



Quantifying the effectiveness of ecological restoration projects on long-term vegetation dynamics in the karst regions of Southwest China

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1 **Quantifying the effectiveness of ecological restoration projects on long-term vegetation**
2 **dynamics in the karst regions of Southwest China**

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20 **ABSTRACT**

21 To alleviate the severe rocky desertification and improve the ecological degradation conditions in
22 Southwest China, the national and local Chinese governments have implemented a series of
23 Ecological Restoration Projects (ERPs) since the late 1990s. This study proposes a remote sensing
24 based approach to evaluate the long term efforts of the ERPs started in 2000. The method applies a
25 time series trend analysis of satellite based vegetation data corrected for climatic influences to reveal
26 human induced vegetation changes. The improved residual method is combined with statistics on the
27 invested project funds to derive an index, Project Effectiveness Index (PEI), measuring the project
28 effectiveness at county scale. High effectiveness is detected in the Guangxi Province, moderate
29 effectiveness in the Guizhou Province, and low and no effectiveness in the Yunnan Province.
30 Successful implementations are closely related to the combined influences from climatic conditions
31 and human management. The landforms of Peak Forest Plain and Peak Cluster Depression regions in
32 the Guangxi Province are characterized by temperate climate with sufficient rainfall generally leading
33 to a high effectiveness. For the karst regions of the Yunnan and Guizhou Provinces with rough terrain
34 and lower rainfall combined with poor management practices (unsuitable species selection, low
35 compensation rate for peasants) only low or even no effect of project implementations can be
36 observed. The distribution is however not homogeneous and counties with a high project effectiveness
37 in spite of complex natural conditions were identified, but also counties with negative vegetation
38 trends despite favorable conditions and high investments. The proposed framework is expected to be
39 of high relevance in general monitoring of the successfulness of ecological conservation projects in
40 relation to invested funds.

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Keywords: RESTREND, Grain to Green Program, rocky desertification, growing season NDVI, Yunnan, Guizhou, Guangxi

Introduction

Rocky desertification is a typical type of land degradation by which a karst area covered by vegetation and soil is transformed into a rocky landscape with limited soil and vegetation resources (Wang et al., 2004; Yuan, 1997). Rocky desertification is influenced by the combined circumstances of geology, geomorphology, soil, warm and wet climate, vegetation, as well as human overexploitation of natural resources (Liu et al., 2008; Wang et al., 2004; Xu and Zhang, 2014). The rocky desertification in the karst regions of Southwest China has been identified as the most severe ecological problem threatening the area (Wang et al., 2004; Yuan, 1997; Yue et al., 2010). Up to 82% of the rocky desertification areas are concentrated in the Yunnan, Guizhou, and Guangxi Provinces (Jiang et al., 2014). To protect and improve the ecological environment, the state and local Chinese governments have launched a series of ecological restoration projects (ERPs), such as the Natural Forest Protection Project, the Grain to Green Program, and the Karst Rocky Desertification Comprehensive Control and Restoration Project. **However, evaluation of the effectiveness of these projects focuses on the north of China (Huang et al., 2013; Li et al., 2016; Wu et al., 2014, 2013; Zhang et al., 2012, 2016) and** the success of the ERPs in Southwest China is uncertain (Trac et al., 2007; Xu et al., 2006).

The primary objectives of ERPs are to protect the existing forests and to increase vegetation coverage by means of afforestation (i.e., planting on previously barren wastelands), reforestation, and cropland to forest/grassland conversion. An increase/decrease in vegetation can thus be interpreted as progress/regression of the effectiveness of ERPs. However, apart from ERPs, also climatic changes influence vegetation dynamics (Choi, 2004; Seabrook et al., 2011), and therefore, to evaluate the performance of large-scale ERPs, a prerequisite is to distinguish between human and climate-induced vegetation changes.

Field surveys can generate accurate information related to vegetation dynamics and their drivers, but *in situ* observations are costly, time-consuming and spatially limited (Li et al., 2006; Xiao et al., 1995). Due to the large area coverage and long time span, satellite based imagery has become a widely used tool in ecological conservation and one of the most important data sources for monitoring vegetation dynamics at large scales (Nemani et al., 2003; Pettorelli et al., 2005; Tucker et al., 2001). The normalized difference vegetation index (NDVI), based on the red and near-infrared spectrum, has shown to be efficient for sensing the green vegetation and monitoring global and regional trends as

76 well as the variability of vegetation (Huete et al., 2002; Pinzon and Tucker, 2014; Running and
77 Nemani, 1988). For areas of pronounced seasonality (as in this study), the growing season NDVI
78 (GSN) has proven to be a robust approximation of the biomass production of a given year (Mbow et
79 al., 2013; Tong et al., 2016).

80 Numerous studies have applied NDVI time series in China showing a recent increase in
81 vegetation productivity in the karst regions (Cai et al., 2014; Tong et al, 2014; Xu and Zhang, 2014;
82 Wang et al., 2007). Yet, it remains to be determined if these positive vegetation trends are driven by
83 climatic or human factors and if any relationships with ERPs exist. Moreover, **time series** based on a
84 short period (less than 30 years), do often not meet the requirements of covering both pre and post
85 conditions of the temporal dynamics of vegetation changes in relation to implementation of ERPs, and
86 trends are usually not linear over a longer period.

