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A study of the variation of rainfall patterns with tree cover change

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Contents

Abstract

According to statistical results, 20% of the Amazon basin's original forest has been converted to pastures or croplands by 2018 due to the deforestation since 1970. Studies with large spatial scale demonstrate that these changes lead to a decrease in evapotranspiration and contribute to a decline in rainfall. However, the effect of this transformation on local precipitation is far from clear. In addition, it still remains unclear that the effect of afforestation on local precipitation. Through the study, it is expected that the results could contribute to a deeper understanding of response of precipitation to vegetation change. By this way, the present study performs the temporal trend analysis and neighboring effect analysis of the annual time-series of Amazonia and southeastern China local precipitation and tree cover data over the period of 1998-2016 (except 2000) and 2001-2016 with the resolution of 0.25º by 0.25º, respectively. The Mann-Kendall (MK) test was applied to quantify the significance of trend and then regression analysis was implemented to explore if there were significant correlations between center position's tree cover and its neighbor's precipitation. In relation to tendencies, downward tree canopy trends were detected in the southeastern Amazonia. In addition, upward tree canopy trends were identified for half of the southeastern China. The neighboring effect is not obvious in both research area. For Amazonia, only 5% results show moderate correlations in each month and this number varies from 3 to 10% in southeastern China of each month. Generally, basing on the research results, it can't be concluded that the local precipitation is associated with local and around tree cover ratio and studies with finer resolutions are expected in the future.

Introduction

According to the United Nations' Food and Agriculture Organization, an estimated 18 million acres (7.3 million hectares) of forest are lost each year. Deforestation is regarded as one of the primary reasons for global climate change as it can affect the global carbon cycle and reduce local biodiversity (Bala et al., 2007; Barlow et al., 2016). In addition, as forest plays an important role in water cycle, the substantial loss of forests can impact water and energy cycle directly or indirectly (D'Almeida *et al.,* 2007; Lettau *et al.,* 1979). The direct effects of a conversion of forest to grassland on the water and energy budgets are relatively well known. Trees can reach water deeper in the ground and consequently to transpire longer into the dry season. While grasses are unable to reach these deeper soil layers which limits the water transpiration. Therefore, the excess radiation at the land surface over a dry grassland will be emitted into the atmosphere as sensible heat (Taylor *et al.,* 2012). However, the effect of these changes in the energy balance on precipitation triggering are less clear. This study will focus on exploring the indirect effect of deforestation on local (0.25-degree x 0.25-degree) precipitation and its spatial patterns. In addition, to get a better understanding of the relationship between tree cover ratio and local precipitation, the effect of afforestation on precipitation with same resolution will also be investigated.

The Amazonian and southeastern China are selected to represent the deforested and afforested areas respectively (Figure 1). And the figure 2 illustrates the annual change of mean tree cover ratio and precipitation of the areas marked by red rectangles in figure 1. Generally, the tree canopy in Amazonia demonstrates a decreasing trend, in contrast, the tree canopy in southeastern China had slightly increased. The Amazonian rain forest has incurred a large-scale deforestation since 1970, when strategic governmental plans first attempted to promote the economic development across the region. And by the early 1990s, more than 10% of the basin's original forest had been converted to pasture or cropland (Fearnside,1993). The situation has been sustained, and the latest survey shows that 20% of Amazonian forested land had been cleared by 2018, following with a series of ecological and social problems (INPE, 2018). Many macroscale studies agree that large-scale deforestation in Amazonia leads to the reductions in precipitation, evapotranspiration, moisture convergence and runoff, along with increments in surface temperature (D'Almeida *et al.,* 2007). In contrast, observational mesoscale studies have linked deforestation to increased precipitation locally (Costa & Foley,1999; Chen *et al*., 2001; Costa *et al*., 2003; Durieux *et al*., 2003; Marengo, 2004; Negri *et al*., 2004). Mesoscale circulations induced by a heterogeneous land surface could enhance cloudiness and local rainfall (Wang *et al*., 2000). One research conducted in Southwest Brazil with the resolution of 0.5^o by 0.5^o found that in the dry season due to the differential heating of the region's varying forestation, there were more precipitation over the deforested and nonforested regions than over areas of dense forest (Negri *et al.,* 2004). Since the deforestation in 1970, kinds of land cover patterns have formulated, and the neighboring effect of vegetation changes on the local precipitation is still unclear. Marengo (1995) proposed a hypothesis that the deforestation may affect the water cycle in Amazonia at subgrid, undetectable scales. Inspiring by this, the present project explores the relationship between tree cover ratio and precipitation with a finer spatial resolution of 0.25^o x 0.25^o, and try to yield a deeper understanding of the response of precipitation to deforestation.

In contrast to the Amazon, due to the reforestation and afforestation programs, the tree canopy in southeastern China has increased 34% in 2016 compared with that in 1982 (Song *et al.,* 2018). Generally, afforestation can mitigate the climate change as the growth of forest could increase carbon capture and carbon sequestration, which will slow the global warming. However, this climate effect of new forests depends on the radiant and turbulent energy fluxes over the plantations, for instance, a lower albedo may cause warming, which negates the climatic benefits of carbon sequestration (Peng *et al.,* 2014). In the respect of the influence of it on precipitation, a large-scale study found that the afforestation in the mid-latitudes results in a northward shift of precipitation belts, and the most notable changed in precipitation over land happened in Brazil, including a drying of the southern edge of the Amazon forest and the increase in precipitation in the Sahel region of Africa (Swann *et al.,* 2012). One model research conducted in east China found that the precipitation significantly increases annually in response to afforestation. Moreover, the rainfall is enhanced locally over the afforested region in summer, while in winter the increases not only occur in afforested region but also the adjacent ocean area (Ma *et al.,* 2013). Differ from the past, in this study, the relationship of afforestation and precipitation will be investigated basing on the data from observations with a more precise degree.

Based on the research objectives the following research question is formulated:

How does the land cover change influence the local rainfall patterns in the Amazon and southeastern China?

In order to answer the main question, following sub-questions needed to be answered:

1. whether rainfall increases or decreases with the change of tree canopy;

2. what the spatial size of this effect is;

3. how does it relate to the amount of deforestation or afforestation;

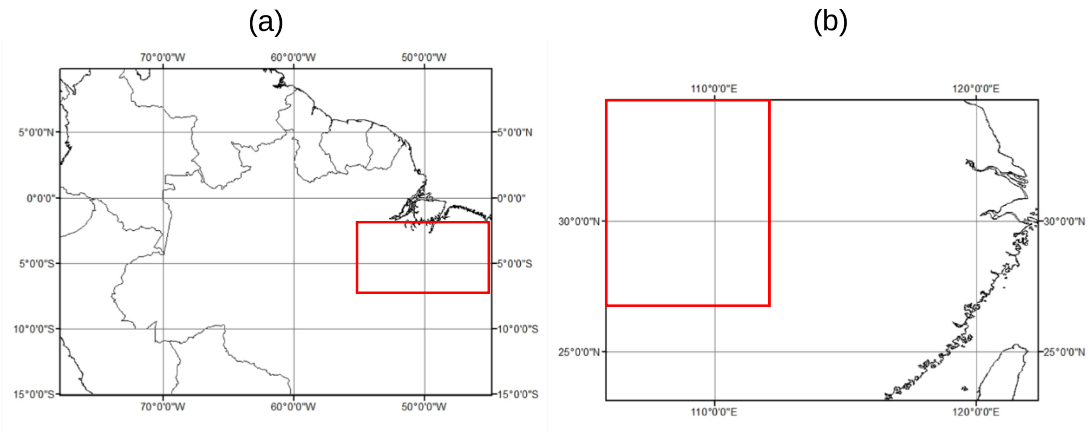


Figure 1. The maps showing the research areas. (a) Amazonia; (b) southeastern China

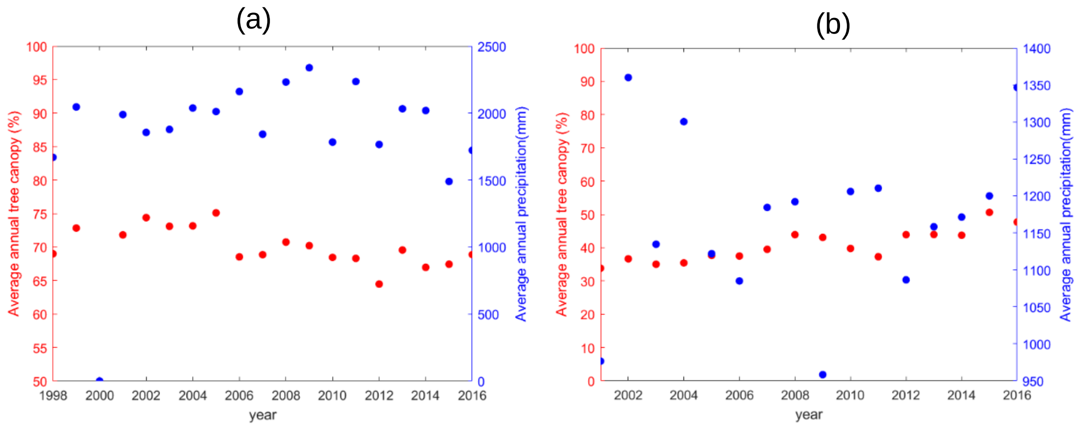


Figure 2. The average annual tree canopy and precipitation change of selected areas in Amazonia(a) and southeastern China(b).

