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Predicting hydrological response to forest changes by simple statistical models: the selection of the best indicator of forest changes with a hydrological perspective

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Abstract. Forest plays an important role in hydrological cycle, and forest changes will inevitably affect runoff across multiple spatial scales. The selection of a suitable indicator for forest changes is essential for predicting forest-related hydrological response. This study used the Meijiang River, one of the headwaters of the Poyang Lake as an example to identify the best indicator of forest changes for predicting forest change-induced hydrological responses. Correlation analysis was conducted first to detect the relationships between monthly runoff and its predictive variables including antecedent monthly precipitation and indicators for forest changes (forest coverage, vegetation indices including EVI, NDVI, and NDWI), and by use of the identified predictive variables that were most correlated with monthly runoff, multiple linear regression models were then developed. The model with best performance identified in this study included two independent variables -antecedent monthly precipitation and NDWI. It indicates that NDWI is the best indicator of forest change in hydrological prediction while forest coverage, the most commonly used indicator of forest change is insignificantly related to monthly runoff. This highlights the use of vegetation index such as NDWI to indicate forest changes in hydrological studies. This study will provide us with an efficient way to quantify the hydrological impact of large-scale forest changes in the Meijiang River watershed, which is crucial for downstream water resource management and ecological protection in the Poyang Lake basin.

1. Introduction

The relationship between forest change and streamflow is an important research subject for a century [1]. To predict hydrological response to forest changes, the first thing is to quantify forest changes. Forest coverage is often used as an indicator to express forest changes simply because it is easy to be obtained [2-8]. However, forest coverage only serves as a basic indicator without differentiating forest species and forest change types, and fails to express the spatial pattern of forest changes and subsequent forest recovery processes. Equivalent roaded area (ERA) and equivalent clear-cut area (ECA) are believed to be better indicators than forest coverage because they can account for dynamic vegetation conditions or changes following forest disturbances. ERA was originally developed in the early 1980s by Region 5 of the USDA Forest Service to evaluate channel destabilization [9]. It works for assessing sediment and erosion yield and is not spatially explicit and the impacts of an activity cannot be tested against its location in a watershed [10, 11]. A similar index developed by the USDA Forest Service is ECA, which is often used to assess the cumulative effects of forest harvesting on annual runoff. The ECA concept has also been widely used in Canada, particularly in British Columbia (BC) and Alberta. Roads, clear-cuts, burned areas, and partial cuts can all be expressed as "equivalent clear-cut area." There are various revised versions of ECA calculation procedures, but the core concepts are similar [12-15]. In a revised version developed by the BC Ministry of Forests, ECA is defined as the area that has been clear-cut, with a reduction factor to account for the hydrological recovery due to forest regeneration [14]. Although it was originally designed for clear-cut areas, ECA can be applied to wildfire-killed areas, roads, and other open spaces. Research has established the relationships between vegetation growth (ages or tree heights) and hydrological recovery rates following logging so that ECA can be derived spatially and temporally in a watershed [16-18]. Although the ECA is believed to be the best indicator for assessing forest change effects on hydrology in large forest-dominated watersheds, its application is limited mainly due to the fact that the ECA calculation for a watershed is time-consuming, and requires detailed historical data of over millions of harvested, burned, and infested blocks. Moreover, professional judgments are always needed in determining the hydrological recovery rates of different tree species for each disturbance type in different watersheds. In China, there is a lack of continuous forest coverage data since forest resources inventory is conducted every five years. In most watersheds, detailed historical records on forests including species, disturbance type, and disturbed area are deficient. This calls for a need to find a new indicator of forest change for predicting forest change-induced hydrological response in China.