87 Applying a long term Earth Observation (EO) data set allows to separate human activities from
88 climatic influences on vegetation dynamics by developing a NDVI-climate model, and monitor the
89 residuals between observed and predicted (using climate variables) vegetation trends (**Archer, 2004;**
90 Evans and Geerken, 2004; Herrmann et al., 2005; Wessels et al., 2007). A number of researchers have
91 realized that it was unreasonable to develop NDVI-climate models by using data over the full time
92 series without considering the existing human impacts, especially the large scale implementation of
93 ERPs in later years (Cao et al., 2006; Horion et al., 2016; Wang et al., 2009). This has been done by
94 introducing a turning point and establishing the model on a reference period of little human
95 interference to predict the vegetation for a period which is supposed to be heavily influenced by
96 humans (Cao et al., 2006; Wang et al., 2009; Li et al., 2011). However, this turning point is usually
97 defined a priori to EO time series analysis. Here we expand on this approach by identifying the
98 turning point from the vegetation time series itself to define a reference period where ERPs impact
99 was not detectable. Without additional information (e.g. statistical or field data), interpretations of
100 residual trends are speculative and the assessment of the efficiency of ERPs remains vague. By using
101 a 30 year time series of NDVI (GIMMS-3g) and climate data (temperature and rainfall) we combine
102 the results of the human induced vegetation trend analysis with statistical data of ERPs, more
103 specifically the Grain to Green Program, which aims at convert farmland into forests and grasslands
104 (Jia et al., 2014; Liu et al., 2014).

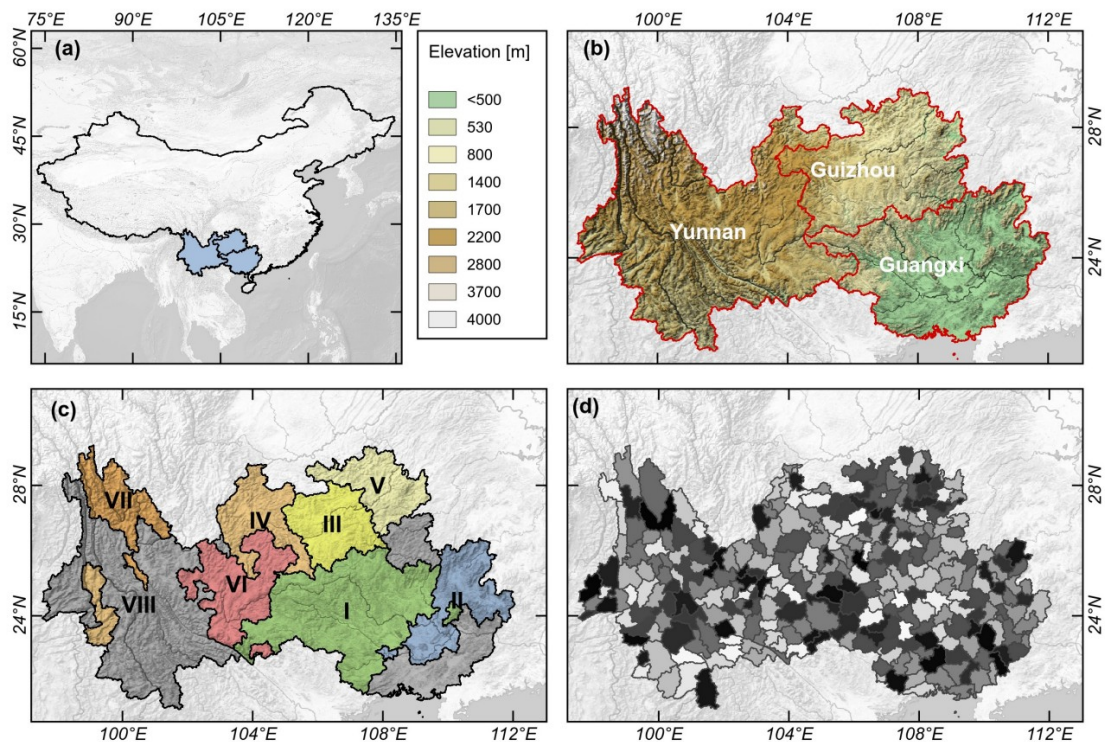
105 The overall objective of this study is thus to assess the effectiveness of ERPs (implemented by
106 the state and local Chinese governments) on long-term vegetation dynamics across Southwest China
107 in recent decades. This is achieved by (1) removing the effects of climate (rainfall and temperature)
108 thereby highlighting human induced vegetation changes and, (2) relating the human induced
109 vegetation trends to the project funds invested at county scale.

110

111 Study area and data sets

112 Study area

113 The study area includes the Yunnan, Guizhou and Guangxi Provinces, Southwest China (Fig. 1a).
114 Dominated by monsoon climate, the study area has a mean annual temperature of 17.6 °C and a mean
115 annual precipitation of 1021 mm. The region has high landscape heterogeneity with a large altitudinal
116 difference from Northwest of Yunnan Plateau (about 4000 m.a.s.l.) to lowland area such as the
117 Xunjiang Plain (about 30 m.a.s.l.) (Fig.1b). The major land cover types are evergreen and deciduous
118 shrubs (42%), evergreen needle leaf forests (17%), evergreen and deciduous broad leaf forests (15%),
119 evergreen broad leaf forests (12%) and farmland (10%) (Wang et al., 2007). The bedrock of the karst
120 regions are dominated by pure carbonate (25%) and impure carbonate (23%) whereas the bedrock for
121 the rest of the region consists of clastic rocks (non-karst region) (Tong, 2009). The study area can be
122 divided into eight (project-) regions based on topography, lithology and geological structural
123 conditions (Yuan, 2014) (Fig. 1c). In this study, the Grain to Green Program serves as a representative
124 ERP which started in 2000 and was implemented within administrative units. The program
125 compensates participating farmers for converting their cropland back to forests or grasslands with a
126 cash subsidy, grain subsidy, and free saplings at the start of reforestation (SFAB, 2000; Trac et al.,
127 2007).



128

129 **Figure 1** (a) Location of the study area in China, (b) Elevation of the three provinces of the study area, (c)
130 location and extent of the different project regions: (I) Peak Cluster Depression, (II) Peak Forest Plain, (III)
131 Karst Plateau, (IV) Karst Gorge, (V) Karst Trough Valley, (VI) Karst Basin, (VII) Middle-high Hill and (VIII)
132 non- karst region respectively, (d) The administrative counties of the study area.