Methodology

Data

Deforestation and precipitation data with the format of Network Common Data Form (NetCDF) are derived from TRMM and MEaSUREs projects respectively. The Tropical Rainfall Measuring Mission is a joint mission between the National Aeronautics and Space Administration and the Japanese Aerospace Exploration Agency designed to monitor and study tropical rainfall, and especially to improve understanding of the distribution and variability of tropical precipitation (Kummerow *et al.,* 1998). The 3B42 product includes daily precipitation rates at 0.25° resolution and is available from 1998 to 2018. The NASA Making Earth System Data Records for Use in Research Environments (MEaSUREs) Vegetation Continuous Fields (VCF) Version 1 data product (VCF5KYR) provides global fractional vegetation cover at 0.05 degree (5,600 meter) spatial resolution at yearly intervals from 1982 to 2016. Fractional vegetation cover (FVC) is the ratio of the area of the vertical projection of green vegetation above ground to the total area, capturing the horizontal distribution and density of vegetation on the Earth's surface. The three bands included in each VCF5KYR Version are: percent of tree cover, non-tree vegetation, and bare ground. The available precipitation data of Amazonia is from 1998 and that of southeastern China is from 2000 and the vegetation change data of 2000 is not included in VCF5KYR product, by this way, the research period of two areas are 1998-2016 (except 2000) and 2001-2016 respectively. The research area of Amazonia contains 13433 grid cells within 15.125°S to 9.875°N, and 77.875 to 44.875°W. The research area of southeastern China contains 3149 grid cells within 23.125 to 34.625°N, and 105.775 to 122.475°E (Figure 1).

Following figure derived from Song's paper relies on VCF5KYR product, showing a long-term change (1982-2016) of tree canopy (TC) cover, short vegetation (SV) cover and bare ground (BG) cover globally. Every land pixel is characterized by its per cent cover of TC, SV and BG, representing the vegetation composition at the time of the local peak growing season (Song *et al.,* 2018).

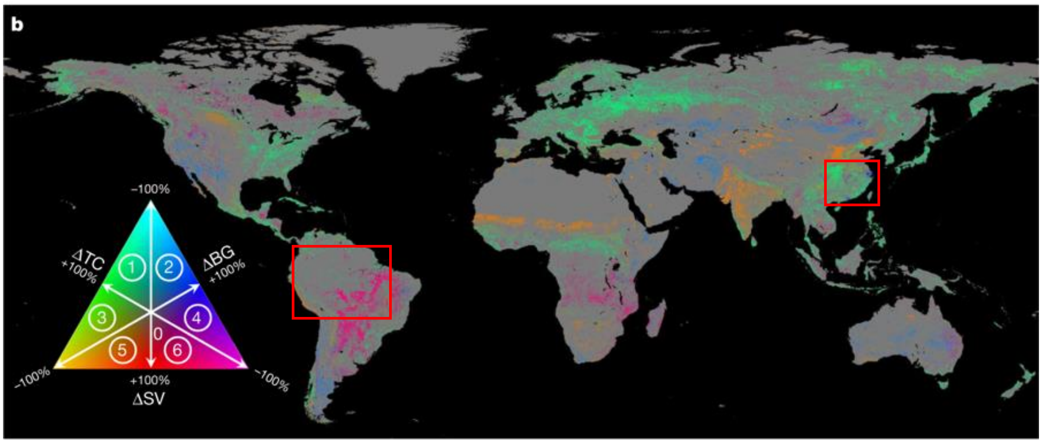


Figure 3. A satellite-based record of global TC, SV and BG cover from 1982 to 2016. Target research areas are in the red boxes. Circled numbers in the color legend denote dominant change directions: 1, TC gain with SV loss; 2, BG gain with SV loss; 3, TC gain with BG loss; 4, BG gain with TC loss; 5, SV gain with BG loss; and 6, SV gain with TC loss (Song et al., 2018).

Statistical analysis

The whole statistics analyses were achieved in Matlab, and the main methods are Mann-Kendall (MK) test and regression analysis. The program is listed in the appendix I.

Preliminary Data Processing In this study, the relationship between monthly precipitation and the tree canopy in each year is explored. As the TRMM data is daily, the first step in the analysis process is to add up the daily precipitation to get the monthly precipitation (Appendix I). Due to the difference between resolutions of two data product, one grid in TRMM product contains 25 grids in VCF5KYR product (Figure 3), by this way, the next step is transferring the resolution of VCF5KYR product into 0.25^ox0.25^o. The following equation is used (Appendix I):

$$T_{new} = (\sum_{1}^{25} T_1)/25 \quad (1)$$

Mann-Kendall test The Non-parametric Mann-Kendall test is commonly employed to detect monotonic trend in series of environmental data, climate data or hydrological data. The null hypothesis, H_0, is that the data come from a population with independent realizations and are identically distributed. The alternative hypothesis, H_A, is that the data follow a monotonic trend. The Z-transformation can be calculated after the test, and for the certain confidence level α, if $|Z| \geq Z_{1-\alpha/2}$, the H_0 is refused which means that the data has significant increase or decrease with the confidence level α (Pohlert, 2016). The procedure is as follows (Huang *et al.,* 2013):

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \mathrm{sgn}(x_j - x_i) \quad (2)$$

$$\mathrm{sgn}(x_j - x_i) = \begin{cases} +1, x_j > x_i \\ 0, x_j = x_i \\ -1, x_j < x_i \end{cases} \quad (3)$$

First, the above formula is applied to calculate the statistic S (Eq.2), and the n is the sample size. S is approximately normally distributed when n≥8, with the mean and the variance as formula (Eq.4) and (Eq.5):

$$E(S) = 0 \quad (4)$$

$$V(S) = \frac{n(n-1)(2n+5) - \sum_{i=1}^{n} t_i i(i-1)(2t+5)}{18} \quad (5)$$

Where t_i is the number of the ties of extent *i*. The standardized statistic (Z) for one-tailed test is formulated as:

$$Z = \begin{cases} \frac{s-1}{\sqrt{\mathrm{Var}(s)}}, S > 0 \\ 0, S = 0 \\ \frac{s+1}{\sqrt{\mathrm{Var}(s)}}, S < 0 \end{cases} \quad (6)$$

In this study, the MK test is conducted to find the grid that the tree cover ratio or precipitation of it had significant changed in the research period with the significance level of 95%(Appendix I). The H_0 is that there is no significant trend of tree cover ratio in the target grid cell or there is no significant trend of the precipitation in the target grid cell. The results than be used as the benchmark for the analysis of neighboring grid cells.

Regression analysis Regression analysis is a set of statistical processes for estimating the relationships among variables. For this study, the tree cover ratio is the independent variable (*X*) and precipitation is regarded as the dependent variable (*Y*), meanwhile, as there is only one independent variable, the simple linear regression analysis is implemented (Eq.7).

$$Y = \beta_0 + \beta_1 X + \epsilon \qquad (7)$$

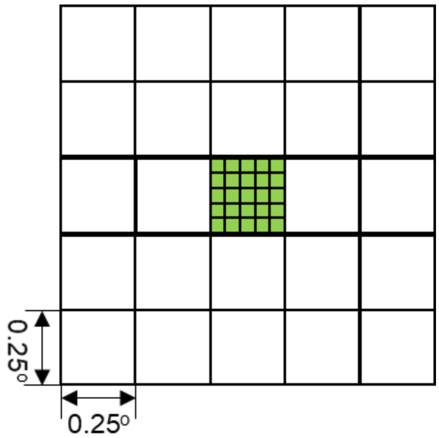


Figure 4.The diagram of statistical analysis. The regression analysis in conducted between green grid cell and surrounding 9 or 24 white grid cells.

Through the analysis, the relationships can be expressed mathematically in terms of a correlation coefficient (R) which varies from -1 to +1, where ±1 indicated the strongest possible agreement and 0 means the strongest possible disagreement. In addition, the R-squared value (coefficient of determination) is used to evaluate the goodness-of-fit of the regression model and can be interpreted as the proportion of response variation "explained" by the regressors in the model. In general, R^2=1 indicates that the fitted model explains all variability in dependent variable, while R^2=0 indicates no linear relationship.

First, the regression analysis is conducted to detect the relationship of tree cover ratio and the local precipitation. Second, in order to explore whether the neighboring effect is different in each direction as well as the scope of this effect , the grid cell which tree cover ratio have significantly changed is selected as the central cell and the regression analysis is applied on its tree canopy and 24 surrounding cells' precipitation (Figure 4 & Appendix I). Furthermore, as the relationship of tree canopy and surrounding mean precipitation is not clear, the regression test is also used to detect the connection between tree canopy and 9 or 24 surrounding cells' mean precipitation (with the resolution of 0.75° and 1.25°, respectively) (Figure 4).

Results

Mann-Kendall test

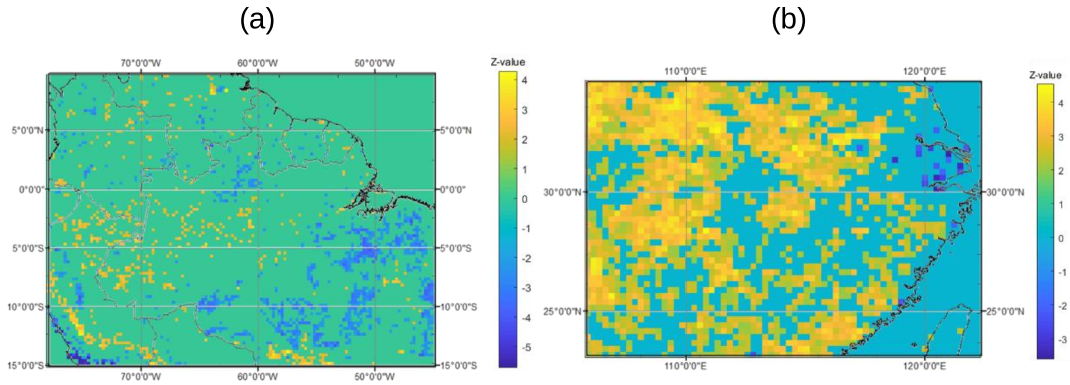


Figure 5.The MK test results of Amazonia and China. (a) shows the grid cells where the tree cover ratio has significant upward or downward trend in the Amazonia from 1998 to 2016 (except 2000). (b) is the result of southeastern China from 2000 to 2016. Strong upward trends happened in the yellow grid cells, while significant downward trends occurred in the blue grid cells.

Tree cover ratio trend Figure 5 is the Mann-Kendall trend test result of tree cover change in Amazonia and southeastern China, and the grid cells that tree cover ratio had significant upward or downward trends with the confidence level of 95% are marked by yellow points and blue points, respectively. The Amazonia research area contains 13,433 grid cells and 1,504 of them had undergone significant tree canopy ratio change, and the significant vegetation changes had occurred in1,566 of 3,149 grid cells in southeastern China. In the figure 5a, large-scale deforestation occurred mainly in the southeastern part of the Amazonia, while near the coastline in the southwest, the tree cover ratio had significantly increased. However, the most negative trends took place along the same coastline. More upward trends distributed dispersedly in the middle and northern Amazonia. In contrast, the significant increase of tree canopy had happened in half of the research area in southeastern China since 2000 and only few downward trends are observed in northeastern area, close the coastline.

