as the first half of study period in Beilun, mangrove growth can be insensitive to precipitation change, and the mangrove area can no longer be explained by precipitation or other macro- climatic and hydrological variables in the wetter period. However, the mangrove area is still strongly correlated with precipitation in drier period (i.e., the second half of study period). It is thus deduced that mangrove growth is more sensitive to the variation of rainfall when precipitation is limited both in space and time. In other words, the change in mangrove distribution is more likely to be uneven when precipitation changes in subtropics. We also observed a spatial change in precipitation in the past two decades in Southern China that is consistent with a predicted spatial shift of precipitation pattern in subtropical regions. For example, the surrounding areas of Mai Po and Beilun became comparatively drier in the second period (Fig. 7 Bottom). This change in the past two decades is in line with the spatial change in precipitation in this century projected by IPCC in 2014 (IPCC, 2014). The high latitudes and equatorial regions are expecting more rainfall, while the mid latitudes and subtropical dry regions are expecting less rainfall. Combined with our findings, the different sensitivities of mangrove forests together with the latitudinal and longitudinal changes in precipitation are bound to cause distribution variation of mangrove over the world, especially in subtropics.

4.3 Hot weather can be more suitable in explaining mangrove area variations for warmer coasts

The pattern analysis also reveals the importance of temperature. For the entire study period, temperature was not selected as key factor influencing mangrove growth in Mai Po. However, in both the first and second halves of study period, the effects from temperature become significant, which indicates the role of temperature is as important as that of precipitation in subtropical mangrove forests. Further to explain, temperature is another important determinant of mangrove growth and especially, mangrove expansion in subtropical regions. In our subtropical study sites, all the correlations with temperature-based variables showed that the increase in temperature favours mangrove expansion. Specifically, the percentage of hot days (> 30 °C) in a year can be regarded as a good indicator in explaining mangrove area variations. Previously, in regions northerner than Southern China, extremely cold weather such as freezes is often used to explain mangrove area variations. During less frequent and intensified extreme freeze period (< -7.6 °C), mangrove plants expanded and especially thrived along the warmer coast in Louisiana (Osland et al., 2017). The cold weather indicator was also used in Florida, where mangrove trees died from continous freezing weathers and then recovered and replaced other wetlands after ten years of warm winters (Stevens, Fox, & Montague 2006). Except freezes, minimum temperature was also commonly used to explain mangrove growth. For example, minimum monthly average of seawater temperature of 20 °C is characterized as the determinant that allows mangrove poleward extension (Saintilan et al., 2014). However, in Southern China, where extreme freezes (< -7.6 °C) are not common, hot weather is found to be more suitable in explaining mangrove area variations. These results indicate that in warmer regions, hot weather is a better indicator of mangrove cover changes than cold weather.

5. Conclusion

In this study, we investigated the relationship between mangrove cover and macro- climatic and hydrological variations at regional and also annual scales. Our study reveals the detailed relationships that can be easily ignored using multi-year-averaged datasets. We found that the tropical mangrove variables demonstrate very limited correlation, while the mangrove variables of the subtropical study sites exhibit relatively strong correlation with temperature- and precipitation- based variables. One should therefore focus on subtropical regions when studying the effects from macro- climate and hydrology upon mangrove forests. Meanwhile, one should focus on the effects from temperature and precipitation because solar radiation and evapotranspiration exhibit limited correlation with mangrove area. We also found that drier regions and drier periods are being more influenced by precipitation, while the precipitation effects on mangrove area also highly depend on the local environmental condition such as salinity, dominant mangrove species and potential evapotranspiration. Considering the nonuniform changes in precipitation in the future, we expect the subtropical mangroves will experience the most obvious latitudinal and longitudinal changes in area. We also recommend using hot weather to explain or predict mangrove cover changes in Southern China and other similar warmer subtropical regions. For example, percentage of hot days (> 30 °C) in a year can be regarded as a good indicator in explaining mangrove area variations. Collectively, our study enhanced our understanding of regional mangrove growth in response to climatic and hydrological changes. It will also support the prediction of mangrove expansion or contraction in the future under different climatic and hydrological scenarios. In the present study, we only extracted the total area of each year, and the directions of mangrove extension are ignored. According to previous studies, increase in temperature and precipitation may shift the mangrove forest poleward (Osland, Feher, et al., 2016; Record, Charney, Zakaria, & Ellison 2013). Meanwhile, as the coastal upland area along the entire coastline of China has extensively been converted to artificial infrastructure, coastal wetland can hardly migrate upland (Ma et al., 2014). These findings together lead to our future research interest in what direction mangrove in Southern China will extend in face of macro- climatic and hydrological variations at regional and annual scale, which is important in studying the balance between mudflat, mangrove and saltmarsh ecosystems.

Acknowledgement

This work was funded by the Seed Funding Programme for Basic Research of The University of Hong Kong (Project code: 201711159090).

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