134 *Data and processing*

135 This study uses the GIMMS-3g NDVI, available in a bimonthly temporal resolution of 8 km
136 spatial resolution from 1982 to 2011 (Pinzon and Tucker, 2014). To reduce contamination caused
137 primarily by cloud and atmospheric variability, we calculated a monthly NDVI by choosing the
138 maximum value of the fortnightly data set. Then the values from April to November were averaged to
139 obtain the growing season NDVI for each year from 1982 to 2011 (Tong et al., 2016).

140 Monthly temperature and rainfall data for 71 weather stations within Southwest China from 1982
141 to 2011 were obtained from the China Meteorological Data Sharing Service System (<http://cdc.cma.gov.cn>). We applied ordinary Kriging to generate gridded fields of temperature and rainfall
142 with the same resolution and geographic coordinate system as those of the NDVI data set. County
143 level statistical data of the Grain to Green Program including project areas (e.g. areas for mountain
144 closure, afforestation, and cropland conversion) and funding (e.g. money allocated for grain and
145 seeding, and cash) from 2001 to 2011 were provided by the Forestry Bureau of the Yunnan, Guizhou
146 and Guangxi Provinces.

148

149 **Methods**

150

151 A linear regression was applied to detect and analyze trends in annual GSN. The slope of the
152 regression was derived as an indication of the direction and magnitude of trends (Fensholt and Proud,
153 2012; Tong et al., 2016). The GSN trends were categorized into three types: **increase** (positive slope),
154 **decrease** (negative slope) and stable (no significant slope at the 95% level).

155 In the present study, we utilized the Sequential version of Mann-Kendall test statistic (Mohsin
156 and Gough, 2009) to detect a potential turning point in the annual GSN trend. This technique
157 calculates two statistical measures, which are the sequential values of a reduced or standardized
158 variable (Chatterjee et al., 2014). A forward sequential statistic is estimated using the original time
159 series, and a backward sequential statistic is estimated in the same way but starting from the end of
160 the series. The year of the intersection between the curves of the two statistics indicates a potential
161 turning point, which is tested for its significance at the 95% level ($p < 0.05$). For details on the method
162 we refer to Chatterjee et al. (2014).

163 Assuming that this turning point was caused by the efforts of ERPs, we used this year to separate
164 the time series into two periods. The first period (named reference period hereafter) was characterized
165 as a baseline (reference) where vegetation was not strongly affected by ERPs. The second period
166 (named conservation period hereafter) was characterized by the implementation and efforts of ERPs.

167 In order to separate climate from human induced vegetation trends, we applied the widely used
168 residual method (Evans and Geerken, 2004; **He et al., 2015**; Huber et al., 2011; **Li et al., 2012**;

169 Wessels et al., 2007). To better reflect the impacts of ERPs on vegetation changes, we used the first
170 (reference) period (rather than the entire period) to develop the multiple regression model between
171 NDVI (response variable) and climate factors (temperature and rainfall as predictors) based on
172 monthly observations. Local conditions (such as geomorphology, hydrology and soil) may influence
173 the relationship between NDVI and climatic variables, and this is especially important in the highly
174 fragmented terrain of Southwest China. To take this into account, we applied a pixel-based
175 regression, i.e. the NDVI-climate model was calculated for each pixel (Evans and Geerken, 2004).
176 Thus, the NDVI-climate regression model using the monthly data from the first period is given in Eq.
177 (1).

$$178 \quad NDVI(i, m) = a * Temp(i, m) + b * Prec(i, m) + c \quad (1)$$

179 Where, i is the location of a pixel; m identifies the month; a is the regression coefficient of
180 NDVI and temperature (**Temp**) of m month; b is the regression coefficient of NDVI and precipitation
181 (**Prec**) of m month; c is a constant. Only those regions with a significant correlation between NDVI
182 and climate (95% level) were kept and the regression coefficients were used to predict the monthly
183 NDVI for the conservation period and generate the predicted GSN for these years (which is assumed
184 to be climate driven only). We then calculated the residuals between the observed GSN and the
185 predicted GSN for the conservation period. These residuals are expected to reflect the human signal,
186 i.e. the vegetation trends which cannot be explained by climate. The temporal trend of the GSN
187 residuals was used to monitor human-induced vegetation trends and termed alike in the following. No
188 trend over time means an insignificant impact of human activities on vegetation trends (no significant
189 impact); a decreasing trend indicates vegetation degradation presumably induced by human activities
190 (negative impact); and an increasing trend suggests improved vegetation conditions which cannot be
191 explained by climate and may be attributed to conservation and restoration efforts (positive impact).

192 To validate these assumptions, we related statistical data on project areas (in km²) of the Grain to
193 Green Program at county level with human induced vegetation trends detected by remote sensing
194 within the same county. Project areas were grouped into 4 classes: 0-50 km² (class 1), 50-100 km²
195 (class 2), 100-200 km² (class 3), >200 km² (class 4). As a linear comparison between pixels and
196 project areas is not feasible due to the effectiveness variability between counties, we applied a t-test
197 and box plots to test the difference in the mean value of classes.

198 In order to assess the project effectiveness, we developed a Project Effectiveness Index (PEI).
199 The PEI is calculated as follows:

$$200 \quad PEI = \frac{S_i}{R_i} \quad (2)$$

201 where S_i refers to the project intensity, which is the ratio of the sum of the invested funding to the
202 project areas for the conservation period in county i after normalization (ranging from 0 to 1). R_i is the
203 ratio of pixels with significant increasing residual trends (human induced trends) in the county i
204 (ranging from 0 to 1). Counties without any pixels of significant increasing residual trends were
205 omitted from further analysis. When S_i equals 0, the PEI reaches a minimum; when S_i equals 1 and R_i

206 is the lowest of all **counties**, then the PEI reaches the maximum. Consequently, the PEI ranges from 0
 207 to $\frac{1}{R_i(\min)}$ and a small/high PEI indicate high/low project effectiveness. We classified the counties into
 208 three types based on their PEI values to assess the level of project effectiveness. A PEI value less than
 209 1 is deemed as high project effectiveness. Values between 1 and 10 are classified as moderate project
 210 effectiveness and values greater than 10 are assigned low project effectiveness.