Precipitation trend Figure 6a illustrates the Mann-Kendall results of the monthly precipitation in Amazonia. Strong increasing trends occurred relatively less and distributed dispersedly, and can be found in the northeastern part in February and the middle region in March and July. In contrast, the distribution of significant decreasing trends is more concentrated and can be observed in the southwestern corner for each month. In January, March, June, September and October, significant decreases took place in the northern part of the Amazonia. Furthermore, large-scale downward trends can be observed in the southeastern region in July and August.

Figure 6b gives the spatial distribution of significant trends in precipitation detected by the Mann-Kendall test in southeastern China. In general, the consistently similarity is not found among the trends of precipitation in different months. In January, February and December, the precipitation in western region of research area demonstrates a decreasing trend, while the increasing trends more happened in the eastern region in May, June, October and November. Strong decreasing trends can also be found in the northern part of July and northwestern of December. The interesting thing is that in

September, the upward trends occurred in large amount of grid cells across the research area from west to east.

(a) (b)

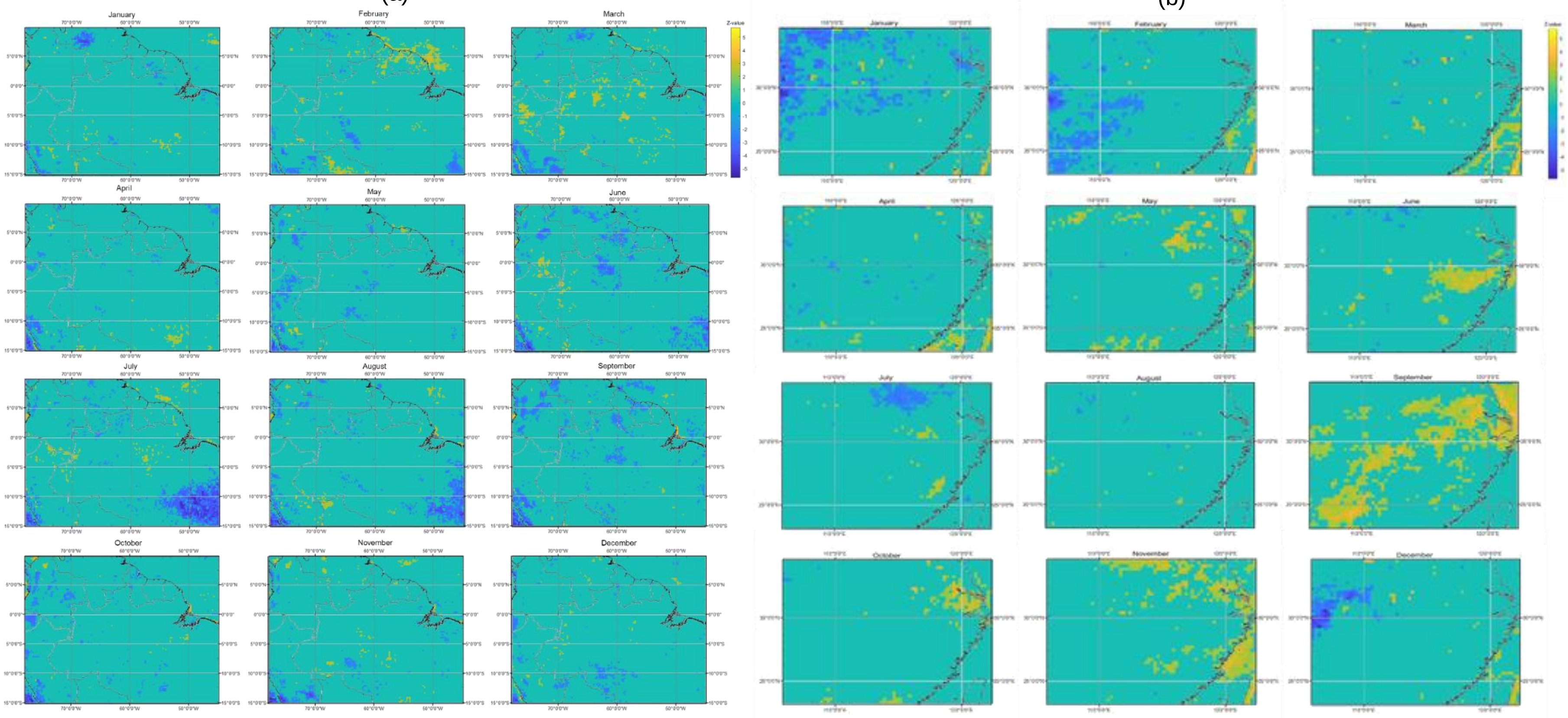


Figure 6.The MK test result of monthly precipitation in Amazonia (a) from 1998 to 2016 (except 2000), and in southeastern China (b) from 2000 to 2016. The green region means that there was no significant change in the research period, while the precipitation in yellow and blue grid cell had significantly increased and decreased, respectively.

Regression test

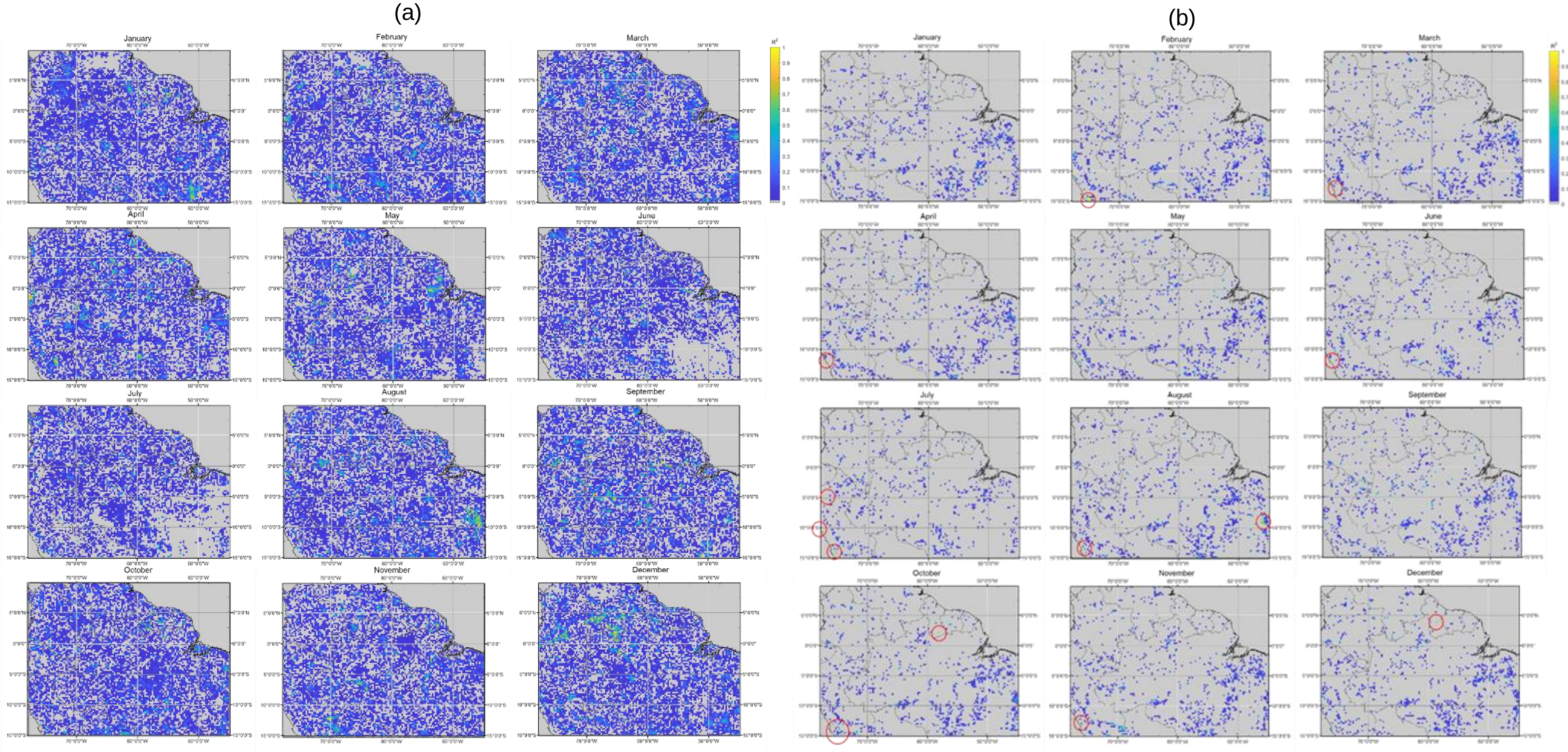


Figure 7. The regression analysis results of tree cover ratio and local precipitation (a), and the results of the cells that tree cover ratio had significantly changed (b) of Amazonia (p=0.05) The grid cell which two variables have strong correlation is marked by red circle (b).

