Supplementary material for "Spatial-temporal analysis of greenness and poverty with their association impacts analysis in China"

Figures.

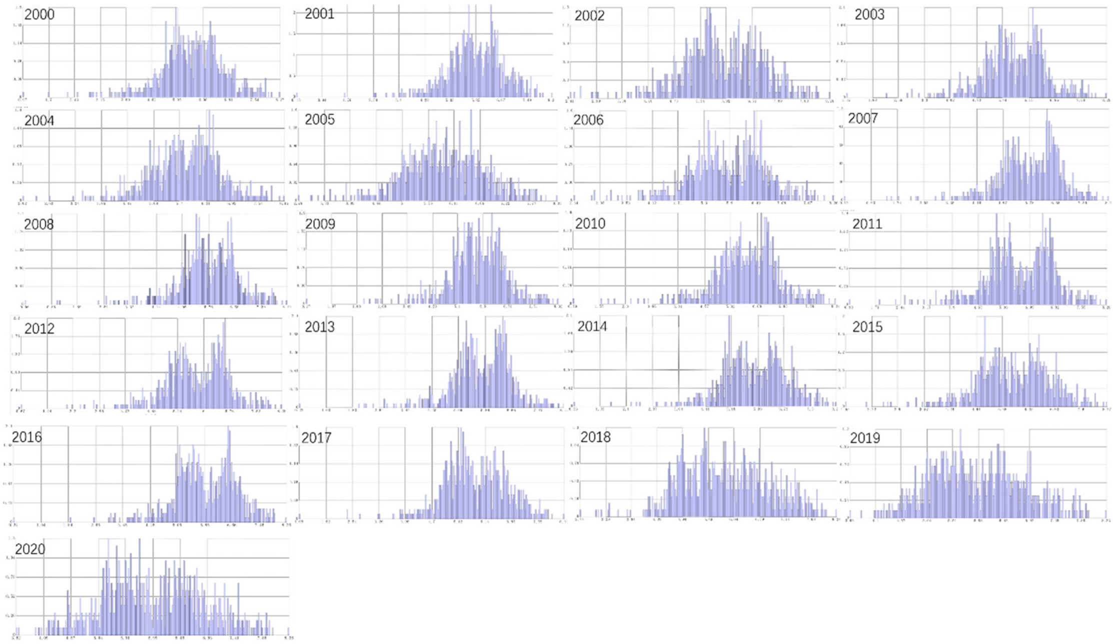

Figure S1. Image histograms generated by MODIS LAI values at a resolution of 500m in all counties of CPSAs in the study area in each year. The horizontal axis represents the range of LAI values, and the vertical axis represents the frequency. The unit of the vertical axis is 10^7. The shape of the image histogram can reveal prior knowledge, that is, the distribution of LAI data is assumed to be a normal distribution.

Figure S1 is to support the assumption that the LAI for each county followed normal distribution, which is sup-ported by the histograms generated for the MODIS LAI values at a resolution of 500m in all poverty-stricken areas and counties.