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212

213 **Results**

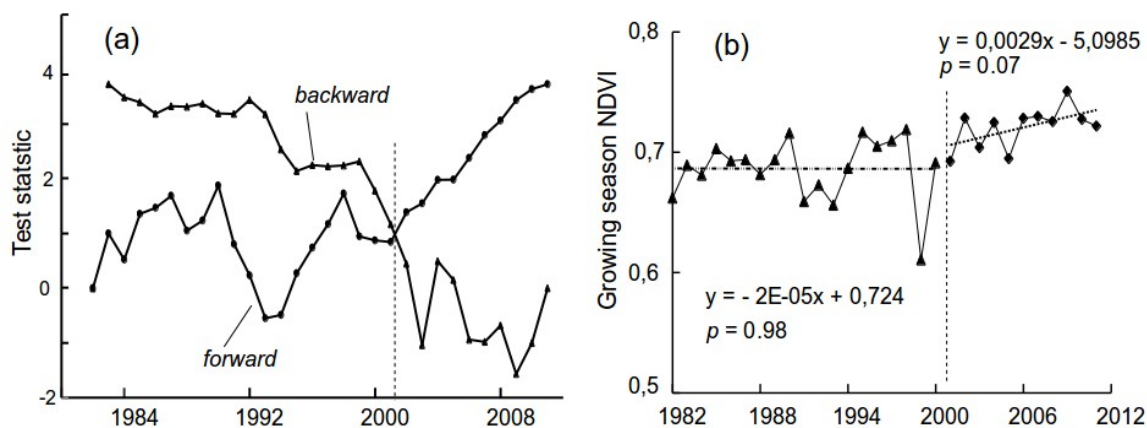
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215 *Vegetation trends and the turning point*

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217 At regional scale, the GSN has increased significantly at the rate of 0.002 GSN year⁻¹ during
 218 1982-2011 ($p=0.002$). However, the GSN trends are not monotonically increasing over the entire
 219 period. Mann-Kendall test statistics showed that the backward trend of annual GSN of the entire study
 220 area intersects the forward trend in the year 2001, which was identified as a turning point (Fig. 2a).
 221 The GSN trend was unstable prior to 2001 but steadily positive after this year (Fig. 2b). Based on this
 222 turning point, we found an overall insignificant ($p=0.98$) decreasing trend for the reference period
 223 (1982-2000) and a moderate significant increasing trend (90% level; $p=0.07$) for the conservation
 224 period (2001-2011) (Fig. 2b).

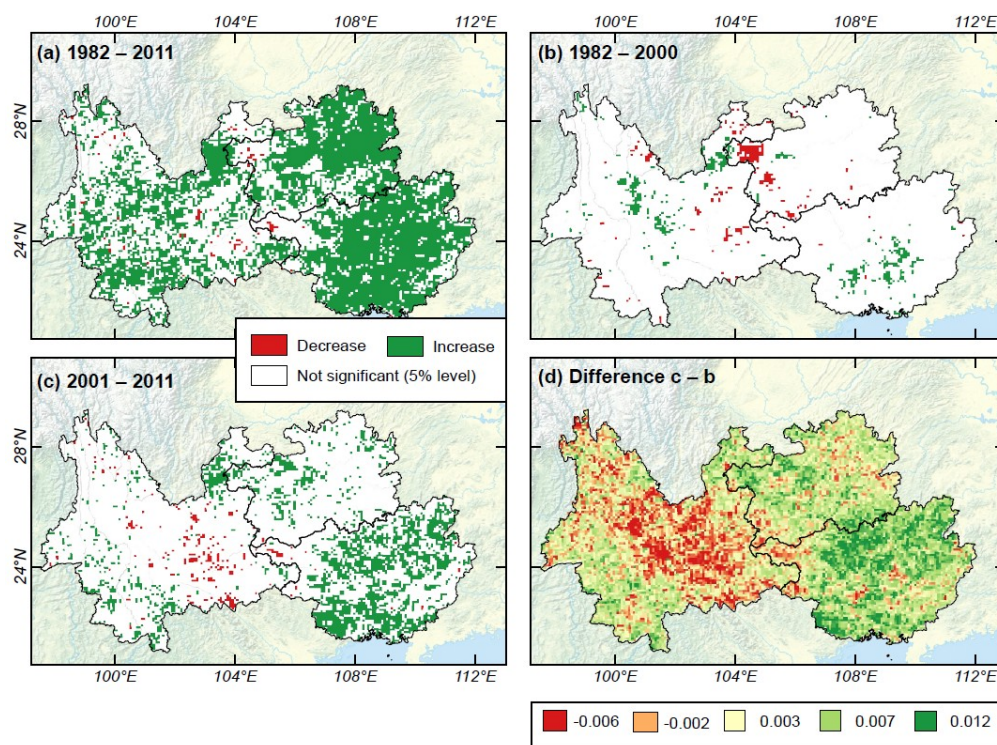
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226 **Figure 2** (a) Abrupt changes in annual GSN as derived from Mann-Kendall test statistics, using a forward and
 227 backward sequential statistics calculation approach. The year of the intersection is the potential turning point.
 228 (b) GSN inter-annual variations and linear trends for the two periods (1982-2000 and 2001-2011).

