Correlation Studies between Land Cover Change and Baidu Index: A Case Study of Hubei Province

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Abstract: Current land cover research focuses primarily on spatial changes in land cover and the driving forces behind these changes. Among such forces is the influence of policy, which has proven difficult to measure, and no quantitative research has been conducted. On the basis of previous studies, we took Hubei Province as the research area, using remote sensing (RS) images to extract land cover change data using a single land use dynamic degree and a comprehensive land use dynamic degree to study land cover changes from 2000 to 2015. Then, after introducing the Baidu Index (BDI), we explored its relationship with land cover change and built a tool to quantitatively measure the impact of changes in land cover. The research shows that the key search terms in the BDI are ‘cultivated land occupation tax’ and ‘construction land planning permit’, which are closely related to changes in cultivated land and construction land, respectively. Cultivated land and construction land in all regions of Hubei Province are affected by policy measures with the effects of policy decreasing the greater the distance from Wuhan, while Wuhan is the least affected region.

Keywords: land cover change; BDI; RS; Land change driving force

1. Introduction

With a rising global population and scientific and technological advancement, human beings are having an increasing impact on their surrounding environments. As one of the basic resources for human survival, land is under increasing pressure. The degree of land use is increasing, and land cover change brought about by continuous urbanization is becoming more and more drastic. Studies show that currently half of the world’s population lives in cities [1], with 66% of the world’s population expected to live in cities by 2050 [2]. The increase in population leads to an increase in the need for food [3] and an increase in the intensity of land use [4], which will change the type of vegetation on the earth’s surface. Due to the inappropriate transformation of land cover types and the excessive use of land, global climate change, reduced biodiversity, species extinction, vegetation destruction, land degradation, environmental pollution and many other severe ecological problems, land vegetation and utilization have attracted increasing attention.

Internationally, some researchers have studied crop types, precision and persistence [5–7]. Admas et al. monitored land cover change in the Brazilian Amazon basin [8], and Anand monitored and predicted vegetation cover in the Manipur River basin in northeast India [9]. Don A et al. studied the interaction between tropical land cover change and soil organic carbon storage [10]. Bhaduri B et al., based on the GIS-NPS model, studied the impact of land cover change on hydrological changes.
in the basin size using long time series [11]. Rashford B S et al. studied the impact of climate change on land cover change and wetland grassland productivity in North America [12]. Selwood K E et al. studied the impact of climate change and land cover change on population rates and population viability [13]. Sterling S M et al. studied the impact of land cover change on the global water cycle [14]. Some scholars have also studied the impact of natural disasters on land cover [15–17]. In China, Liu Jiyuan systematically studied and built a data platform for land use change processes [18]. Long, Hualou et al. studied the driving force of land cover change in rural areas along the east coast of China [19]. The relationship between vegetation change and climate change in mainland China has also been widely discussed [20,21]. Yang Yuejuan et al. explored the impact of land cover change on the ecological functions of agricultural and pastoral areas in the North [22]. Li Shihu studied the relationship between land cover types and water pollution in the lake basin of Fuxian County under a multi-scale relationship [23]. Li Fei et al. studied the relationship between surface vegetation and heat islands in Hangzhou, China, from 2000 to 2015 [24]. Li Pingxing studied the relationship between different land policies and urban expansion [25]. Chen, Yi et al. studied the utilization efficiency of construction land in China [26]. Liu Yansui analyzed land strategy adjustments [27]. Zhang Weiwei et al. studied the impact of land use intensity [28]. As a new technology, Internet search indexes have been applied in many fields, such as tourism [29–31], rhinitis [32], dengue fever [33], AIDS [34], hand, foot and mouth disease [35], stock prices [36,37], spatial and temporal characteristics [38], sales volume [39], hotel demand [40] and urban network research [41].

From previous studies, it can be seen that most research focuses on monitoring, simulation and driving force analysis of land use change, as well as policy studies [42], examining the spatial distribution of land vegetation cover and the impact of climate [43], river [44], ecology, human activities [45] and social policies on land use. However, few people have designed specific methods to study the relationship between the Baidu Index (BDI) and land cover change, which is undoubtedly important. The purpose of this paper is to reveal the relationship between the BDI and land cover change, and their mutual influence. The devised method comprises the introduction of the BDI, tests the relationship between the BDI and land cover change and uses this relationship to build an index that shows the impact of government policies on land cover change.