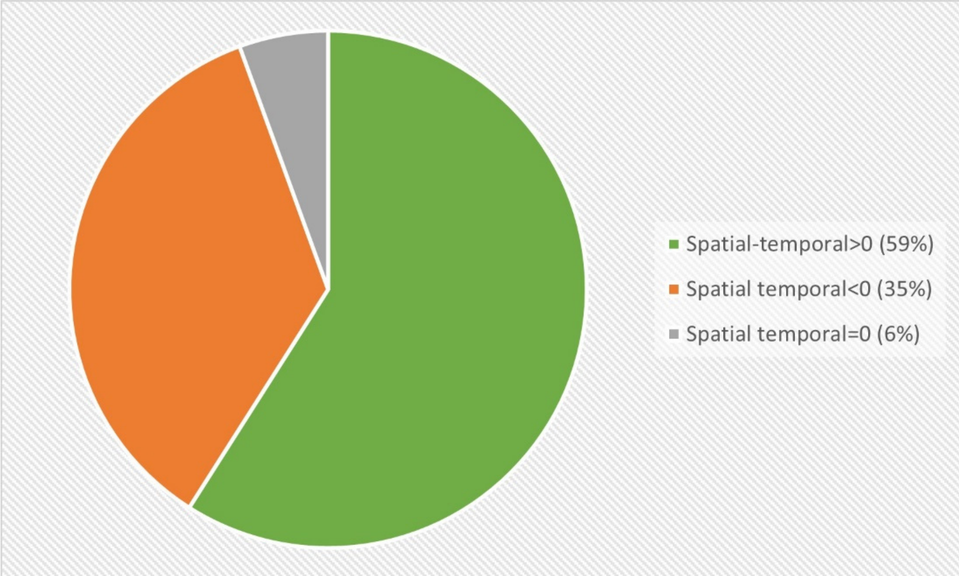

Figure S2. Proportion of greenness changes

In Figure S2, from 2000 to 2020, the spatial-temporal change result $b_0 + b_{1i}$ value of greenness in 59% of the poverty counties was greater than 0, in 35% of the poverty counties was less than 0, and in 6% of the poverty counties was not significantly.

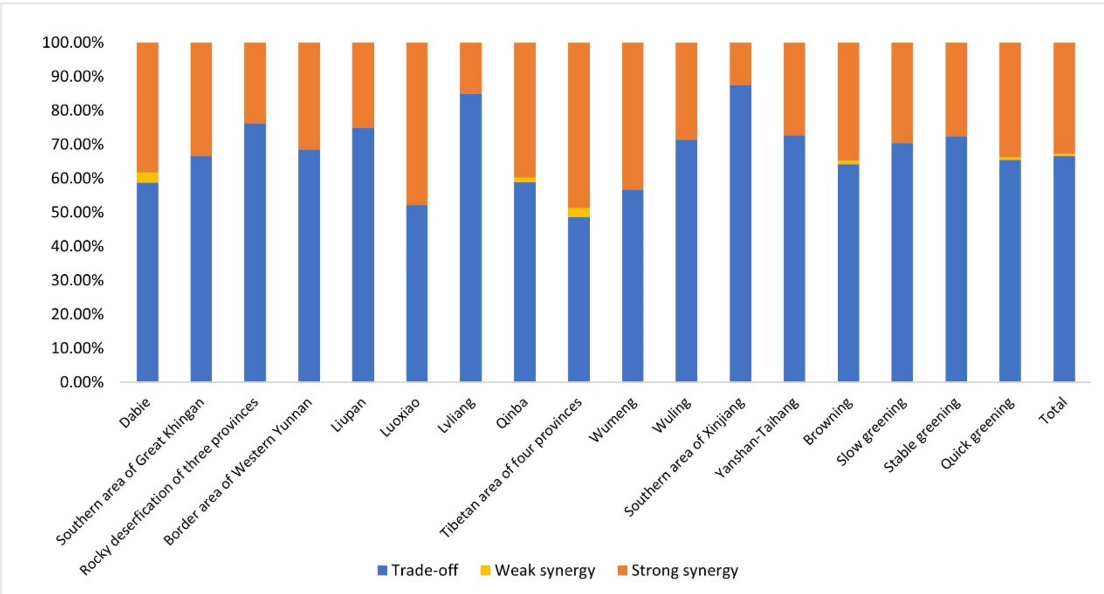

Figure S3. Synergies and tradeoffs percentage accumulation of the relationship between greenness change and poverty change in CPSAs and the relationship affected by browning, slowly greening, stable greening and quick greening areas [18].

According to each poverty-stricken area as the scope, we calculated the proportion of different coupling relationships in the total area of the poverty-stricken area and obtained Figure S3 as the result.