229 At pixel scale (8 km), the trends in annual GSN over the last 30 years showed distinct spatial
 230 differences (Fig. 3a). Whereas 45% of the study area had no significant trend (**stable**), a significant
 231 uptrend (**increase**) was found for 54% of all pixels, mostly concentrated in the Guangxi and Guizhou
 232 Provinces. In contrast, only 1% of the study area showed a significant downtrend (**decrease**) mostly
 233 located in the Yunnan Province. Vegetation trends vary greatly between the reference and
 234 conservation period (Fig. 3b, c). In the reference period, 94% of the study area showed no significant

235 trend and only 4% and 2% were characterized by significant increasing and decreasing (concentrated
 236 in the Guizhou Province) trends respectively. However, during the conservation period, vegetation
 237 significantly increased in 19% of the area (primarily in the Guangxi Province). During the
 238 conservation period, downtrends were found in the Yunnan Province accounting for 2% of the study
 239 area. The slope difference between these two periods also showed distinct spatial differences (Fig.
 240 3d). Regions where the GSN slope during the conservation period was greater than the reference
 241 period (a sign of vegetation growth acceleration) covered 72% of the study area. The largest slope
 242 difference (greater than 0.04 GSN year⁻¹) was mainly observed in the Guangxi Province. Areas where
 243 the GSN slopes during 2001-2011 were lower than that prior to 2001 (a sign of vegetation growth
 244 deceleration) were located especially in the Yunnan Province.



245

246 **Figure 3** (a-c) Vegetation trends for different periods (a: 1982-2011, b: 1982-2000 and c: 2001-2011) based on
 247 the GSN. (d) Vegetation trend slope difference of the reference (1982-2000) and conservation (2001- 2011)
 248 periods.

249

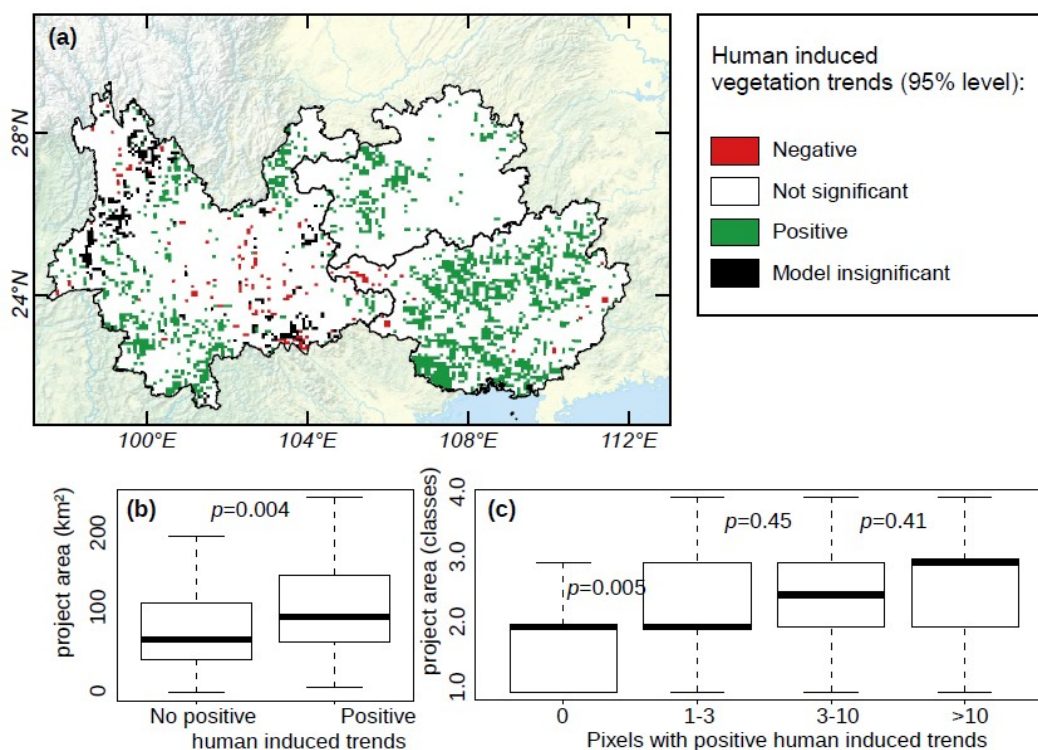
250 *Human induced vegetation trends*

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252 The majority (96%) of the pixels had a significant ($p < 0.05$) correlation between NDVI and
 253 climate variables (rainfall and temperature) and the analysis was subsequently focused on these
 254 regions. Here, 16% showed a significant impact from human activities, with about 1% of the pixels
 255 having a significant negative human induced trend and 15% a significant positive trend (Fig. 4a).
 256 Human activities showed no significant impact on vegetation dynamics in other regions (84%).

257 Negative trends were found in the **middle and east of the Yunnan Province**. Here, vegetation growth
 258 was lower than **it was expected** from the climate dynamics, indicating human activities presumably
 259 induced the vegetation degradation (negative impact). Positive trends were mostly located in the
 260 Guangxi Province, the west portion of the Guizhou Province and the southwestern part of the Yunnan
 261 Province. Vegetation in these regions **has** been greening up to a larger extent than explained by
 262 climate alone, suggesting the improved vegetation conditions may be attributed to conservation and
 263 restoration efforts (positive impact).

264 The averaged GSN residuals of each province all showed an increasing trend, but only in the
 265 Guangxi Province the trend is moderately significant (90% level; $p=0.064$). We calculated the mean
 266 slope of pixels where the human induced trend was significantly positive for each province, and found
 267 the strongest trends located in the Guangxi Province (0.0104 GSN year⁻¹), followed by Guizhou
 268 (0.0088 GSN year⁻¹), and the Yunnan Province (0.0080 GSN year⁻¹). This indicates that the ERPs
 269 implemented in the Guangxi Province had a larger positive effect on vegetation than in other
 270 provinces. The Yunnan Province had the most negative human induced trends (-0.0075 GSN year⁻¹),
 271 followed by the Guangxi Province (-0.0067 GSN year⁻¹), and no negative human induced trends were
 272 found in the Guizhou Province. This indicates that on-going degradation caused by human activities is
 273 mostly pronounced in the Yunnan Province.