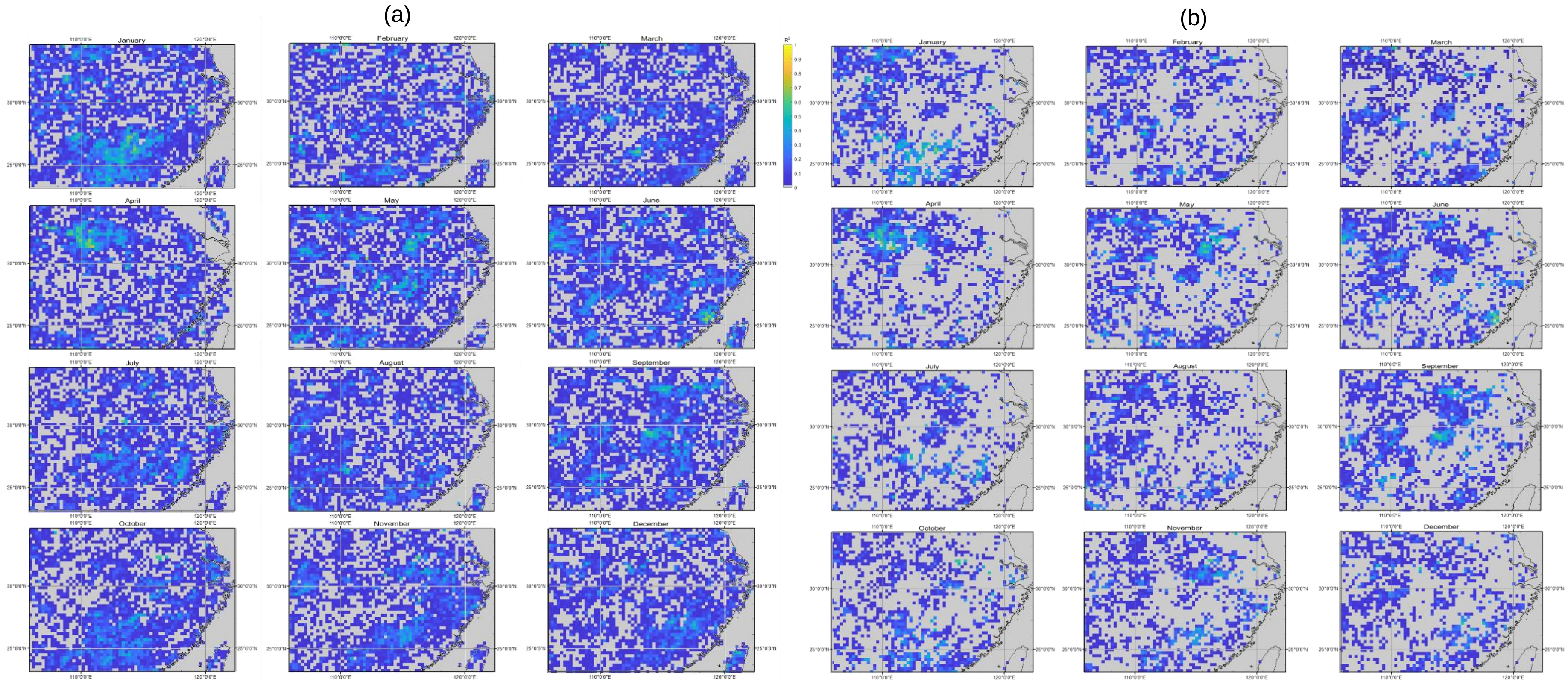


Figure 8. The regression analysis results of tree cover ratio and local precipitation (a), and the results of the cells that tree cover ratio had significantly changed (b) of southeastern China (p=0.05)

Local regression test Figure 7a and figure 8a illustrate the regression results of each cell in Amazonia and southeastern China, respectively. Overall, large-scale of high correlation relationships (R^2>0.49, p=0.05) didn't occur in both research areas. In addition, for southeastern region of Amazonia, tree cover ratio and local precipitation are completely unrelated in June and July. When only considering the cells that tree cover ratio had significantly changed, it is obvious that few grid cells with strong correlation between two variables are detected in the analysis. For Amazonia, the majority of cells with R^2 larger than 0.8 (p=0.05) are found in the northwestern corner, along the coastline of the research area (figure 7b). Other points of which two variables had moderate correlation (0.25<R^2<0.49, p=0.05) distribute through the whole region. When it comes to southeastern China, grid cells with R^2 larger than 0.5 (p=0.05) distribute centrally in the southern part in January, northwestern part in April, northeastern part in May and middle region in September.

Neighboring effect. In order to explore the neighboring effect of tree cover ratio on different directions and distances, the regression analysis is than conducted between the grid cell which tree cover ratio have significantly changed and 24 grid cells centered around it (figure 4). In total, 36,076 and 33,336 groups of data in every month of Amazonia and China are analyzed, respectively. For Amazonia, the distribution of different ranges of R^2 in each month is similar that approximately 20% of results have low correlations (0.09<R^2<0.25, p=0.05) and less that 5% show moderate correlations (0.25<R^2<0.49, p=0.05) (Figure 9). The percentages of R^2 larger than 0.25 in February, May and September are nearly as twice as that in other months. For southeastern China, data sets with low correlation account for 22-30%, and that with moderate correlation account for 3-10%. Moreover, the high percentage occurred in January and September.

The maps that showing the neighboring effect results of Amazonia in May and southeastern China in January, since there are more results with higher R^2, are displayed in the figure 10. For Amazonia, in the southwestern corner of the research area, near the coastline (red circle in figure 10a), moderate correlations are found between the neighbors. In contrast, the results of regression tests conducted on the same area with the data sets covering the tree canopy and local precipitation indicate no correlation. In addition, data sets with R^2 is larger than 0.49 are not found in other area. When it comes to southeastern China, it is obvious that the data sets from southern and part of northern region (circled in figure 10b) are moderately correlated which is consistent with the finding of local regression test in the same area in January. Meanwhile, the neighboring effect seems to be effective in each direction, and still exerts influence on the farthest cells (the linear distance is near 71km) from the center.

Figure 11 and 12 demonstrate the results of the neighboring effect on mean precipitation in Amazonia and southeastern China. For Amazonia, similar to other regression results, extremely few moderate correlations are detected in both scales. In addition, the moderate correlations that found in the analysis with resolution by 0.75°, also happened in that with 1.25°. However, in November, Amazonia, moderate correlations are only detected in the southern part (marked by red circle) with the resolution of 1.25° (figure 11b). For southeastern China, the results are very similar with both resolutions, furthermore, they resemble to the local regression results that the moderate correlations are discovered in the same area in each month (figure 12).

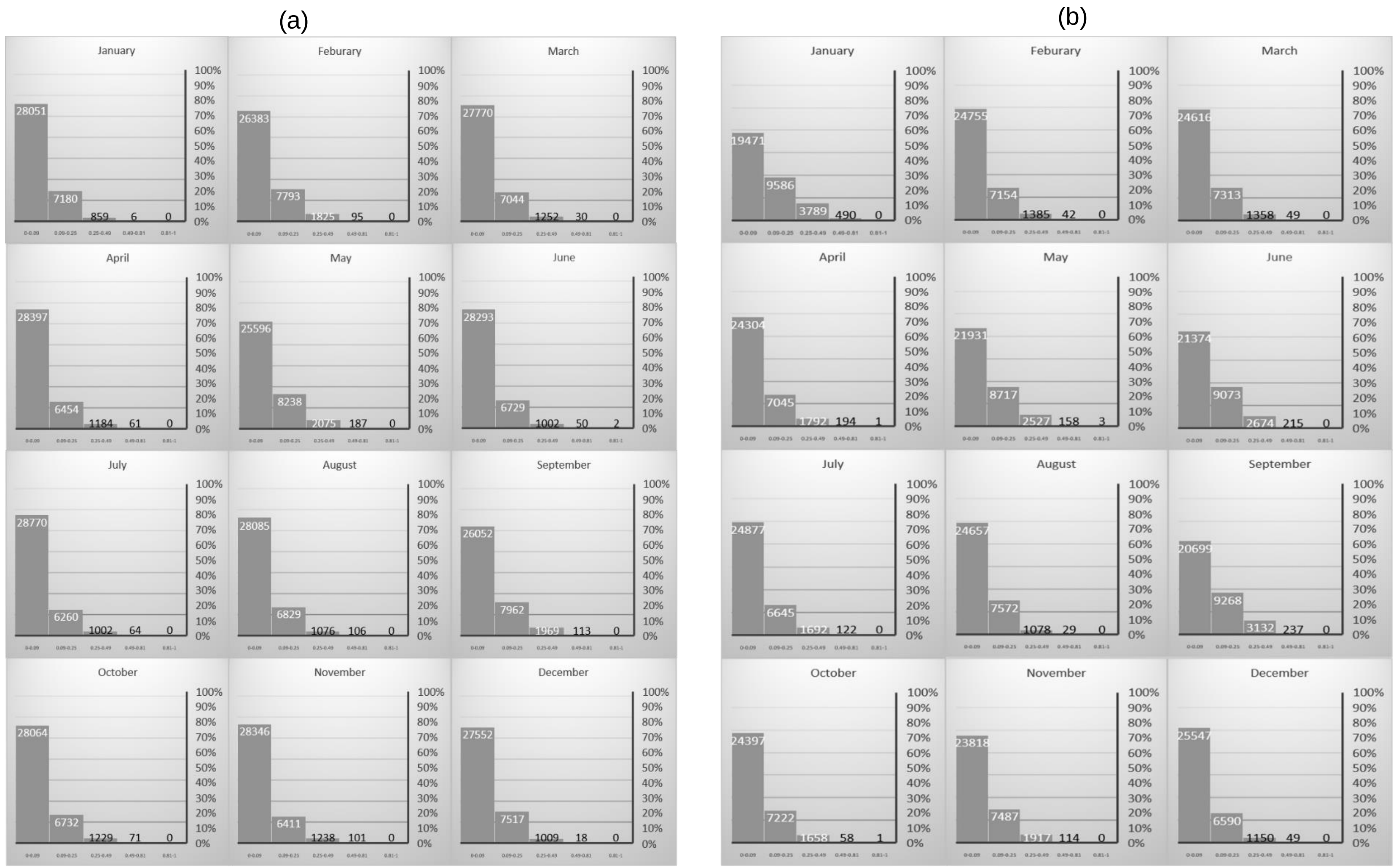


Figure 9. The histogram showing the results of neighboring effect analysis of Amazonia (a) and southeastern China (b), respectively.