Bayesian spatial-temporal modelling approach

Bayesian hierarchical model was applied to identify the spatial and temporal change pattern of LAI from 2000 to 2020 [35]. We assumed that the LAI for each county followed normal distribution. Here, y_{it} represent the annual average LAI value in *i*th county at *t*th year.

$$y_{it} \sim Normal(\mu_{it}, \sigma^2) \quad \text{(S1)}$$

μ_{it} can be modeled as:

$$\mu_{it} = \alpha + s_i + b_0 t + v_t + b_{1i} t \quad \text{(S2)}$$

In this model, the observed space–time variability of greenness condition is decomposed into the following components. The spatial coefficient, s_i, describes the stability of the spatial pattern of the entire study area during a 20-year observation period. $b_0 t + v_t$ represents the trend over the twenty years in the whole study area. The overall time trend is decomposed by a linear function ($b_0 t$) with an additional term (v_t), which allows for nonlinearity in the overall trend pattern [36,37]. The stable component of greenness change was represented by combining the common spatial pattern and the common time trend together. The term $b_{1i} t$ allows each county to have its own change trend. While b_0 is the overall rate of change in greenness change, b_{1i} measures the departure from b_0 for each county. For instance, a negative value of b_{1i} indicates a declining trend in greenness change over time and α is the intercept term [38]. The prior distributions of s_i and b_{1i} are determined by Besag York Mollie (BYM) model [35].

Model parameters in Model (S1) were assigned to follow the normal distributions. The BYM model is a convolution of a spatially structured random effect and a spatially unstructured random effect. We used the conditional autoregressive (CAR) prior with a spatial adjacency to impose spatial structure. In the spatial adjacency matrix W of size $N \times N$, if areas i and j share a common boundary, its diagonal entries $W_{ii} = 0$ and the off-diagonal entries $W_{ij} = 1$, otherwise $W_{ij} = 0$. This implies that adjacent counties tend to have similar overall vegetation coverage. The same BYM prior is assigned to b_{1i}. We assumed that nearby counties have changes of vegetation coverage have higher similarity compared with counties far away.

The model can be implemented using a statistical software, OpenBUGS (https://openbugs.net/), which is specially designed for Bayesian analysis [39]. We ran MCMC chains for the model with 200,000 iterations. With the chains, 10,000 MCMC draws in total were used for inference. Standard trace plots and autocorrelation plots is showing in Figure S4. The convergence was judged by the Gelman–Rubin statistic, a standard tool for assessing convergence of MCMC chains. When the Gelman–Rubin statistic was < 1.05 for all model parameters, the convergence was achieved.

The steps of running model in OpenBUGS could be referred to the manual documents of OpenBUGS. (https://chjackson.github.io/openbugsdoc/Manuals/Contents.html)