Remote sensing sensor systems detect reflected or emitted radiation from features on the Earth's surface. New techniques have been developed for future extraction where Enhanced Vegetation Index (EVI) [19], Normalized Difference Vegetation Index (NDVI) [20, 21] and Normalized Difference Water Index (NDWI) [22] are most widely used for satellite image processing in recent decades. The emergence of these vegetation indices (NDVI, EVI, NDWI) derived from remote sensing data makes the assessment of historical forest changes feasible at a larger spatial scale. The remote sensing vegetation indices-based approach requires fewer fieldworks to collect detailed vegetation information from stand-level to watershed-level as compared to their counterparts. Moreover, it is an integrated index that can express all types of forest changes including both forest loss (deforestation due to logging, pest infestation, fire, urbanization, landslides) and forest gain (afforestation and reforestation). However, a question arising here then is which vegetation index has best performance when assessing hydrological response to forest changes in a large forested watershed. In order to answer this question, this study used the Meijiang River, one of the headwaters of the Poyang Lake as an example to identify the best indicator of forest changes to predict forest change-induced hydrological responses. Non-parametric correlation analysis was conducted first to detect the relationships between monthly runoff and its predictive variables including antecedent monthly precipitation and indicators for forest changes (forest coverage, vegetation indices including EVI, NDVI, and NDWI), and by use of the identified predictive variables that were most correlated with monthly runoff, multiple linear regression models were then developed. The indicator of forest change included in the model with best performance can be viewed as the best indicator to predict forest change-induced hydrological impact.

2. Study Area

The Meijiang watershed, situated in the upper of the Ganjiang River, the Poyang Lake basin of China (Figure 1). The majority of its tributaries start from Ningdu and Shicheng. The Meijiang River originates from the northeast of Ganzhou and flows southwest, and then merges into the Gongjiang River near Yudu. The Gongjiang River and Zhangjiang River converge in the territory of Ganzhou Region and make up the Ganjiang River. Hence the Meijiang River is called the source of the Ganjiang River. The drainage network of the Meijiang River watershed is very dense and the drainage area is approximately 6310 km^2.

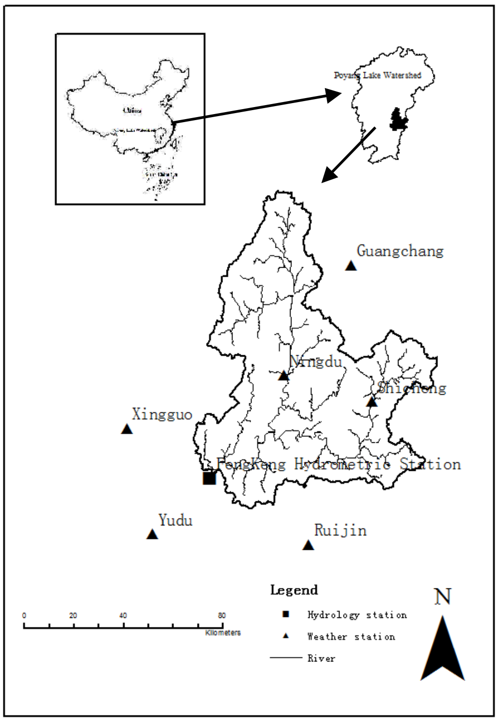


Figure 1. Location of the Meijiang watershed.

The average elevation for the Meijiang watershed is 379 m and most of it is from 300 to 500 m. Soil types mainly include mountainous red soil, purple soil and yellow soil, with light loam and sandy loam in texture. The watershed is rich in forest resources with diverse tree species. Forest coverage is about 71% in 2006. Main vegetation types in this watershed are subtropical evergreen broad-leaved and coniferous forests. The dominant tree species include Pinus massoniana Lamb.， Castanopsis fabri, Castanopsis fissa, Cunninghamia Lanceolata and moso bamboo. Most of the forests distribute on the north, southeast and southwest of the Meijiang River watershed.

The climate in the Meijiang watershed belongs to humid subtropical monsoon featured with hot summer and long rainy season. Average annual mean temperature is 18.7 ℃. The maximum temperature is observed in July (monthly average 28.5 ℃) with the minimum temperature in January (monthly average 7.5 ℃). The rainy season lasts from April to June and the dry season is from September to November. Average annual precipitation is 1804.1 mm from 1989 to 2006. From the 1960s to the early 1980s, the watershed underwent many disturbances, especially, soil erosion due to early deforestation. After the large-scale reforestation and protection programs in the mid-1980s, the forest coverage increased from 41% in 1989 to 71% in 2006 in the watershed [23].