2. Materials and Methods

2.1. Study Area

Hubei Province is located in central China, covering a total area of 185,900 square kilometers, with a total population of 58.52 million in 2015 [46]. The latitude ranges from 29°01 '53 " to 33°6' 47", and the longitude ranges from 108° 21 ' 42 " to 116° 07' 50 " . Hubei is surrounded by Anhui Province, Shaanxi Province, Henan Province, Jiangxi Province and Hunan Province and contains 17 prefecture cities, namely, Enshi Tujia and Miao Autonomous Prefecture, Yichang, Shennongjia Forest Region, Shiyan, Xiangyang, Suizhou, Jingmen, Jingzhou, Qianjiang, Tianmen, Xiaogan, Xiantao, Wuhan, Ezhou, Huanggang, Huangshi, Xianning, as shown in Figure 1.
2.2. Data sources

Land cover data are derived from Landsat TM remote sensing images (the synthesized remote sensing image is shown in Figure 2) downloaded from the geographic cloud [47], which are interpreted manually and visually. Land cover classification data on the resources and environment database technology standard classifications are divided into cultivated land, forest land, grassland, water area, construction land and unused land, obtained in 2000, 2005, 2010 and 2015, creating four sets of land cover data. All data are classified as level 1 class data precision to accord with the ‘strategic leading science and technology projects of the Chinese Academy of Sciences’, requiring accuracy of more than 90%. Baidu is the largest Internet search engine in China, and the BDI is calculated based on the search data of netizens, reflecting people’s behaviors [48].
Figure 2. Remote sensing image of the research area in 2000. This is a remote sensing image of Hubei province synthesized by landsat-5. The extraction method of land cover type is visual interpretation, and other information is required for interpretation.

2.3. Data Processing

This paper analyses primarily the change in land cover in Hubei Province from 2000 to 2015 through the land transfer matrix [49], the dynamic attitude of single land use and the dynamic attitude of comprehensive land use [50], and uses ARCGIS spatial analysis and mathematical statistics to reflect the spatial distribution of land cover change. The relationship between BDI and land cover change was studied using Spearman’s rank correlation coefficient, and the influence index of unit policy influence on land cover change was constructed to study quantitatively the influence of policy on land cover change.

The land transfer matrix can accurately indicate the origin and direction of land cover change, reflecting spatial changes in land cover. Through ARCGIS, land use data from two periods in the research area can be superimposed and analyzed, and then the land transfer matrix can be generated. Land cover change can be expressed quantitatively by the dynamic attitude of single land use and the dynamic attitude of comprehensive land use. The dynamic attitude of single land use reflects the speed and trend of a certain type of land cover change. The expression is shown in Formula (1). The comprehensive dynamic attitude of land use can represent the source and direction of land cover change in the study area, and its calculation is expressed as Formula (2).

\[
K = \frac{U_b - U_a}{U_a} \times \frac{1}{T} \times 100\%. \quad (1)
\]

\[
LC = \frac{\sum_{i=1}^{N} \Delta LU_{ij}}{2 \sum_{i=1}^{N} LU_i} \times \frac{1}{T} \times 100\%. \quad (2)
\]

where, in Formula (1) \( U_a \) and \( U_b \) are the area of a certain type of land at the beginning and end of the study period, \( T \) is the time between the two phases of land cover (unit: year), \( LU_i \) is the area of
land cover type i at the starting point of the study, and $\Delta LU_{ij}$ is the area of land cover type i transformed into non-i during the study period.

The search index is based on the data of people's search volume in Baidu and takes keywords as the statistical object to scientifically analyze and calculate the weighted sum of search frequency of each keyword in the Baidu web search. The BDI is a search index of a large number of internet users downloaded from the Baidu website, and the number of internet users increased by 3.7% from 2014 to 2015. By 2015, the internet penetration rate had reached 46.8% in Hubei Province [51], which means that one out of every two people could access the Internet. As the Internet has reached a certain amount of coverage in China, government policies are released through the Internet, and internet users can also search the web to find relevant policies. Therefore, the behavior of netizens reflects the degree of their concern for policies, and the driving force behind the occurrence of a large number of such concerns may be the effect of policies, corresponding to the consistent changes in land cover changes. Therefore, we studied the relationship between the BDI and land cover change to further explore the relationship between land cover change and policy. Our data processing procedure is as follows: 1) use remote sensing data to obtain land use data of the corresponding time through visual interpretation; 2) collect relevant policies according to a certain type of land cover and extract a series of keywords; 3) search the keyword with the search engine, and download the corresponding data. The Baidu index data is based on the content of the Baidu search engine search data volume, and the number of Internet users who have searched various pages, weighted sum. It is not a direct search volume—it is a number obtained by the weighted sum of search volume and can reflect the concerns and needs of Internet users. This value is zero or positive with no range requirements. The greater the people's attention, the greater the impact. It can carry to the statistics according to the space area and the time scope; 4) the correlation analysis of the Baidu index and land cover change data is carried out to determine influential keywords; 5) the influence value can be obtained by substituting the BDI and land cover data of these keywords into formula (3). We selected representative keywords for policy, retrieved its BDI and identified the corresponding degree and type of land cover change that occurred due to public attention. The records from 2010 to 2015 contained all the required keyword search data, which fully reflected relevant situations. Therefore, the search keywords from 2010 to 2015 were selected. As the BDI follows a non-normal distribution, and we sought to find a relationship between keywords in the BDI and land cover change, we used Spearman's rank correlation coefficient test to identify the correlation between the two. We constructed the index quantity as shown in Formula (3). Finally, we selected cultivated land and construction land, which may be affected by policy, for spatial analysis. A flow chart of the complete data processing method is shown in Figure 3.