(a)

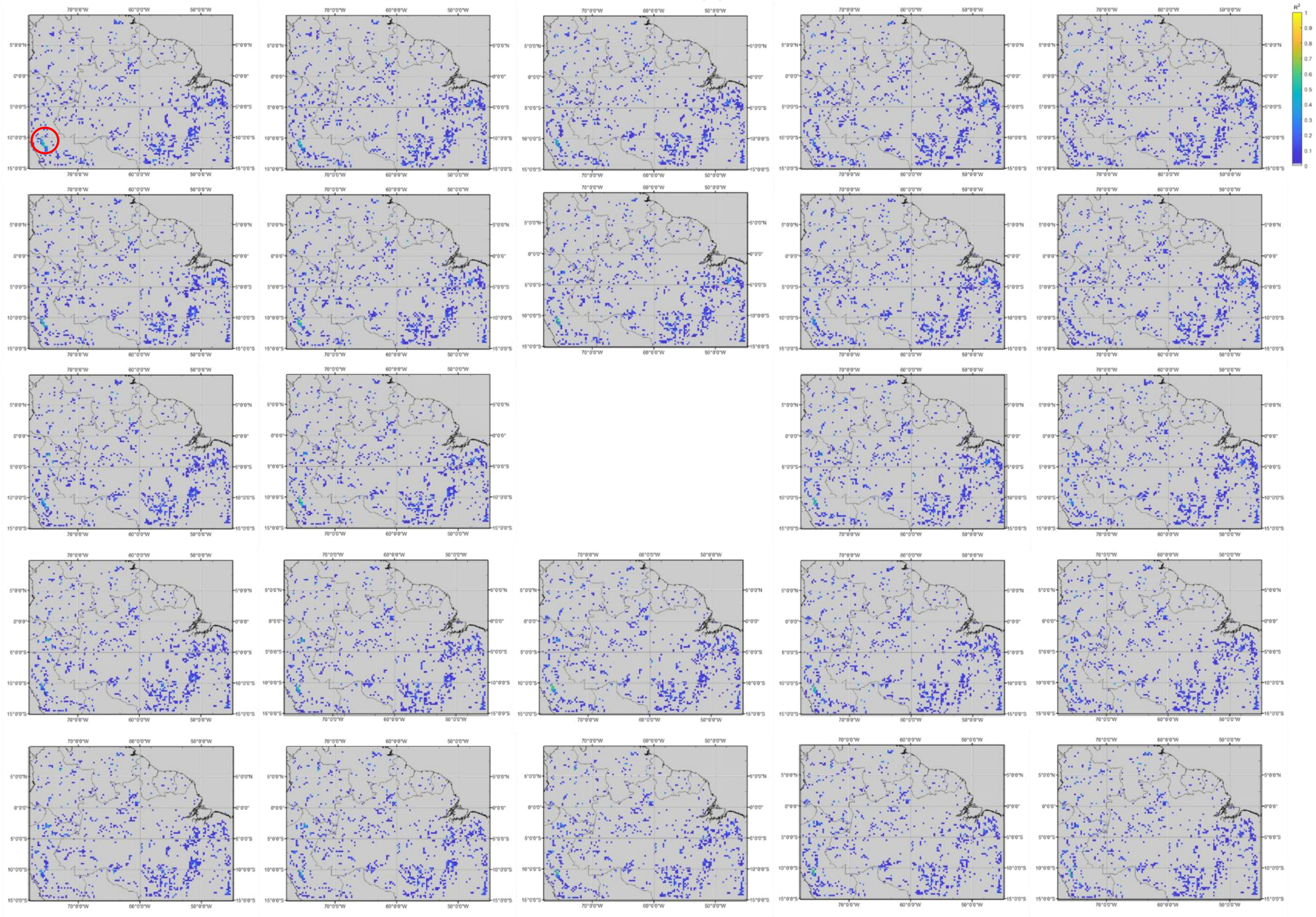
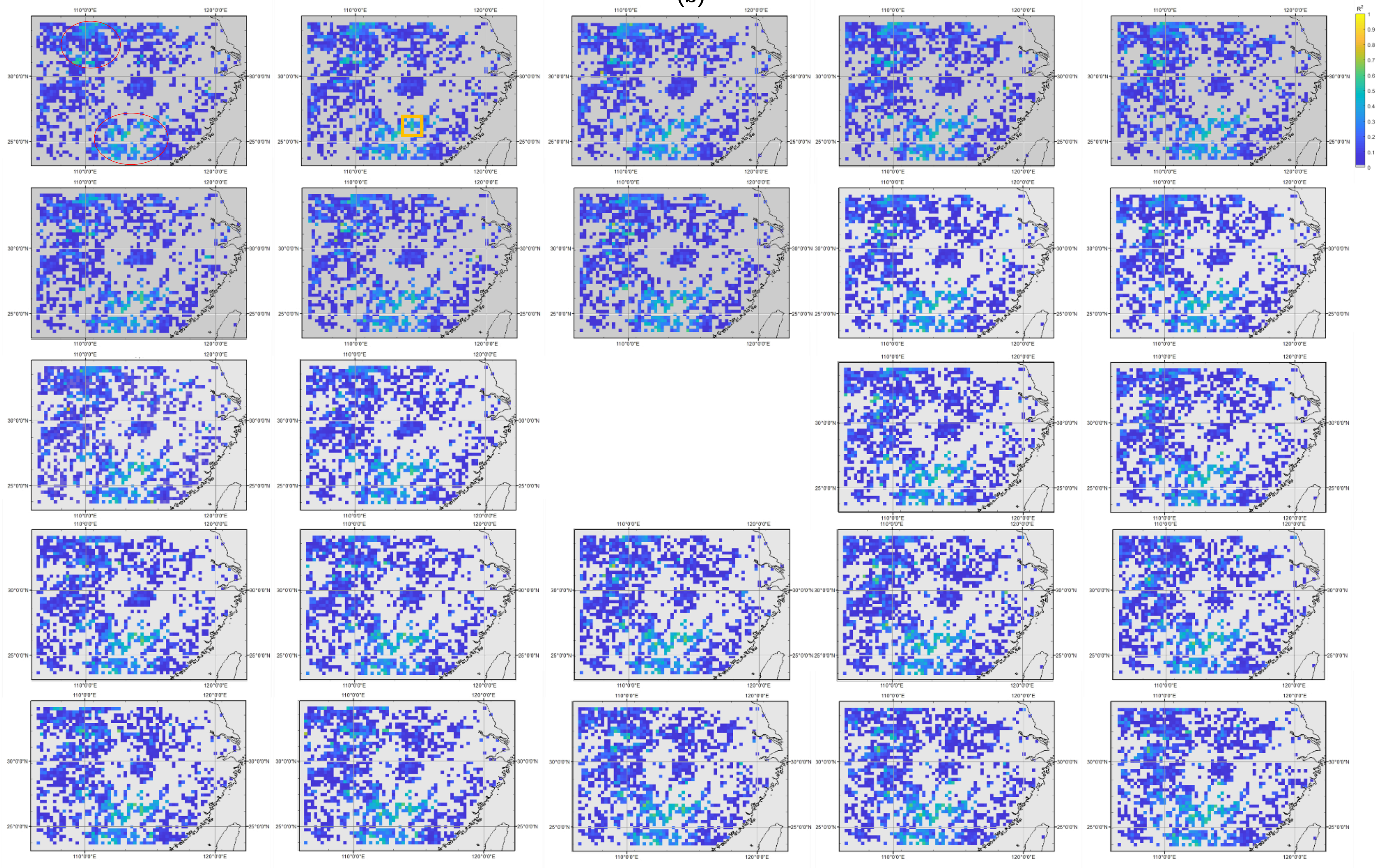


Figure 10. The maps showing the neighboring effect results of Amazonia (a) in May and southeast China in January(b). The same as the diagram in the figure 3, 24 maps in (a) and (b) illustrate the R^2 between the central cell' tree cover ratio and its 24 neighbors' precipitation.

(b)



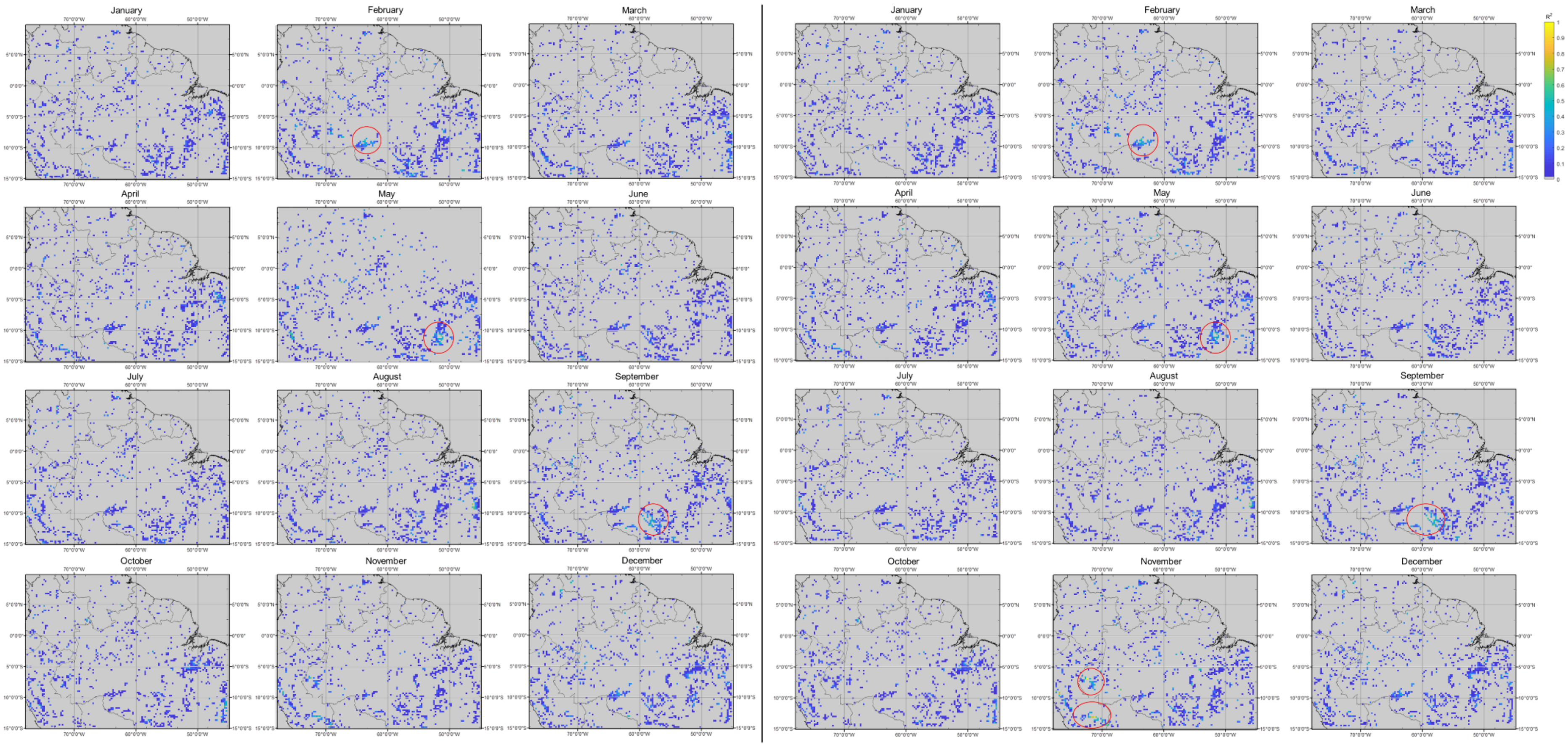


Figure 11. The maps showing the regression analysis test results of tree canopy and mean precipitation of 9 (a) and 24(b) surrounding cells in Amazonia.