3. Data description

3.1. Hydrological and climate data

Daily flow data from 1989 to 2006 were collected from Fenkeng hydrometric station (Figure 1), situated at the outlet of the Meijiang watershed, which were used to calculate monthly runoff. There are six active national weather stations available within and around the Meijiang watershed (Figure 1). In this study, the historical climate data including precipitation and temperature was used. Given the high spatial variability of precipitation in the mountainous region, precipitation data from one station fails to capture the detailed spatial variation in precipitation input for the whole watershed. Thus, we use the ANUSPLIN model to generate spatially interpolated precipitation data. This approach is widely used to generate spatial interpolation of hydrometeorological variables [24].

3.2. Vegetation data

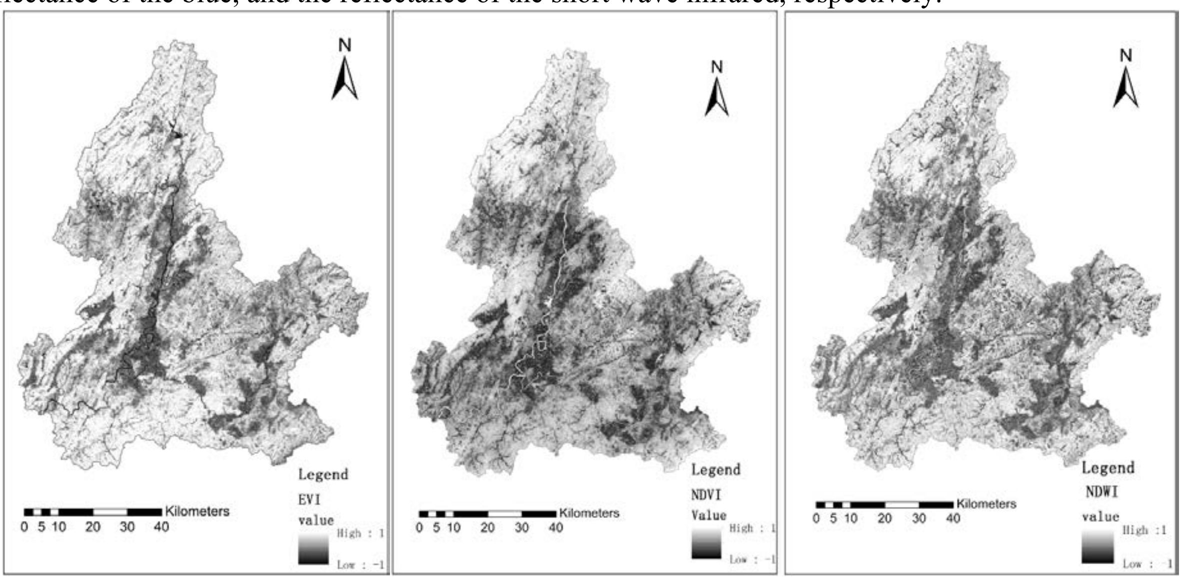
There are two types of vegetation data: forest coverage and remote sensing-based vegetation indices. Forest coverage data were provided by the Ganzhou Regional Forestry Bureaus of Jiangxi Province [23]. According to the forest coverage data, forest coverage rapidly increased from 41% in 1989 to 65% in 1994 due to the implementation of various large-scale reforestation programs, and steadily rose to 71.0% in 2006 in this watershed. Remote sensing data Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM) images for the Meijiang River watershed were downloaded from the United States Geological Survey (http://glovis.usgs.gov/). The Landsat-5 TM satellite was launched by The National Aeronautics and Space Administration (NASA) in 1984. Although more advanced satellite images are available, only time series of Landsat TM images with cloud cover less than 10% were selected in order to cover the whole study period from 1989 to 2006. Several ETM images were also used when TM images were missing. In this study, 48 high quality images with a resolution of 30 m were processed and extracted to calculate vegetation indices including EVI, NDVI, and NDWI. The EVI is developed to enhance the vegetation signal by reducing influences form the atmosphere and canopy background and to improve sensitivity in high biomass regions [19]. The NDVI is a simple numerical indicator that can be used to analyze remote sensing measurements from a remote platform and assess whether the target or object being observed contains live green vegetation or not [25]. The NDWI is utilized for assessing water substance of vegetation canopy [22]. The processing of the images involved the conversion of digital numbers into reflectance values and a relative atmospheric correction to normalize remotely sensed images for further analysis. Then, the values of EVI, NDVI, and NDWI from the processed images were calculated by the following equations for the whole watershed (Figure 2).