$$IN_j = \frac{\rho_i \Delta LT_j}{BDI_j},$$  \hspace{1cm} (3)

Here, $\Delta LT_j$ is the land area transferred/transferred out of the i-class land during the study period, $BDI_j$ is the Baidu Index of the search terms corresponding to the policy impact on the i-class land cover type, $\rho_i$ represents Spearman's rank correlation coefficient for the ith search term and the corresponding land use change, IN represents the land change area under the influence of attention per unit. The larger $IN_j$ is, greater the land cover change may be influenced by the policy.
The software used in the study included ARCGIS and SPSS. ARCGIS software is used for visual interpretation of remote sensing data, spatial analysis and graph drawing, and SPSS software is used for correlation analysis of land change area and the BDI.

3. Results

3.1. General characteristics of land use change

Through the statistical analysis of the land cover data obtained from the interpretation, the statistical results of 2000, 2005, 2010 and 2015 are given in Table 1. As can be seen from the data in the table, the sum of cultivated land and forestland in each year accounts for more than 80% of the total area of Hubei Province, while other land cover types occupy a smaller area. Cultivated land showed a decreasing trend year by year, and the percentage of cultivated land in 2000–2005, 2005–2010 and 2010–2015 decreased respectively by 0.42%, 0.47% and 0.64%, forest land by 0.02%, 0.11% and 0.20%, grassland 0.02%, 0.11% and 0.20% and unused land by 0.01%, 0.01% and 0%. The water area increased by 0.34%, 0.08% and 0.03% each year, and construction land increased by 0.11%, 0.52% and 0.84%. On the whole, cultivated land and construction land have changed significantly. The main change to cultivated land was its conversion into construction land, while the main change to construction land is from the transformation of other land cover types into construction land, that is, cultivated land shows a decrease and construction land shows an increase. The decrease in cultivated land and the increase in construction land demonstrated an accelerating trend. The dynamic attitude of land use reflects the speed and extent of land cover change, as shown in Table 2. In terms of the overall trend, land cover change shows an increasing trend. The comprehensive land use dynamic attitude increased from 0.06 in 2000 to 0.09 in 2015, indicating that land cover change is becoming more and more drastic. Through the change in the dynamic attitude of single land use, cultivated land, woodland, grassland and unused land display a decreasing trend, with cultivated land changing at the greatest rate. The area of water and construction land has increased, with construction land showing a strong growth trend.
Table 1. Proportion of land cover in Hubei province.

| Year | 2000 | 2005 | 2010 | 2015 |
|------|------|------|------|------|
|      | Area (ha) | P (%) | Area (ha) | P (%) | Area (ha) | P (%) | Area (ha) | P (%) |
| F    | 6835341 | 36.81 | 6756702 | 36.39 | 6670143 | 35.92 | 6550901 | 35.28 |
| FL   | 9278666 | 49.97 | 9275809 | 49.95 | 9254055 | 49.84 | 9216650 | 49.64 |
| G    | 695408  | 3.75  | 693508.5 | 3.74  | 691444.4 | 3.73  | 687025.1 | 3.70  |
| WA   | 1152567 | 6.21  | 1216831 | 6.55  | 1231251 | 6.63  | 1237472 | 6.66  |
| CL   | 565394.9 | 3.05 | 586582.8 | 3.16 | 683340.8 | 3.68 | 839050.1 | 4.52 |
| UL   | 40639.06 | 0.22 | 38582.75 | 0.21 | 37781.83 | 0.21 | 36894.18 | 0.20 |

The number of various land cover types in Hubei Province in each year, and the meanings of the letters in the table are as follows: F = Farmland; FL = Forest land; WA = Water area; CL = Construction land; UL = Unused land; G = Grassland; P = Percentage of land.