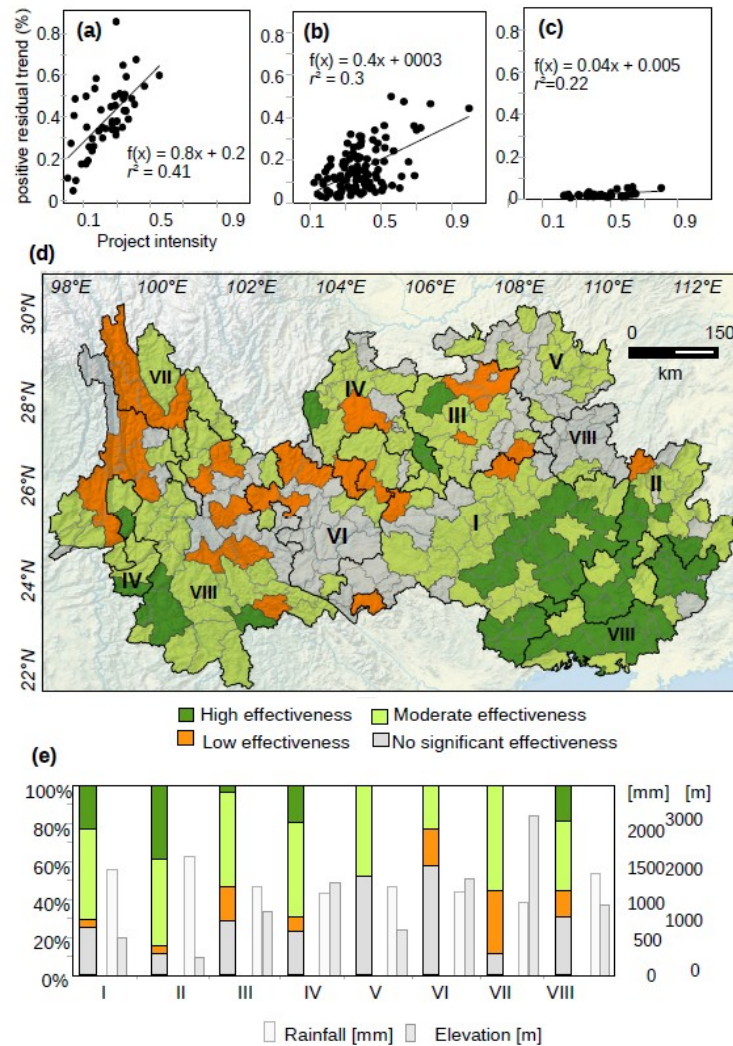
274 **Figure 4** (a) Human induced vegetation trends grouped as significantly positive, negative, and no trend. Pixels
 275 without a significant relationship between climate and NDVI are shown in black. (b) The project areas (in km²)
 276 are compared for counties without and with significant positive human induced trends. (c) The number of pixels
 277 with positive human induced trends is compared with the project area (in classes) per county.
 278
 279

280 *Relationship between human induced trends and the intensity of ERPs*

281

282 There is a strong significant ($p=0.004$) relationship between project areas (in km²) and positive
283 human induced trends at county scale (Fig. 4b), supporting the methodological assumption of
284 extracting human induced trends. It is clearly shown that positive trends are mostly found in counties
285 with larger project areas and a relation between the number of pixels with positive trends and project
286 area can be observed (Fig. 4c). However, the difference between the groups is not significant and the
287 variation between counties is considerable as larger area does not always imply more positive trends
288 (Fig. 4c). To account for this, we introduce two measures relating the significant (95% level) positive
289 human induced trend with statistical data on conservation projects: (1) the project intensity (a measure
290 of the funding invested per area) and (2) the PEI (a measure of the project effectiveness). At county
291 scale (Fig. 1d), we found 90 counties (out of 291 in total) without any significant increasing human
292 induced trend, indicating no significant project effectiveness. Most of these counties were found in the
293 Yunnan and Guizhou Provinces (Fig. 4a). The shares of pixels with significant increasing human
294 induced trends in other counties were between 0.01 (1%) and 0.86 (86%), with PEI ranging from 0 to
295 39.

296 Counties were grouped according to the project effectiveness (high, moderate and low
297 effectiveness) (Fig. 5a-c), comparing the project intensity with the percentage of pixels with a
298 significant positive human induced trend. In total, 55 counties were characterized by a high project
299 effectiveness (PEI<1) (Fig. 5a) and most of them were concentrated in the Guangxi Province (Fig.
300 5d). Moderate project effectiveness (PEI between 1 and 10) was found in 115 counties (Fig. 5b). In 31
301 counties the project effectiveness was low (PEI>10) and these were mainly located in the Yunnan
302 Province (Fig. 5c and Fig. 5d). At county scale, a clear relationship is observed between the invested
303 funding per area (project intensity) and the percentage of positive human induced trends. This
304 relationship is most pronounced in counties with high effectiveness ($r^2=0.41$, $p<0.01$, slope=0.8), and
305 weakens for the groups with moderate ($r^2=0.30$, $p<0.01$, slope=0.4) and low effectiveness ($r^2=0.22$,
306 $p<0.01$, slope=0.04).



307

308 **Figure 5** Relationships between the percentage of pixels with significant increasing human induced vegetation
 309 trend in a county and the normalized project intensity (funding invested per area). (a) Counties with high project
 310 effectiveness; (b) counties with moderate project effectiveness; (c) counties with low project effectiveness. (d)
 311 Spatial distribution of the levels of project effectiveness at the county scale and (e) levels of project
 312 effectiveness per project region (see Fig. 1c) with associated mean rainfall and elevation.