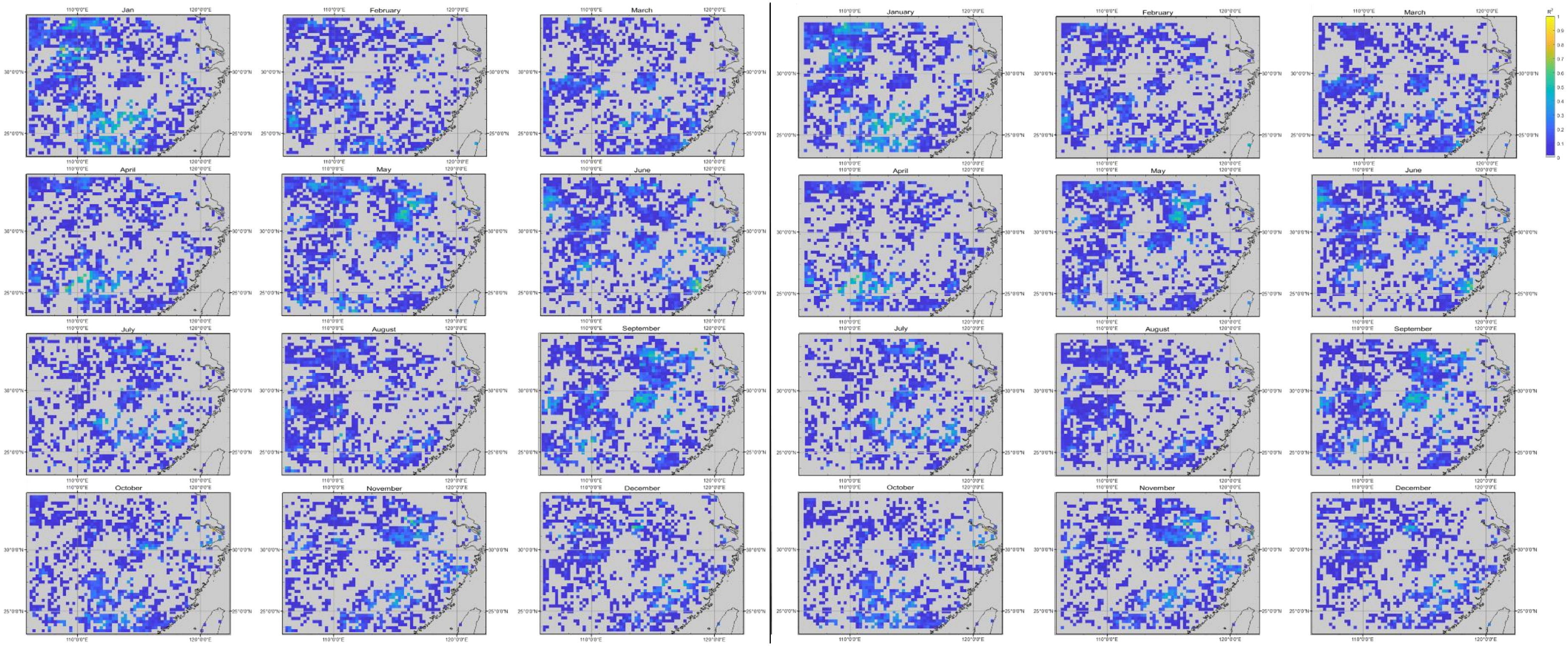


Figure 12. The maps showing the regression analysis test results of tree canopy and mean precipitation of 9 (a) and 24(b) surrounding cells in southeastern China.

Discussion

In relation to tendencies, the present study suggests that large-scale decrease trends of precipitation happened in July and August in the southeastern Amazonia, which is consistent with the large amount of areal deforestation. However, on the basis of regression results, strong correlations between tree cover ratio and precipitation are not found at the same time and place, meanwhile, when integrating all results, it has been discovered that the deforestation in Amazonia seems to exert little influence on local and around precipitation. The reasons behind it are various, apart from the local vegetation, there are many large-scale weather disturbances that can influence the rainfall, for instance, the sea surface temperature, continental surface heating and El Nino Southern Oscillation events (Chen *et al.,* 2001; Marengo *et al.*, 1993; Marengo *et al*., 1998).

Except the factors mentioned above, the resolution of dataset may also affect the results (D'Almeida *et al*., 2007; Negri *et al*., 2004). In two studies of the impact of deforestation on precipitation over the Amazon, Durieux et al. (2003) examined 10 years of 3-hourly infrared data with the resolution of 2.5° x 2.5°, while Negri et al. (2004) analyzed 14 years of 8-hourly data with the resolution of 0.5° x 0.5° of the same research area (8 to 13°N, 60 to 65°W). They obtained opposite results in the end, the study with better degree of resolution found an increased probability of rain over the deforestation in August, during the transition from dry to wet season, while the other one did not. The reason is regarded to the resolution, Negri explained that when compared to the 0.5° by 0.5° cell, the topography and vegetation patterns were more complicated in the cell of 2.5°. Meanwhile, both of them in agree with the statement that the sharp meridional gradient in precipitation make the effect of deforestation more complex, which is more obvious in the dry season.

The resolution of the neighboring effect in present study is 0.25°-1.25°, however, the results contrast with that found by Negri. Through comparing the analysis technique, it is found that the precipitation data analyzed by Negri are the average for 1960-78 and 1979-90 in each month. Thus, the difference between the results may due to the study period: 1960 to 1990 and 1998 to 2016, respectively; and the diverse of time scale, one is an inter-decadal study while the present study is inter-annual.

Significant increases of tree cover ratio are observed in most part of southeastern China, while the precipitation in each month displayed different tendencies. Decreasing trends mostly happened during the winter period in the northern part, while in the summer period, especially in September, large-scale of increasing trends appeared. The reason is regarded as the influence of the East Asian monsoon (Zhou, 2011). Similar as the discovery in Amazonia, when comparing the figure 5b against figure 7b, it is found that few proportions of the significant trends of precipitation can be 'explained' by the local tree cover ratio. This phenomenon can be observed obviously in January, that moderate correlations are detected at where the precipitation didn't change significantly. This finding supports the statement that the precipitation in southeastern China is more influenced by the East Asian summer monsoon and East Asian winter monsoon (Gemmer *et al*., 2011; Zhou, 2011).

The significant neighboring effects are detected in the northern part of southeastern China, that the tree cover ratios of central cells exert moderate impacts on precipitations of its neighbors. However, same correlation also happened in the local regression test. When considering that the afforestation program is organized and the change of areal forest cover is very similar, there is a possibility that the moderate correlations in this area may be due to the similarity existing in forest cover ratio data. In order to prove this hypothesis, the tree canopy and precipitation data of 25 grid cells (marked by yellow square in figure 10b) where moderate correlations happened more is analyzed. From figure 13, high correlations (R^2>0.49) and very high correlations (R^2>0.81) happened in almost all results. Comparing to the neighboring effect results in figure 10b, it is clear that the significant neighboring effect are detected between the cells that the tree cover ratio is highly correlated. This finding supports the hypothesis above, meanwhile, points out that the neighboring effect results are unreliable.

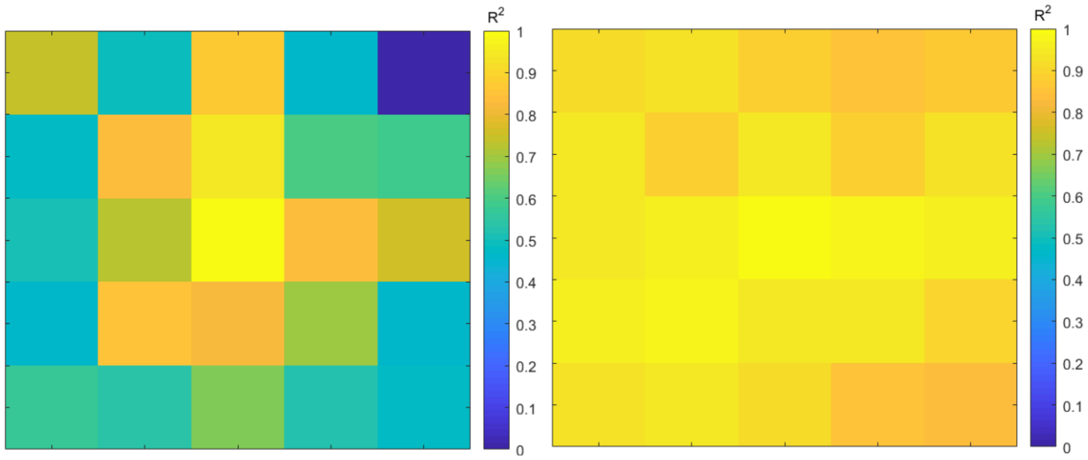


Figure 10. (a) is the correlation relationship between tree canopy in peripheral and central cells; (b) is the correlation relationship between precipitation in peripheral and central cells.