$$EVI = 2.5\times(\rho_{nir} - \rho_{red}) / (1 + \rho_{nir} + 6\rho_{red} - 7.5\rho_{blue}) \tag{1}$$

$$NDVI = (\rho_{nir} - \rho_{red}) / (\rho_{nir} + \rho_{red}) \tag{2}$$

$$NDWI = (\rho_{nir} - \rho_{swir}) / (\rho_{nir} + \rho_{swir}) \tag{3}$$

where ρ_{nir}, ρ_{red}, ρ_{blue} and ρ_{swir} are the reflectance of the near-infrared, the reflectance of the red, the reflectance of the blue, and the reflectance of the short wave infrared, respectively.



(a) (b) (c)

Figure 2. (a, b, c) The values of EVI, NDVI and NDWI distributed in the Meijiang watershed on December 21, 2006.

4. Method

In this study, statistical analysis including non-parametric tests (Mann-Kendall and Spearman rank tests) and stepwise liner regression were utilized to identify the best indicator of forest change in hydrological prediction.

4.1. Correlation analysis

The correlation analysis is found to be an effective approach to investigate the relationships among environmental variables, particularly in identifying the causal relationships from possible explanatory variables [26, 27]. In this study, non-parametric correlation tests including Mann-Kendall and Spearman rank tests were firstly performed to detect the relationships between monthly hydrological variables (monthly runoff (Q(t)), one-month antecedent monthly runoff (Q(t-1)), one-month and two-month subsequent monthly runoff (Q(t+1) and Q(t+2))) and their predictive variables including precipitation, forest coverage and vegetation indices (Table 1). In the prediction of monthly runoff, climatic variables such as antecedent monthly precipitation (P(t-1)) is believed to a powerful predictor. Thus, antecedent monthly precipitation was also adopted in this analysis. Vegetation indicators used included antecedent monthly forest coverage (FC(t-1)), monthly EVI(t), NDVI(t), and NDWI(t). The predictive variables that were most correlated with hydrological variables were further adopted in the development of multiple linear regression model for the prediction of hydrological response to forest changes.

4.2. Stepwise linear model

Multiple linear regression is a popular alternative technique for hydrological modelling with limited data requirements on watershed conditions. In this study, the choice of predictive variables is carried out by the stepwise selection that automatically keeps the significant independent variables in the multiple linear regression model. The generated multiple linear regression models were then used to predict monthly runoff response to forest changes. The model performance was evaluated by the statistics coefficient of determination (R^2) and Nash-Sutcliffe model efficiency coefficient (E), which are widely used in hydrological modelling and are proved to be excellent in measuring the effectiveness of a model in terms of its prediction ability [28, 29]. Value of R^2 and E can be calculated by Equation 4 and 5. Traditionally, hydrological models were calibrated and validated by split-sample tests where available data were simply divided into two sets by time, which may failed to capture dynamic interactions between runoff and its drivers. To overcome the shortcomings of the traditional split-sample test, a random selection approach was adopted where the data were randomly selected and then grouped into calibrated and validated periods. In this study, 36 sets of data were used in the calibration while 12 sets of data were applied in the validation.