Table 2. Dynamic attitude of land use in Hubei province (%).

| Dynamic type | Type      | Time interval |
|--------------|-----------|---------------|
|              | 2000-2015 | 2000-2005 | 2005-2010 | 2010-2015 |
| MDA          | F         | -0.28 | -0.23 | -0.26 | -0.36 |
|              | FL        | -0.04 | -0.01 | -0.05 | -0.08 |
|              | Grassland | -0.08 | -0.06 | -0.06 | -0.13 |
|              | WA        | 0.49  | 1.12  | 0.24  | 0.10  |
|              | CL        | 3.23  | 0.75  | 3.30  | 4.56  |
|              | UL        | -0.61 | -1.01 | -0.42 | -0.47 |

This table is the comprehensive and single land use dynamic attitude calculated according to formulas (1) and (2), indicating the drastic degree of comprehensive or single land use type change. The letters in the table have the following meanings: MDA = Mono-dynamic attitude; IDA = Integrated dynamic attitude; F = Farmland; FL = Forest land; WA = Water area; CL = Construction land; UL = Unused land.

As mobile phone data obtained from the BDI from 2010 to 2015 are relatively comprehensive, the corresponding dynamic attitude of comprehensive land use in each region of Hubei Province during this period was studied. Specifically, the dynamic attitude of comprehensive land use in Hubei Province is shown in Figure 4. On the whole, the dynamic attitude of land use in the areas near Wuhan is relatively large, while the comprehensive land use in the areas far away from Wuhan is relatively small. The dynamic attitude of comprehensive land use in Wuhan and Ezhou is 0.28 and 0.32, respectively. The degrees of comprehensive land use in Xiaogan, Jingzhou and Qianjiang are 0.17, 0.14 and 0.16, respectively. Enshi Tujia and Miao Autonomous Prefecture, Shennongjia Forest District and Yichang city were lower, at 0.02, 0.02 and 0.05. The comprehensive land use change in other areas was higher than that in Tujia and Miao Autonomous Prefecture, but lower than that in Xiaogan.
Figure 4. Comprehensive land use dynamic attitude from 2010 to 2015. This figure is calculated according to formula (2) and represents the overall change of land use. The darker the color, the more drastic the change.

Separately, cultivated land presents different characteristics, as shown in Figure 5. The total area of cultivated land has been decreasing continuously for many years at an accelerating rate. Relatively speaking, the rate of conversion of cultivated land into other land cover types in Wuhan and surrounding areas has been faster. The single dynamic attitude of cultivated land in Wuhan reached 0.87, while in Xiaogan and Ezhou it was 0.42 and 1.11, respectively. Ezhou is the region with the largest single dynamic attitude for land, while Jingmen, Yichang, Shennongjia and Enshi Tujia Autonomous Prefecture had the lowest dynamic attitude for cultivated land use, with values of 0.16, 0.17, 0.02 and 0.10, respectively. Shennongjia is the region with the lowest dynamic value for cultivated land. With an increased distance from the Wuhan area, the attitude of cultivated land use change gradually decreased. One abnormal area is Shiyan area, the cultivated land use change of which was also higher.
Figure 5. Land use change attitude from 2010 to 2015—arable land. The chart shows the rate of conversion of cultivated land to other land use types in each region. According to formula (1), the larger the value, the faster the change.

The change in construction land is totally different from that of cultivated land, as shown in Figure 6. Suizhou, Shiyan, Shennongjia and Enshi Miao Tujia Autonomous Prefecture displayed the highest level of dynamic attitude toward construction land, with values of 10.44, 23.09, 47.48 and 11.20, respectively. The dynamic attitude of construction land in Shennongjia was the highest in the study area. Wuhan and its neighbouring areas of Xiaogan, Ezhou, Xianning and Xiangyang displayed lower values, while land use in Yichang, Qianjiang, Tianmen and Xiantao changed relatively slowly, at 0.56, 1.58, 0.96 and 1.52, respectively. In addition to Suizhou, Shiyan, Shennongjia, Enshi Tujia and Miao Autonomous Prefecture, as a whole, the dynamic attitude of land use for construction land remain centered on Wuhan, and the dynamic attitude changed with the larger values in the center and smaller values further from the center.