Basing on the present results, the strong neighboring effect of tree canopy on precipitation is not found in both research area. One limitation is the coarse resolution of precipitation (0.25° x0.25°), as the resolution of original tree canopy data is 0.05°, in order to unify the resolutions of two variables, the average value of tree canopy is applied. Some features may lose during this process, resulting in the unreliable of the results. For future studies, a resolution within 0.05°-0.1° is recommended as a better data base to explore the research question in this thesis. Furthermore, due to the afforestation program in China is organized, the strong similarity happened in the forest canopy data in Southeast China, and absolutely has impact on neighboring effect results. How to diminish this influence should be explored in the future study.

Conclusion

Amazonia and southeastern China have experienced large-scale of deforestation and afforestation, respectively. Understanding the response of precipitation to those changes is an important requirement to estimate the impacts of land cover change on water cycle. The Mann-Kendall test conducted with satellite girded data of tree canopy and precipitation with the resolution of 0.25° illustrates the spatial distributions of significant trends. The regression analyses presented in this study give a spatially consistent picture of precipitation–tree canopy relationships of Amazonia and southeast China. The main findings are summarized as follows:

1. In relation to tendencies, present study suggests that large-scale deforestation occurred mainly in the southeastern part of the Amazonia, while the tree cover ratio had significantly increased near the coastline in the southwest. And the most negative trends took place along the same coastline. In total, the tree canopy of 11.2% grid cells had underwent significant changes. For the precipitation in Amazonia, relatively less upward trends occurred, and downward trends concentrated in the southwestern corner for each month and southeastern region in July and August. When it comes to southeastern China, half (49.7%) of the annual series of tree canopy presented significant upward trends. Opposing this, significant increasing trends of precipitation are only found in September across the research area and few regions during the summer and autumn period. Furthermore, strong downward trends happened in the northern part during the winter period.
2. The neighboring effect is not obvious in both research area. For Amazonia, low correlations account for approximately 20% in each month, only 5% results show moderate correlations as well as high correlations are extremely few. For southeastern China, data sets with low correlation account for 22-30%, and that with moderate correlation account for 3-10%. According to the results that the high proportion of cells with moderate correlation appeared in January. Although moderate correlations had been detected in the northern region of southeastern China in January, the credibility of this is not high since this may result from the high similarity existing in tree cover ratio data in that area.
3. On the basis of the results, it can't be concluded that the local precipitation is associated with local and around tree cover ratio. In addition, the current research results can't make an answer to the sub-question 2 and 3. Future studies with a finer resolution are expected. The present study, as well as future studies, will be helpful in estimations of response of the precipitation to vegetation change.

Acknowledgement

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Appendix

Appendix I Statistical Analysis

Precipitation monthly in Amazonia

```
clear all
close all
clc

month = [31,28,31,30,31,30,31,31,30,31,30,31];
m = 1;
     total_precip=zeros(1,1);
    for j = 1:12
        imax = month(j);
        for y = 1998:1999
            for i=1:imax
                total_precip=zeros(1,1);
                precip = ncread(['3B42_Daily.',num2str(y,'%4d'),num2str(j,'%02i'),
num2str(i,'%02i')
'.7.nc4.nc4@precipitation[408%3A540][139%3A239],lon[408%3A540],lat[139%3A239]'],'preci
pitation');
                total_precip =total_precip+precip;
                m = m+1;
            end
            data_p{j,y-1997}= flipud(total_precip);
            clear total_precip
        end
    end
    m = 1;
    for j = 1:12
        imax = month(j);
        for y = 2001:2016
            for i=1:imax
                total_precip=zeros(1,1);
                precip = ncread(['3B42_Daily.',num2str(y,'%4d'),num2str(j,'%02i'),
num2str(i,'%02i')
'.7.nc4.nc4@precipitation[408%3A540][139%3A239],lon[408%3A540],lat[139%3A239]'],'preci
pitation');
                total_precip =total_precip+precip;
                m = m+1;
            end
            data_p{j,y-1998}= flipud(total_precip);
            clear total_precip
        end
    end
    data_p_monthly=data_p;
    save ('result.mat','data_p_monthly','-append')
```

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Precipitation monthly in southeastern China

```
clear                                                                   all
close                                                                   all
clc
```

```
month                   =                      [31,28,31,30,31,30,31,31,30,31,30,31];
m                                  =                                             1;
     total_precip=zeros(1,1);

       for                     j                        =                     1:12
        imax                             =                                month(j);
        for                     y                  =                       2001:2016
        for                                                                 i=1:imax
            total_precip=zeros(1,1);
            precip    =    ncread(['3B42RT_Daily.',num2str(y,'%4d'),num2str(j,'%02i'),
num2str(i,'%02i')                            '.7.nc4.nc4'],'precipitation');
            total_precip                                      =total_precip+precip;
            m                                  =                                m+1;
        end
        data_p{j,y-2000}=                                     flipud(total_precip);
      clear                                                           total_precip
        end
    end
    data_p_monthly=data_p;
    save ('china.mat','data_p_monthly','-append')
```

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Tree caver ratio of Amazonia

```
clear                                                                   all
close                                                                   all
clc
```

```
m=1;
for                         k                        =                   1998:1999
            treecover     =     ncread(['VCF5KYR_',num2str(k)     '001.nc'],'Band1');
            treecover0=treecover(2041:2705,1496:2000);
            treecover0(isnan(treecover0)==1)                  =                    0;

treecover1=reshape(sum(reshape(treecover0,size(treecover0,1),5,[]),2),size(treecover0,
1),[]);
            treecover2=reshape(sum(reshape(treecover1,5,101,133),1),133,101);
            total_tree=treecover2/25;
            m=m+1;
            data_t{k-1997,1}=                                     rot90(total_tree);
end
for                         k                        =                   2001:2016
            data_everyyear_tree=zeros(1,1);
            treecover     =     ncread(['VCF5KYR_',num2str(k)     '001.nc'],'Band1');
            treecover0=treecover(2041:2705,1496:2000);
            treecover0(isnan(treecover0)==1)                  =                    0;

treecover1=reshape(sum(reshape(treecover0,size(treecover0,1),5,[]),2),size(treecover0,
1),[]);
```

```
            treecover2=reshape(sum(reshape(treecover1,5,101,133),1),133,101);
            total_tree=treecover2/25;
            m=m+1;
            data_t{k-1998,1}                    =                    rot90(total_tree);
end
save  ('result.mat','data_t','-append')
```

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Tree caver ratio of southeastern China

```
clear                                                                                   all
close                                                                                   all
clc
m=1;
for                        k                        =                           2001:2016
    data_everyyear_tree=zeros(1,1);
    treecover       =       ncread(['VCF5KYR_',num2str(k)       '001.nc'],'Band1');
    treecover0=treecover(5716:6050,2261:2495);
    treecover0(isnan(treecover0)==1)                        =                          0;

treecover1=reshape(sum(reshape(treecover0,size(treecover0,1),5,[]),2),size(treecover0,
1),[]);
    treecover2=reshape(sum(reshape(treecover1,5,47,67),1),67,47);
    total_tree=treecover2/25;
    m=m+1;
    data_t_china{k-2000,1}                    =                    rot90(total_tree);
end
save  ('china.mat','data_t_china')
```

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Transforming the precipitation data for next step.

```
clear                                                                                   all
close                                                                                   all
clc
load                           result.mat                                  data_p_monthly
  for                                                                              n=1:18
  precip_Jan{n,1}=data_p_monthly{1,n};
  precip_Feb{n,1}=data_p_monthly{2,n};
  precip_Mar{n,1}=data_p_monthly{3,n};
  precip_Apr{n,1}=data_p_monthly{4,n};
  precip_May{n,1}=data_p_monthly{5,n};
  precip_June{n,1}=data_p_monthly{6,n};
  precip_July{n,1}=data_p_monthly{7,n};
  precip_Aug{n,1}=data_p_monthly{8,n};
  precip_Sept{n,1}=data_p_monthly{9,n};
  precip_Oct{n,1}=data_p_monthly{10,n};
  precip_Nov{n,1}=data_p_monthly{11,n};
  precip_Dec{n,1}=data_p_monthly{12,n};
  end
save                                           ('result.mat','precip_Jan','-append')
save                                           ('result.mat','precip_Feb','-append')
save                                           ('result.mat','precip_Mar','-append')
```

```
save ('result.mat','precip_Apr','-append')
save ('result.mat','precip_May','-append')
save ('result.mat','precip_June','-append')
save ('result.mat','precip_July','-append')
save ('result.mat','precip_Aug','-append')
save ('result.mat','precip_Sept','-append')
save ('result.mat','precip_Oct','-append')
save ('result.mat','precip_Nov','-append')
save ('result.mat','precip_Dec','-append')
```

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```
clear all
close all
clc
load china.mat data_p_monthly
  for n=1:16
  precip_Jan{n,1}=data_p_monthly{1,n};
  precip_Feb{n,1}=data_p_monthly{2,n};
  precip_Mar{n,1}=data_p_monthly{3,n};
  precip_Apr{n,1}=data_p_monthly{4,n};
  precip_May{n,1}=data_p_monthly{5,n};
  precip_June{n,1}=data_p_monthly{6,n};
  precip_July{n,1}=data_p_monthly{7,n};
  precip_Aug{n,1}=data_p_monthly{8,n};
  precip_Sept{n,1}=data_p_monthly{9,n};
  precip_Oct{n,1}=data_p_monthly{10,n};
  precip_Nov{n,1}=data_p_monthly{11,n};
  precip_Dec{n,1}=data_p_monthly{12,n};
  end
save ('china.mat','precip_Jan','-append')
save ('china.mat','precip_Feb','-append')
save ('china.mat','precip_Mar','-append')
save ('china.mat','precip_Apr','-append')
save ('china.mat','precip_May','-append')
save ('china.mat','precip_June','-append')
save ('china.mat','precip_July','-append')
save ('china.mat','precip_Aug','-append')
save ('china.mat','precip_Sept','-append')
save ('china.mat','precip_Oct','-append')
save ('china.mat','precip_Nov','-append')
save ('china.mat','precip_Dec','-append')
```

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Transforming the tree cover data for next step

```
load china.mat data_t_china
b=cell2mat(data_t_china);
for m=1:47
    for n=1:67
    t_eachcell=b([m    47+m    94+m    47*3+m    47*4+m    47*5+m    47*6+m    47*7+m    47*8+m...
        47*9+m    47*10+m    47*11+m    47*12+m    47*13+m    47*14+m    47*15+m    ],[n]);
    data_t_eachcell_china{m,n}=t_eachcell;
    end
```