$$R^2 = [\sum_{i=1}^{n}(Q_{o,i} - \bar{Q}_o)(Q_{s,i} - \bar{Q}_s)]^2 / [\sum_{i=1}^{n}(Q_{o,i} - \bar{Q}_o)^2 \sum_{i=1}^{n}(Q_{s,i} - \bar{Q}_s)^2] \tag{4}$$

$$E = 1 - \sum_{i=1}^{n}(Q_{o,i} - Q_{s,i})^2 / \sum_{i=1}^{n}(Q_{o,i} - \bar{Q}_o)^2 \tag{5}$$

where $Q_{s,i}$ is the simulated monthly runoff for the ith month; $Q_{o,i}$ the observed monthly runoff for the ith month; $\bar{Q}_s$ is the average simulated monthly runoff for the whole period; $\bar{Q}_o$ the average observed monthly runoff for the whole study period and n the number of months for the whole study period.

5. Results

5.1. Correlation analysis

As suggested by both Mann-kendall and Spearman rank tests, significant correlations between antecedent monthly runoff (Q(t-1)) and antecedent monthly precipitation (P(t-1))/NDVI(t) / NDWI(t) were detected at α =0.01(Table 1). Thus, these variables were kept as input candidates in stepwise linear models with antecedent monthly runoff (Q(t-1)) as a dependent variable. However, in order to compare the performance of different vegetation indicators, we also built the model including FC (t-1) and EVI(t).

Table 1. Results of non-parametric correlation tests.

Parameter	Test	Q (t-1)	Q(t)	Q(t+1)	Q(t+2)
P(t-1)	Kendall's correlation coefficient	**0.627***	**0.439***	**0.444***	0.259
	Spearman correlation coefficient	**0.807***	**0.611***	**0.642***	0.377
FC(t-1)	Kendall's correlation coefficient	0.021	0.179	0.229	0.174
	Spearman correlation coefficient	0.044	0.244	0.327	0.290
EVI	Kendall's correlation coefficient	0.166	0.173	-0.030	-0.182
	Spearman correlation coefficient	0.229	0.245	-0.050	-0.283
NDVI	Kendall's correlation coefficient	**0.368***	0.173	0.034	-0.272
	Spearman correlation coefficient	**0.507***	0.289	0.045	-0.410
NDWI	Kendall's correlation coefficient	**0.375***	0.281	0.081	-0.252
	Spearman correlation coefficient	**0.538***	0.428	0.122	-0.380

*Significant at α =0.01

We took the time of remote sensing images (t) for benchmarks

5.2. Model selection

Table 2 provides the descriptions of five multiple linear regression models developed using selected input variables. Table 3 shows the performance of fitted models in both calibration and validation periods. According to the values of R^2 and E in both calibration and validation periods, model RM3 with P(t-1) and NDWI(t) as predictors showed best performance as compared to RM1, RM2, RM4 and RM5. Thus, the RM3 model was eventually used to predict the monthly runoff change due to forest changes (Figure 3) and NDWI was identified as the best indicator of forest changes in hydrological prediction in the Meijiang watershed.