Figure 6. Land use change attitude from 2010 to 2015—construction land. This chart shows the dramatic degree of change of construction land in various regions. According to formula (1), the higher the value, the faster the change of construction land.
3.2. The relationship between BDI and land cover change

The BDI is a number that can be converted by recording the number of keyword searches on the internet. By displaying the search behaviors of users, the index can reflect the concerns of netizens, and the use of specific keywords can also show the influence of specific policies. This study collected representative data from the Baidu website and some of the top keyword searches regarding, in addition to unused land cover types, cultivated land reclamation fee, cultivated land tax, grassland, water area, Measures for the registration of certifications for aquaculture on beaches, construction land planning permit, and construction land plot ratio measures for the management of land in the countryside. See Table 3 for the BDI of each search term from 2010 to 2015. In order to establish a model of the impact of policies on land use change, correlation analysis was carried out for the search terms and types of land cover change representative of the BDI (unused land is not recorded in the Baidu Index and not considered). The correlation is shown in Table 4. Among them, the correlation coefficient of cultivated land occupation tax was 0.806, the compensation standard for forestland was 0.833, and the planning license for construction land was 0.931. The correlation between grassland and water area was relatively low, so it was not considered. As arable land and construction land are greatly influenced by policy, and their economic value is high, we chose ‘cultivated land usage tax’ and the corresponding ‘construction land planning permit’ as two search terms in the BDI, respectively, and the land cover type change of the corresponding arithmetic, as shown in Formula (3), to determine the policy impact on land cover change.
Table 3. Baidu Index of keywords from 2010 to 2015.

| District     | Cultivated Land | Forest Land | Grassland | WA | Construction Land |
|--------------|-----------------|-------------|-----------|----|-------------------|
|              | LRF  | FCT | FLC | WCS | Grassland | WA | MCRATF | CLUP | MMPRCL | RCL |
| Ezhou        | 1146 | 7179| 342 | 285 | 8750      | 684| 688    | 5674 | 1146   | 114 |
| Enshi        | 2417 | 13697| 2180| 1659| 9808      | 741| 59     | 9504 | 2119   | 3725|
| Huanggang    | 2587 | 25818| 1543| 857 | 16518     | 686| 285    | 13717| 2754   | 114 |
| Huangshi     | 1897 | 12409| 571 | 523 | 13011     | 631| 291    | 7291 | 1311   | 57  |
| Jingmen      | 4022 | 18114| 1620| 631 | 10424     | 743| 232    | 8481 | 1207   | 342 |
| Jingzhou     | 2006 | 16183| 459 | 572 | 14060     | 1331| 633    | 10229| 2021   | 632 |
| Qianjiang    | 515  | 2638 | 57  | 57  | 2968      | 171| 114    | 2453 | 173    | 0   |
| Shennongjia  | 0    | 0    | 0   | 0   | 0         | 0  | 0      | 0    | 0      | 0   |
| Shiyan       | 3227 | 18854| 1956| 1838| 15257     | 1142| 1037   | 10175| 1370   | 574 |
| Suizhou      | 1315 | 6644 | 1087| 1379| 3325      | 228| 57     | 3206 | 456    | 0   |
| Tianmen      | 574  | 3495 | 0   | 114 | 1543      | 171| 57     | 1484 | 171    | 0   |
| Wuhan        | 18621| 97011| 10878|7991| 122981    | 21835|1775  | 94149|10320  | 7213|
| Xiantao      | 402  | 4470 | 0   | 171 | 2804      | 57 | 0      | 2630 | 114    | 171 |
| Xianning     | 1720 | 10292| 855 | 407 | 9164      | 228| 116    | 7868 | 1604   | 228 |
| Xiangyang    | 3489 | 30081| 1028| 969 | 14060     | 1148|399    | 13037|1543   | 342 |
| Xiaogan      | 2521 | 15858| 462 | 574 | 14306     | 800 |173    | 9902 | 1834   | 342 |
| Yichang      | 3745 | 29902| 3347| 1836| 21206     | 1488|346    | 18285|1661   | 632 |

This table shows the Baidu index of each keyword in each region obtained from the Baidu search engine. The letter combination in the table represents each keyword. The larger the value, the higher the degree of concern and the greater the impact. The letter combinations have the following meaning: LRF = Land Reclamation Fees; FCT = Farmland Conversion Tax; FLC = Forest Land Circulation; WCS = Woodland Compensation Standard; WA = Water Area; MCRATF = Measures for Certification and Registration of Aquaculture in Tidal Flats; CLUP = Construction Land Use Permit; MMPRCL = Measures for the Management of Plot Ratio of Construction Land; RCL = Rural Construction Land.
Table 4. Spearman Test between each keywords and land change types.