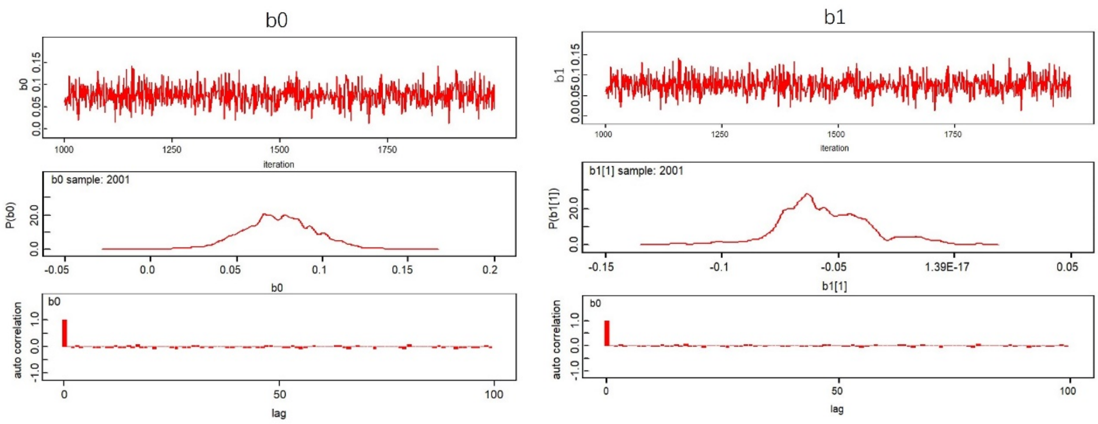

Figure S4. Traceplots (first row), the posterior densities (second row) and autocorrelation plots (third row) for selected variables in Model (b0=overall slope; b1=departure from the overall slope for county). Trace plots for all these variables show mixing and the autocorrelation plots show no evidence of high autocorrelation for the chains. The resulting posterior densities are smooth based on the MCMC iterations.

OpenBUGS codes for implementing：

```
model {
	for (i in 1:N) {
		for (tt in 1:T) {
			y[i,tt] ~ dnorm(theta[i,tt],tau)
			####	U[i]=alpha + s_i in Equation 2
			theta[i,tt] <- U[i] + gamma_overall[tt] + gamma[i,tt]
					#+ beta_eth * simpson[i] + beta_owned * p_owned[i]
					#+ beta_detached * p_detached[i]
		}
		####	BYM on level of burglary (at mid time point)
		mu.u[i] <-	alpha + s[i]
		U[i] ~ dnorm(mu.u[i],tau_U)
	}
	####	spatially-structured random effects
	s[1:N] ~ car.normal(adj[],weights[],num[],tau_s)

	####	variance of spatially-structured random effects
	sigma_s ~ dnorm(0,10)I(0,)
	tau_s <- pow(sigma_s,-2)

	####	variance of spatially-unstructured random effects
	sigma_U ~ dnorm(0,10)I(0,)
	tau_U <- pow(sigma_U,-2)

	####	variance of overdispersions
```

```
sigma ~ dnorm(0,10)I(0,)
tau <- pow(sigma,-2)

####    overall intercept
alpha ~ dflat()

####    overall time trend   (centred at mid time point 2.5)
st <- mean(gamma_overall_temp[1:T])
for (tt in 1:T) {
    gamma_overall[tt] <- gamma_overall_temp[tt] - st
    gamma_overall_temp[tt] ~ dnorm(mu_gamma_overall[tt],tau_gamma_overall)
    mu_gamma_overall[tt] <- b0 * (tt-mt)
}
tau_gamma_overall <- pow(sigma_gamma_overall,-2)
sigma_gamma_overall ~ dnorm(0,10)I(0,)

####    linear local departures in trend (centred at mid time point)
for (i in 1:N) {
    b1[i] ~ dnorm(mu_beta_sp[i],tau_b1)
    mu_beta_sp[i] <- beta_sp[i]# + beta_ncc * ncc[i]
    for (tt in 1:T) {gamma[i,tt] <- b1[i] * (tt - mt)}
}
####assign weights
for(k in 1:sumNumNeigh) {
            weights[k] <- 1
        }
####    spatially-structured random effects on slopes
beta_sp[1:N] ~ car.normal(adj[],weights[],num[],tau_beta_sp)

####    random effect variances on slopes
sigma_beta_sp ~ dnorm(0,10)I(0,)
tau_beta_sp <-pow(sigma_beta_sp,-2)
sigma_b1 ~ dnorm(0,10)I(0,)
tau_b1 <-pow(sigma_b1,-2)

####    overall slope
b0 ~ dflat()

####    priors on regression coefficients
#beta_eth ~ dnorm(0,0.001)
#beta_owned ~ dnorm(0,0.001)
#beta_detached ~ dnorm(0,0.001)
#beta_ncc ~ dnorm(0,0.001)
```

```
    for (tt in 1:T) {time[tt] <- tt}
    mt <- mean(time[1:T])

    #spatial temporal
    for (i in 1:N) {spatial.temporal[i] <- b0 +mu_beta_sp[i]}
}
```