6. Discussion

6.1. Relationship between vegetation change and monthly runoff

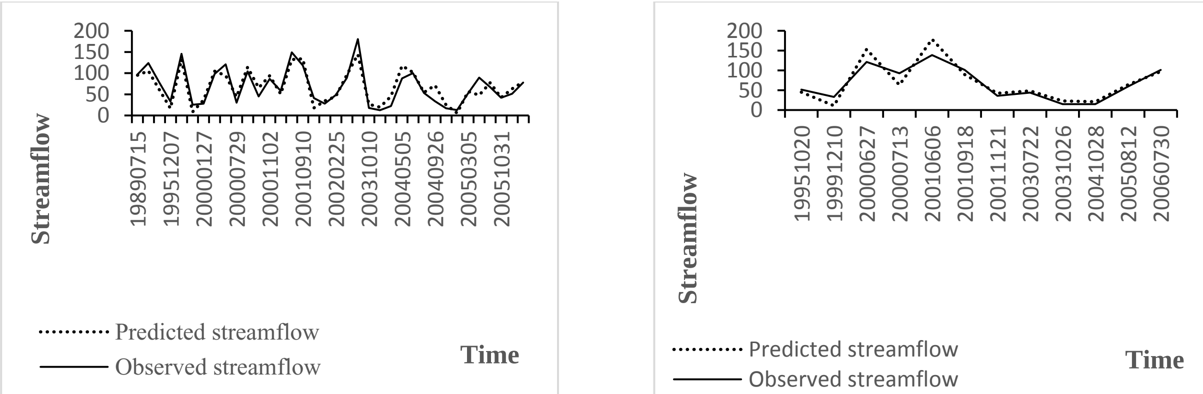
As suggested by the correlation analysis, monthly runoff can significantly grow with increasing vegetation indices due to continuous reforestation or afforestation. It indicates that more forests will lead to more monthly runoff in the study watershed. This could be related to the fact that planted tree species was mainly Pinus massoniana Lamb after native forests were logged. Unlike previous native forests, most planted forests in the Meijiang watershed are featured with low canopy closure and very poor understory vegetation. After plantation, the watershed may thus have lower transpiration by newly planted trees and understories than before. Therefore, more runoff is expected after large-scale tree plantation. This is in accordance with some studies in Russia and China, as well as in some cloud forests [1]. However, this finding is different from many small watershed studies where forest increase has reduced monthly runoff due to the fact that forest growth can increase interception and evapotranspiration, resulting in less water being available for runoff generation [30]. Thus, a definite conclusion the relationship between forest and water remains inconsistent.

Table 2. The list of model candidates.

Models	Dependent	Independent	Model Structure
RM1	Q(t-1)	P(t-1)	Q(t-1)=15.98+0.43×P(t-1)
RM2	Q(t-1)	P(t-1),NDVI	Q(t-1)=-45.55+0.41×P(t-1)+107.41×NDVI
RM3	**Q(t-1)**	**P(t-1),NDWI**	**Q(t-1)=-30.23+0.40×P(t-1)+240.17×NDWI**
RM4	Q(t-1)	P(t-1), FC	Q(t-1)=69.84+0.43×P(t-1)+77.45×FC
RM5	Q(t-1)	P(t-1), EVI	Q(t-1)=0.85+0.41×P(t-1)+60.10×EVI

Table 3. The performance of five models for both the calibration and validation periods.

Period	Evaluation statistics	RM1	RM2	**RM3**	RM4	RM5
Calibration period (training)	R^2	0.74	0.78	**0.84**	0.75	0.76
	E	0.74	0.78	**0.83**	0.75	0.76
Validation period (testing)	R^2	0.82	0.85	**0.87**	0.81	0.74
	E	0.73	0.79	**0.77**	0.73	0.67



(a) (b)

Figure 3. Predicted and observed streamflow in the calibration period (a) and the validation period (b)

6.2. *Quantification of forest changes*

Forest change is often expressed by forest coverage simply because it is easy to be obtained [7, 8]. However, forest coverage only serves as a basic indicator without differentiating forest species and forest disturbance types, and fails to express the spatial pattern of forest changes and subsequent forest recovery processes. Equivalent roaded area (ERA) and equivalent clear-cut area (ECA) are believed to be better indicators than forest coverage because they can account for dynamic vegetation conditions or change following disturbance, but their application is limited mainly due to the fact that the ERA or ECA calculation for a watershed is time-consuming, and requires detailed historical data of over millions of harvested, burned, and infested blocks. In China, there is a lack of continuous forest coverage data since forest resources inventory is conducted every five years. In most watersheds, detailed historical records on forests including species, disturbance type, and disturbed area are deficient or with poor control of data quality, especially in the remote mountainous region. This study suggests that vegetation indices such as NDVI and NDWI derived from remote sensing data can be effective indicators of forest changes when assessing hydrological response to forest changes. The NDWI was found to be the best indicator of forest changes in the Meijiang watershed as indicated by model performance of five multiple linear regression models. This is may be due to the great sensitivity of NDWI to water substance of vegetation canopy. The quantification of forest changes by NDWI requires fewer fieldworks to collect detailed vegetation information from stand-level to watershed-level as compared to other indicators of forest changes. Moreover, it is an integrated index that can express all types of forest changes including both forest loss (deforestation due to logging, pest infestation, fire, urbanization, landslides) and forest gain (afforestation and reforestation) over time (since 1980s). Therefore, NDWI can be widely applied in forested watersheds in China to quantify forest changes as well as to be used for the prediction of forest change-induced runoff changes. A brief comparison of pros and cons between these indicators is presented in Table 4.