| Object type          | Way  | Keywords | Coefficient | Sig. |
|----------------------|------|----------|-------------|------|
| plowland             | out  | LRF      | 0.748       | 0.001|
|                      |      | FCT      | 0.806       | 0.000|
|                      | in   | FLC      | 0.842       | 0.000|
|                      |      | WCS      | 0.833       | 0.000|
| woodland             | in   | FLC      | 0.776       | 0.000|
|                      |      | WCS      | 0.782       | 0.000|
| grassland            | in   | grassland| 0.531       | 0.028|
|                      |      | grassland| 0.541       | 0.025|
| aquatorium           | out  | aquatorium| 0.652      | 0.005|
|                      |      | MCRATF   | 0.611       | 0.009|
|                      |      | CLUP     | 0.931       | 0.000|
| construction land    | in   | MMPRCL   | 0.797       | 0.000|
|                      |      | RC       | 0.720       | 0.001|

This table is the Correlation test of land cover change and each keyword of the Baidu index, and the significance is set as 0.05. The greater the Coefficient value, the greater the correlation. The meaning of each letter combination is as follows: LRF = Land Reclamation Fees; FCT = Farmland Conversion Tax; FLC = Forest Land Circulation; WCS = Woodland Compensation Standard; MCRATF = Measures for Certification and Registration of Aquaculture in Tidal Flats; CLUP = Construction Land Use Permit; MMPRCL = Measures for the Management of Plot Ratio of Construction Land; RC = Rural Construction. In represents conversion of other types to object type; out means that the target type is converted into other types. Correlations of other search terms are less than 0.5, not recorded.

From Figure 7, we see the level of public interest in policy, and we can also see the impact of policies on cultivated land. In general, it can be seen that in Hubei, Tianmen city, Qianjiang city and Jingzhou city, policy had the greatest impact on changes to cultivated land, with corresponding values of 0.91, 0.95 and 0.83, respectively. Suizhou, Xiaogan, Xiantao, Xianning and Ezhou were higher than other areas close to Wuhan, at 0.55, 0.64, 0.45, 0.39 and 0.49, respectively. Enshi Tujia and Miao Autonomous Prefecture, Yichang, Jingmen, Huangshi and Wuhan were lower at 0.09, 0.23, 0.24, 0.21 and 0.17, respectively. Shennongjia Forest District, being a forest district outside of the city, with zero internet search volume, was not considered. On the whole, policies have a great impact on cultivated land around Wuhan. Wuhan, as the cultural, economic and political center of Hubei Province, is less affected by policies pertaining to its own cultivated land. Meanwhile, farmland in remote areas such as Enshi Tujia and Miao Autonomous Prefecture is also less affected by policies.
Figure 7. Influence of policies on changes in cultivated land from 2010 to 2015. The Shennongjia search volume is zero, therefore is not considered. The value in the figure is calculated by using the Baidu index of farmland occupation tax calculated by formula (3). The figure shows the extent to which farmland is affected by the policy. The darker the color, the greater the impact.

In addition to the impact of public attention on arable land, we also studied the impact of policies on construction land. See Figure 8 for the distribution map of the impact of policies on various regions. In the diagram, Jingzhou city is the most significant area affected by policies, followed by Shiyan and Suizhou with values of 1.48, 1.33 and 2.23, respectively. Tianmen city, Xiantao city, Xiaogan, Xianning city and Huanggang city, Xiangyang city had values of 1.05, 0.85, 1.29, 0.96, 1.08 and 1.00, respectively, while Enshi Tujia and Miao Autonomous Prefecture had the lowest values with 0.44 and 0.22, Yichang, Jingmen, Qianjiang, Ezhou and Huanggang sat in the middle of the above two areas. The Shennongjia forest region, as a protected forest area, saw a search volume of zero and was not considered. On the whole, there are more concentrated areas around Wuhan. Compared with Figure 5, the overall impact is greater than that of cultivated land.
4. Discussion