```
end
save ('china.mat', 'data_t_eachcell_china','-append')
```

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The Mann-Kendall test of southeastern China

```
Z=zeros(47,67);
for                                                          m=1:47
    for                                                      n=1:67
        y=data_t_eachcell_china{m,n}(1:16,1);
        l=length(y);
        s1=0;
for                                        j                  =2:l
  for                                     i              =1:(j-1)
      sgn=y(j)-y(i);
        if                                                   sgn>0
          sgn=1;
        else
            if                                               sgn<0
          sgn=-1;
            else
                sgn=0;
            end
        end
       s1=s1+sgn;
  end
end
Var=l*(l-1)*(2*l+5)/18;
if                                                            s1>0
Zmk=(s1-1)/sqrt(Var);
else
    if                                                        s1<0
        Zmk=(s1+1)/sqrt(Var);
    else
        Zmk=0;
    end
end
if                                                        Zmk>1.96
    Zmk=Zmk;
else
    if                                                   Zmk<-1.96
        Zmk=Zmk;
    else
        Zmk=0;
    end
end
Z(m,n)=Zmk;
n=n+1;
    end
    m=m+1;
end
Z_T_china=Z;
save('china.mat','Z_T_china','-append')
```

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The neighboring effect analysis of Amazonia

```
clear all
close all
clc

load('result.mat')

logic = Z_T>1.9;
[a,b] = size(p_eachcell_Jan);
sel = cell (5,5);
data_larger = cell (a,b);
data_smaller = cell (a,b);

for i = 3:a-2
    for j = 3:b-2
        if Z_T(i,j) > 1.9 % the tree cover have increased siginificantly
            for m = 1:5
                for n = 1:5
                    sel{m,n} = p_eachcell_Jan{i+m-3,j+n-3};
                end
            end
            sel{3,3} = data_t_eachcell{i,j}; % set the center data is the tree cover
data
            data_larger{i,j} = sel;
        end
        if Z_T(i,j) < -1.9 % the tree cover have decreased siginificiantly
            for m = 1:5
                for n = 1:5
                    sel{m,n} = p_eachcell_Jan{i+m-3,j+n-3};
                end
            end
            sel{3,3} = data_t_eachcell{i,j};
            data_smaller{i,j} = sel;
        end
    end
end

R =cell(5,5);
R_Square_larger =cell(101,133);
R_Square_smaller =cell(101,133);

for i=1:101
    for j=1:133
        inc=data_larger{i,j};
        if ~isempty(inc)
          for n=1:5
             for m=1:5
                precip=inc{n,m};
                tree=inc{3,3};
                precip=precip(:)';
                tree=tree(:)';
                Precip=[ones(length(tree),1),precip'];
                Tree=tree';
                [b, bint, r, rint, stats]=regress(Tree,Precip,0.05);
```

```
                R_S(n,m)=stats(1,1);
                R_Square_larger{i,j}=R_S;
            end
        end

    end
  end
end

for i=1:101
  for j=1:133
      dec=data_smaller{i,j};
      if ~isempty(dec)
        for n=1:5
            for m=1:5
                precip=dec{n,m};
                tree=dec{3,3};
                precip=precip(:)';
                tree=tree(:)';
                Precip=[ones(length(tree),1),precip'];
                Tree=tree';
                [b, bint, r, rint, stats]=regress(Tree,Precip,0.05);
                R_S(n,m)=stats(1,1);
                R_Square_smaller{i,j}=R_S;
            end
        end

    end
  end
end
```

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```
clear all
close all
clc

load ('result.mat')

N9=cell(101,133);
sel=cell(3,3);
a=cell(3,3);
R_square=cell(101,133);
R9=zeros(101,133);

for i = 2:100
    for j = 2:132
        if Z_T(i,j)~=0
            for m = 1:3
                for n = 1:3
                    sel{m,n} = p_eachcell_Dec{i+m-2,j+n-2};
                end
            end
            sel{2,2} = data_t_eachcell{i,j}; % set the center data is the tree cover
data
            N9{i,j} = sel;
        end
    end
```

```
end

for                                                          i=1:101
    for                                                      j=1:133
        if                                             ~isempty(N9{i,j})

            for                                              k=1:18
                p=0;
            for                                              m=1:3
                for                                          n=1:3
                if              m~=2            &&           n~=2
                        p1=N9{i,j}{m,n}(k,1);
                        p=p+p1;
                end
                end
            end
            p=p/8;
            p_y(k,:)=p;
            end
                    for                                      x=1:3
                        for                                  y=1:3
                                a{x,y}=p_y;
                        end
                    end
            a{2,2}=N9{i,j}{2,2};
        N9{i,j}=a;
        end

    end
end

 for                                                         i=1:101
    for                                                      j=1:133
        if                                             ~isempty(N9{i,j})
          for                                                n=1:3
             for                                             m=1:3
                precip=N9{i,j}{m,n};
                tree=N9{i,j}{2,2};
                Precip=[ones(length(tree),1),precip];
                Tree=tree;
                [b,     bint,     r,     rint,     stats]=regress(Tree,Precip,0.05);
                R_S(n,m)=stats(1,1);
                R_square{i,j}=R_S;

             end
          end

       end
    end
end

 for                                                         i=1:101
     for                                                     j=1:133
         if                                       ~isempty(R_square{i,j})
             R9(i,j)=R_square{i,j}(1,1);
         end
     end
 end
```

```
 R9_Dec=R9;
 save('result.mat','R9_Dec','-append')
 imagesc(R25_Jan)
 title('Jan')
 h=colorbar;
set(get(h,'title'),'string','R^2');
set(gca, 'CLim', [0 1]);
```

The neighboring effect analysis of southeastern China

```
clear all
close all
clc

load ('china.mat')

logic =Z_T_china>1.9;
a =47;
b =67;
sel = cell (5,5);
data_larger = cell (a,b);
data_smaller = cell (a,b);

for i = 3:a-2
    for j = 3:b-2
        if Z_T_china(i,j) > 1.9
            for m = 1:5
                for n = 1:5
                    sel{m,n} = p_eachcell_Jan_china{i+m-3,j+n-3};
                end
            end
            sel{3,3} = data_t_eachcell_china{i,j}; % set the center data is the tree cover data
            data_larger{i,j} = sel;
        end
      if Z_T_china(i,j) < -1.9 % the tree cover have decreased siginificiantly
            for m = 1:5
                for n = 1:5
                    sel{m,n} = p_eachcell_Jan_china{i+m-3,j+n-3};
                end
            end
            sel{3,3} = data_t_eachcell_china{i,j};
            data_smaller{i,j} = sel;
        end
    end
end

R =cell(5,5);
R_Square_larger =cell(47,67);
R_Square_smaller =cell(101,133);

for i=1:47
    for j=1:67
        inc=data_larger{i,j};
        if ~isempty(inc)
          for n=1:5
```

```
            for m=1:5
                precip=inc{n,m};
                tree=inc{3,3};
                Precip=[ones(length(tree),1),precip];
                Tree=tree;
                [b, bint, r, rint, stats]=regress(Tree,Precip,0.05);
                R_S(n,m)=stats(1,1);
                R_Square_larger{i,j}=R_S;
               stats1_larger{i,j}=stats;
            end
         end

      end
   end
end
for i=1:47
    for j=1:67
        dec=data_smaller{i,j};
        if ~isempty(dec)
          for n=1:5
            for m=1:5
                precip=dec{n,m};
                tree=dec{3,3};
                precip=precip(:)';
                tree=tree(:)';
                Precip=[ones(length(tree),1),precip'];
                Tree=tree';
                [b, bint, r, rint, stats]=regress(Tree,Precip,0.05);
                R_S(n,m)=stats(1,1);
                R_Square_smaller{i,j}=R_S;
            end
          end

        end
    end
end
```

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```
clear all
close all
clc

load ('china.mat')

N9=cell(47,67);
sel=cell(3,3);
a=cell(3,3);
R_square=cell(47,67);
R9=zeros(47,67);

for i = 2:46
    for j = 2:66
        if Z_T_china(i,j)~=0
           for m = 1:3
               for n = 1:3
                   sel{m,n} = p_eachcell_Dec_china{i+m-2,j+n-2};
```

```
            end
        end
        sel{2,2} = data_t_eachcell_china{i,j}; % set the center data is the tree
cover                                                                      data
        N9{i,j}                             =                              sel;
    end
  end
end
```

```
for                                                                      i=1:47
  for                                                                    j=1:67
    if                                                           ~isempty(N9{i,j})

      for                                                                k=1:16
          p=0;
      for                                                                 m=1:3
          for                                                             n=1:3
          if                    m~=2                  &&                  n~=2
                  p1=N9{i,j}{m,n}(k,1);
                  p=p+p1;
          end
          end
      end
      p=p/8;
      p_y(k,:)=p;
      end
              for                                                         x=1:3
                  for                                                     y=1:3
                          a{x,y}=p_y;
                  end
              end
      a{2,2}=N9{i,j}{2,2};
    N9{i,j}=a;
    end

  end
end
```

```
 for                                                                     i=1:47
  for                                                                    j=1:67
    if                                                           ~isempty(N9{i,j})
      for                                                                 n=1:3
        for                                                               m=1:3
          precip=N9{i,j}{m,n};
          tree=N9{i,j}{2,2};
          Precip=[ones(length(tree),1),precip];
          Tree=tree;
          [b,     bint,     r,     rint,     stats]=regress(Tree,Precip,0.05);
          R_S(n,m)=stats(1,1);
          R_square{i,j}=R_S;

        end
      end

    end
  end
end
```

```
for                                                                                    i=1:47
    for                                                                                j=1:67
        if                                                               ~isempty(R_square{i,j})
            R9(i,j)=R_square{i,j}(1,1);
        end
    end
end
R9_Dec_china=R9;
save('china.mat','R9_Dec_china','-append')
imagesc(R9_Dec_china)
title('December')
h=colorbar;
set(get(h,'title'),'string','R^2');
set(gca, 'CLim', [0 1]);
```