313

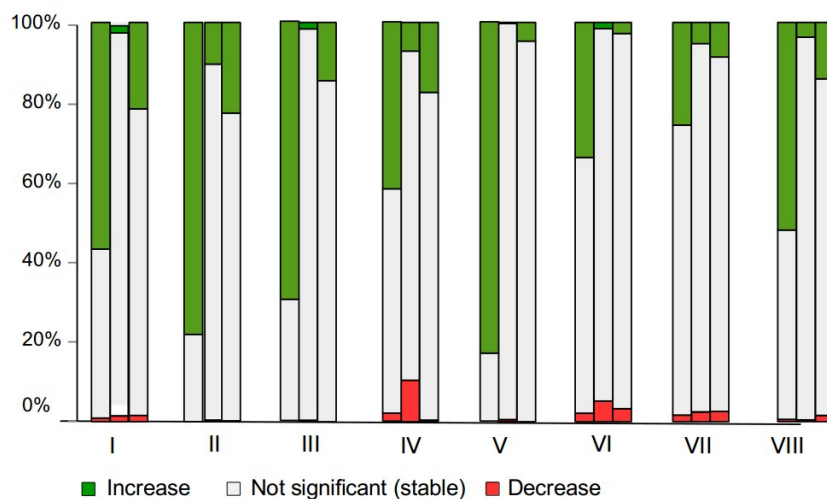
314 *Spatial differences of vegetation trends under different karst landforms*

315

316 Differences in vegetation trends between project regions were analyzed for the entire study
 317 period, reference period and conservation period respectively (Fig. 6). The vegetation showed an
 318 overall improvement in most of the regions during the entire study period (1982-2011). More
 319 specifically, vegetation in the Karst Trough Valley region (V) shows the largest share of increasing
 320 vegetation trends (about 83%), followed by the Karst Peak Forest Plain (II) (78%) and Karst Plateau
 321 (III) (69%). Vegetation in other regions showed no significant trends, especially in the Middle-high
 322 Hill region (VII) (73%) and Karst Basin region (VI) (64%). Only a small percentage of the pixels
 323 were found to have a decreasing trend. With 2% in the Karst Basin (VI) and the Karst Gorge region
 324 (IV), these are the only regions with a noticeable share of significant decreasing vegetation trends.

325 If split into two periods, most pixels during the reference period (1982-2000) showed no
 326 significant trends (*stable*), especially in the Karst Trough Valley (V) (99%) and Karst Plateau (III)
 327 (98%). The largest share of significant positive trends (*increase*) was detected in the Peak Forest Plain
 328 region (II) (10%) and the Karst Gorge region (IV) (7%), respectively.

329 Regarding human induced vegetation trends during the conservation period (2001-2011), most
 330 pixels in each region (76%) were insignificant, showing no significant impact of human activities,
 331 especially in the Karst Trough Valley (V) (95%) and Karst Basin regions (VI) (94%). The percentage
 332 of pixels with increasing human induced vegetation trends in the Peak Forest Plain (II) and Peak
 333 Cluster Depression (I) regions was 23% and 22%, respectively, which was the largest among all
 334 regions. The percentage of pixels with decreasing human induced trends in the Karst Basin region
 335 (VI) (3%) was larger than any other region, being an indication of ongoing human induced
 336 degradation.



337 **Figure 6** The area ratio (percentage cover) of vegetation trends during different periods (full period:1982-2011
 338 (left bar), reference period:1982-2000 (middle bar) and conservation period: 2001-2011 (right bar)) in different
 339 project regions (Fig 1c).

340
 341

342 Discussion

343

344 *Effectiveness of ERPs variability between different counties*

345

346 We identified the effect of invested project funds through the implementation of Ecological
 347 Restoration Projects (ERPs) at county scale and found varying results of the Project Effectiveness
 348 Index (PEI) indicating different degree or extent of effectiveness of ERPs implementation. Many of
 349 the spatial patterns of the PEI can be explained by the interplay between climatic and terrain
 350 conditions as well as human management. In the past 30 years, the temperature of Southwest China
 351 during the growing season increased significantly ($p < 0.01$), and combined with an insignificant

352 ($p>0.01$) decrease in rainfall (Cai et al., 2014), this has created challenging conditions for newly
353 planted vegetation to survive. Additionally, frequent droughts have become a serious hazard in recent
354 years (Guan et al., 2015; Zhai et al., 2005). For example, the severe drought in 2009 was reported to
355 have adverse impact on the vegetation in the Yunnan, Guizhou and Guangxi Provinces (Barriopedro
356 et al., 2012). Combined with a warm and dry climate, these extreme weather events negatively impact
357 on the survival and growth of planted trees (Wu et al., 2014). High effectiveness of ERPs is mostly
358 found in the Peak Forest Plain (II) and Peak Cluster Depression regions (I) in the Guangxi Province
359 (Fig. 5d). These areas have much more favorable growing conditions (24°C and 1662 mm rainfall)
360 than other regions (Fig. 5e). In contrast, low or no effectiveness was detected in large parts of the
361 Yunnan and Guizhou Provinces and especially the Middle-high Hill (VII) and the Karst Trough
362 Valley (V) regions characterized by unfavorable growing conditions (17°C and 1134 mm rainfall) and
363 rough terrain (high elevation and slope) show low or no effect of ERPs, in spite of high investments.

364 Apart from climate and terrain, human management plays an important role for the success of
365 ERPs. Proper management includes the selection and planting of species adapted to local climatic
366 conditions, the continuous monitoring of plantations, but also the incorporation and compensation of
367 the local population. The Grain to Green Program aims to transform cropland into ecologic (used for
368 timber production) or economic (orchards or plantations with trees for medical use) forests. The
369 government pays subsidies to the owner of the transformed cropland for 8 year (ecologic forest), 5
370 years (economic forest) or 2 years (grassland) (Xu et al., 2004). Peasants generally prefer to convert
371 their cropland into forest rather than grassland to receive a higher compensation. However, not all
372 regions are equally well suited for forest growth and in some areas abiotic conditions allow only grass
373 or scrub to grow (Trac et al., 2007). Limited by a low water use efficiency, planted trees grow slowly
374 (or do not grow at all) and the ecological value is thereby questionable (Cao, 2011; Trac et al., 2007;
375 Uchida et al., 2005; Weyerhaeuser et al., 2005). Hence, large investments in tree planting do not
376 necessarily have the expected high effect, if the local conditions are not considered and the selection
377 of inappropriate species resulted in many planting failures (Cao, 2011).