For a long time, studies on the spatial distribution of land cover change have been concerned primarily with natural factors such as climate, temperature and precipitation, as well as social factors such as the economy, population and population density. However, few studies have been conducted on the quantitative impact of policies on land use. Previous studies have conducted traditional analysis of land cover types such as land transfer matrixes, the single land use dynamic degree and the comprehensive land use dynamic degree on the basis of Internet data, selecting key search terms such as farmland reclamation, cultivated land usage tax, transfer, compensation standard, grassland, water area and fishery tidal flats, the certificate registration method, construction land planning permit, plot ratio measures for the administration of construction land and rural construction land. Because these keyword searches rank higher, they are more commonly used and are used by a broader part of the population. At the same time, they are all keywords frequently appearing in government policies, potentially indicating the influence of policies. We chose two land cover types sensitive to government policy, cultivated land and construction land, with keyword correlation coefficients above 0.80, to determine the policy impact with two types of spatial distribution diagrams, shown in the figures for both cultivated land and construction land. As a whole, the area surrounding Wuhan is more greatly affected by policy, while Wuhan itself is less affected.

4.1. General features

The central and eastern part of Hubei province is dominated by hills and plains with a large area of farmland, while the western part is mountainous with a large number of forested areas, which together account for more than 80% of the total area of the province, while other land use types cover only a small area. From the three study periods, namely 2000–2005, 2005–2010 and 2010–2015, it can be seen that the area of cultivated land has been decreasing continuously, mainly because a large amount of cultivated land has been converted into construction land. As China is in the process of urbanization, a large amount of cultivated land has been occupied. In addition to the impact of
urbanization, some woodlands have been converted into construction land, but the mountainous areas in the west are not suitable for conversion into construction land, so the area of land converted into construction land in this region is much smaller. Grasslands and unused land also show a slight tendency to decline, stemming from China’s urbanization process, while water areas show an increase, caused by the expansion of inundated areas in Hubei province that have encroached on the land.

As a whole, it can be seen in Table 2 that land cover change in Hubei Province is increasing. The comprehensive land use dynamic attitudes in the three periods from 2000 to 2005, 2005 to 2010 and from 2010 to 2015 are 0.06, 0.08, and 0.09, respectively, indicating that land cover change is becoming more and more drastic, and land is being increasingly impacted by human activity. Among all types of land cover, cultivated land, forest land, grassland and unused land show a decreasing trend. The absolute value of unused land is the largest. The area of cultivated land is decreasing at an increasing rate, while the area of woodland and grassland is also decreasing. This can be attributed primarily to changes in the cities and the expansion of construction land, with the arable land being most affected. The areas of construction land show an increasing trend. The construction area is increasing at the fastest rate, with a considerable part of other land use types expected to be converted into construction land. The change in water area has also been significant, which is somewhat related to flooding.

4.2. Land cover change by region

As can be seen from Figure 4, the significant changes observed in Wuhan and Ezhou are mainly due to the fact that Wuhan, as the political, economic and cultural center of Hubei Province, is affected by various factors and experiences various types of land cover changes frequently. Ezhou, which is adjacent to Wuhan, is also greatly affected. Tianmen, Xiantao, Qianjiang, Jingzhou and Xiaogan are all close to Wuhan and experience flow-on effects from Wuhan, with land cover changes also greater than other areas. Enshi Tujia and Miao Autonomous Prefecture and Yichang city in the western mountains are far away from Wuhan and are less affected. In summary, Wuhan has the largest dynamic attitude for comprehensive land use in the whole province and has experienced the most drastic land cover change. Moreover, the surrounding areas have also experienced relatively drastic changes, while areas further away from Wuhan have experienced smaller land use change.

As can be seen from the comparison between Figure 5 and Figure 6, the overall change in construction land is much more drastic than that of cultivated land, which is also greatly influenced by policy. On the one hand, as China undergoes a significant urbanization process, a large number of other types of land cover are being converted into construction land, including a considerable area of cultivated land. On the other hand, land is a scarce resource in cities with a high population density, and construction land can bring more benefits than other types of uses. Driven by a range of interests, construction land has become the preferred type of land cover.

To be specific, in both Figure 5 and Figure 6, the main differences in the areas with a high attitude for land cover change are concentrated around Wuhan, while the others are relatively low. However, changes in Suizhou, Shiyan city and Enshi Tujia and Miao Autonomous Prefecture are mainly due to the conversion of a large area of land into construction land. Therefore, the construction land dynamic attitude is high, and the farmland dynamic attitude is lower. Enshi Tujia and Miao Autonomous Prefecture is an economically lagging area. Now, the Prefecture is experiencing a process of urbanization and the expansion of construction land due to an increase in population. With the original construction area being smaller, Formula (1) shows that the result of a small denominator will be larger, so construction land use in this area is more dynamic.