Table 4. Methods for quantifying forest disturbances

Name	Advantage	Disadvantage
Forest coverage	Simple calculation	Only available for single disturbance No consideration of hydrological recovery
ERA (Equivalent roaded area/acre)	Accounts for various types of disturbance: assesses erosion risk and sediment yield	Complex calculation No consideration of hydrological recovery Lacks spatial representation(such as position of harvest)
ECA (Equivalent clear-cut area)	Accounts for various types of disturbance, Considers disturbance severity and hydrological recovery	Complex calculation Lacks spatial representation (such as position of harvest) [31]
NDWI (Normalized Difference Water Index)	Simple calculation, objectivity, Considers water substance of vegetation canopy	Poor accuracy No consideration of hydrological recovery

6.3. A new approach for forest-runoff modelling

The large watershed studies on hydrological response to forest changes are fewer than small watershed studies, which is mainly constrained by the lack of a suitable and efficient methodology, the lack of a comprehensive indicator for forest changes over space and time, and the availability of long-term data on hydrology, climate, and forest. In this study, the multiple linear regression model where the antecedent monthly runoff served as a dependent variable, and the antecedent monthly precipitation and NDWI served as independent variables was found as the best fitted model to predict monthly runoff response to forest changes. In comparison to expensive experimental watershed approach and time-consuming and data-intensive hydrological modelling, this statistical model appears to be a very efficient tool for assessing hydrological response to forest changes. It can be applied to predict historical or future runoff response due to forest changes in both small and large watersheds where remote sensing, hydrological and climate data are available. It can also be used to predict runoff with precipitation and NDWI data in ungauged forested watersheds. This can be particularly true given that in the remote area of Southwest China, for example, covered by dense native forests with only short-term or without hydrological data, we can use this simple approach to estimate runoff by use of radar-precipitation and remote sensing data. This prediction can also be very useful in water resource management and forest protection. For example, the West Route of South–to-North Water Transfer Project involves drawing water from the Upper Yangtze River in the Southwest China and supplying water to the Yellow River. The large-scale project will cause negative effects on forests in water source region. Thus, we can use this model to predict the impact of the project-associated forest changes on runoff of watersheds in Southwest China in an efficient way.

7. Conclusions

This study used the Meijiang watershed as an example to identify the best indicator of forest changes to predict forest change-induced hydrological responses and to develop a statistical model to provide an efficient assessment on hydrological response to forest changes. According to this study, NDWI is the indicator of forest change that is most related to monthly runoff in the Meijiang watershed. It indicates that NDWI is the best indicator of forest change in hydrological prediction while forest coverage, the most commonly used indicator of forest change is insignificantly related to monthly runoff. It also showed that a multiple regression model two independent variables -antecedent monthly precipitation and NDWI can be a very efficient way to predict monthly runoff, as well as to quantify the hydrological impact of large-scale forest changes in the Meijiang River watershed or other similar watersheds, which is crucial for downstream water resource management and ecological protection in the Poyang Lake basin. However, it is important to note that the success of this statistical model is heavily dependent on the quality of remote sensing images, for example, images with low cloud cover

10%. And hydrological processes cannot be fully explained in this model. Therefore, this approach as a substitute for hydrological models can be a very useful tool for forest resources and water resources management in watersheds with limited data.

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