378 The population of China is growing rapidly leading to an increasing demand for food. The
379 subsidies for conservation received by the peasants do not compensate them adequately, which forces
380 many peasants to return their grass/forest land back into cropland (Trac et al., 2007). Thus,
381 Weyerhaeuser et al. (2005) suggested that the subsidies provided to the peasants should be more
382 attractive and at least compensate for the losses of converting the land for the sustainability of the
383 Grain to Green program. Peasants are willing to participate in initial planting because they are paid
384 for their labor, but they pay less attention to the protection of planted trees/grasses (especially the
385 ecologic forest), since they do not receive any following payment from the government or any
386 economic profit from the ecologic forest. Many areas of implementation are in regions away from
387 urban centers without any project offices and limited access (e.g. northern Yunnan Province), thereby
388 making it difficult for the government to monitor the successfulness of project conservation. This is in

389 line with reports of unsuccessful growth of trees/grasses in these regions (Trac et al., 2007).

390 In contrast to this general pattern, we identified several counties with high effectiveness in spite
391 of unfavorable climatic and terrain conditions. Examples are Shidian in the Yunnan Province and also
392 Qiaojia and Dafang in the Guizhou Province. In depth research at the local scale is needed to identify
393 the reasons and drivers for successful vegetation improvements in these counties. Even though the
394 success is not uniform, we have shown numerous areas with a positive human induced trend, being an
395 indication that projects, if properly implemented, can greatly benefit China in combating
396 desertification (Du, 2001; Xu et al., 2006; Xu and Cao, 2001). However, we also identified areas of
397 low and no effect in spite of high investments, and special attention is needed in these areas to find the
398 reasons for the unsuccessful implementation.

399

400 *Limitations and uncertainties*

401

402 Applying a remote sensing approach in ecological conservation allows for rapid monitoring and
403 mapping of project efforts for large areas over a long time period. There are, however, limitations to
404 the approach as the applied methodology is based on assumptions/choices which may introduce
405 uncertainties. Firstly, there is a trade-off between spatial and temporal resolution. The coarse spatial
406 resolution of the data set used (8 km) does not allow for the detection of small scale changes, but the
407 GIMMS-3g data used here remains the only available data set for continuous time series analysis
408 dating back to the 1980's with a sufficient quality in regards to the transition between multiple sensors
409 involved (Tian et al., 2015). We thus assume that conservation projects have large scale impact and
410 the footprint of the project efforts is homogeneous and visible within 64 km² (8x8 km). This may
411 conceal small scale degradation and especially human activities which are rarely uniform at this scale.
412 Therefore, the results presented primarily give insights at regional (county) scale but less so at the
413 local scale. However, a recent study by Tong et al. (2016) applying MODIS data with a 250 m
414 resolution (2001 to 2013) showed that for the Guangxi and Guizhou Provinces the overall spatial
415 patterns of vegetation conditions are comparable with the results presented here. Li et al. (2016) also
416 applied the RESTREND method using MODIS data for the Beijing-Tianjin Sand Source region in
417 China thereby providing results with more spatial details than the current study. However, since
418 MODIS is only available since 2000, Li et al. (2016) were not able to develop the NDVI-climate
419 model for a period without project influences, which lowers the reliability of the assessment of the
420 specific impact from ERPs. Secondly, this study uses a vegetation index (NDVI) as proxy for
421 ecosystem health. NDVI has shown to be a function of herbaceous and woody cover and density, soil
422 and vegetation color and soil moisture, and is widely used to measure the chlorophyll abundance in
423 vegetation. However, NDVI does not provide information on the vegetation and species composition.
424 Moreover, the average NDVI over the growing season months serves as a robust proxy for the net
425 primary production of this period, but does not take into account spatial and inter-annual

426 dynamics/changes in plant phenology, land cover and climate.

427

428 **Conclusions**

429

430 Climate changes and human activities drive vegetation trends in Southwest China. This study
431 evaluated the effectiveness of Ecological Restoration Projects (ERPs), more specifically the Grain to
432 Green Program, by developing a NDVI-climate model for a reference period (1982-2000), and
433 predicting the annual growing season NDVI (GSN) for the period 2001 to 2011 to quantify the effects
434 of project activities on vegetation trends. These human induced trends were found to be related to
435 conservation projects and the following conclusions can be drawn:

436 (1) After a period of an overall decrease (1982-2000), vegetation increased in most areas between
437 2001 and 2011. The largest rate of increase was found in the Guangxi Province.

438 (2) Vegetation improvement caused by ERPs accounted for 15%, whereas vegetation degradation
439 induced by human activities covered 1%. Human activities showed no significant impact on
440 vegetation dynamics in other regions (84%). The ERPs implemented in the Guangxi Province had a
441 larger positive effect on vegetation dynamics than in other provinces. Human activities in the Yunnan
442 Province had a larger negative effect on vegetation than in the Guangxi Province.

443 (3) Vegetation improved more in the Peak Forest Plain and the Peak cluster Depression than in
444 other regions during 2001-2011, whereas vegetation degradation caused by human activities was
445 mostly pronounced in Karst Basin regions.

446 (4) There was a significant relationship between positive human induced trends and project
447 intensity (funding invested per area). In total, 55 counties showed high project effectiveness as
448 measured by the Project Effectiveness Index (PEI), 115 counties were characterized by moderate
449 project effectiveness and 31 counties had low project effectiveness. No significant effects of project
450 implementation were detected in the remaining 90 counties.

451 (5) Even though areas characterized by high project effectiveness were found, this does not apply
452 to the entire study area, and especially areas with an unfavorable climate, rough terrain conditions and
453 poor management practices (unsuitable species selection, low compensation rate for farmers) show
454 limited or no effect of project implementation.

455 (6) Remote sensing has shown to be a valuable tool for monitoring the effectiveness of
456 conservation project. However, the coarse spatial resolution of the data set used leaves uncertainties
457 which can only be overcome by field studies combined with temporal snap-shots of higher resolution
458 imagery.

459

460

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