4.3. Correlation between land cover type and BDI

There is a close relationship between land use type change and BDI, which can be clearly seen from Table 3. The five kinds of land cover changes can be divided into three types of indicators, namely, administrative licensing, economic regulation and technical indicators. Administrative licensing, such as the construction land planning permit, reached 0.931, policy and economic rules,
such as the forest land compensation standard, showed a correlation of 0.833, and technical index management methods, such as the construction land plot ratio, reached a correlation of 0.797. It can be seen that the three types of indicators are closely related to land cover change, with the administrative licensing category having the greatest impact, the economic regulation category the second greatest impact, and the technical index category having the least impact. Cultivated land and construction land were found to be highly impacted by policy, with the construction land planning permit and the cultivated land occupation tax being two more representative search terms, representing the administrative license category and the economic regulation category, respectively. Their use in the construction of Formula (3) is of great practical significance in studying the impact of policies on land use types.

4.4. Policy impact on arable land and construction land

By using Formula (3) to calculate the impact of public attention on land cover types, an impact diagram can be established. This influence reflects the dominant role of policy factors behind it (Figure 7 and Figure 8). In Figure 7, it can be seen that cultivated land is more affected by policy in areas close to Wuhan, among which Jingzhou city, Qianjiang city and Tianmen city are the most affected. In addition to being affected by policies, these areas are also affected by natural disasters such as flooding and encroachment on land, which is shown as the highest level on the map. Because these areas are located in the Four-Lake region, they are subject to flooding, with the corresponding IN value increasing with decreases in cultivated land. Further research in this area is required in the future. Remote Enshi Tujia and Miao Autonomous Prefecture and other areas are less affected because are a mountainous area, the available arable land is limited, the economy is not developed, and the arable land has a high economic value, so the area is less affected by the farmland occupation tax. It is worth noting that the impact of cultivated land in Wuhan city is the smallest, largely because the city is the Province's political, economic and cultural center and various other resources are relatively abundant. Furthermore, Wuhan has a long history, with the various land cover types being relatively fixed, so only minor changes in land cover could be observed.

The policy impact on construction land is shown in Figure 8, with the main changes being concentrated around Wuhan as the economic center of the region. As a result of a radiation effect, these areas have a high economic value, which leads to other land cover types being used for construction purposes. The IN value here is high, meaning this area is more affected by policy. Due to the abundant resources and increased opportunities in Wuhan, the highest economic benefit may not be obtained when the land is converted into construction land. Therefore, the diversification of land use is optimal. By comparing Figure 7 and Figure 8, it can be seen that policy has a larger reach with more construction land being established, mainly because China is undergoing a process of urbanization. Urban construction land has high economic value and is welcomed by people in many areas.

In addition, construction land in Shiyan city is also highly affected by policy with a corresponding value is 1.43. The main reason is that Shiyan is one of the largest commercial vehicle production bases in the whole of China [52] and the world's third-largest automobile production base. The city, therefore, enjoys corresponding supporting measures to encourage the development of enterprises, and the government has eased restrictions on land, with a large area of cultivated land being used by enterprises as construction land. Therefore, construction land expansion in the region is extensive. Meanwhile, Suizhou was upgraded from the original county-level administrative system to the city-level administrative system in 2000 [53]. Due to the improvement in administrative level, the corresponding urban area was expanded to meet the needs of the administration, and various institutions were either upgraded or newly established, resulting in the occupation of a large area of cultivated land. Both of the above results in the conversion of cultivated land into construction land, resulting in a lot of construction land appearing in the region, so the IN value is very high.

Compared with the above two, Jingzhou city differs, with its degree of influenced reaching 1.59. Jingzhou city is located in the expansive Jianghan plain with numerous rivers and lakes. Due to the high economic value of urban construction land, a large amount of land will be built around the lake,
and the occupied water area will be converted into construction land if permitted. Of course, due to the proximity to Wuhan, a large amount of arable land will also be converted into construction land. In summary, Jingzhou city has cultivated land that will be converted into construction land, water area that will be converted into construction land, and forest land that will be converted into other uses.

4.5. Other factors

The impact of a city on land cover is great, and the evaluation of city suitability is also a problem worth considering. There is a complex relationship between cities and land cover [54]. In the current land cover change, land provides possible space for urban expansion, and a lot of land is occupied. Cities with large populations, in turn, dramatically alter the patterns of land cover on the surface. Of interest is the relationship between “source” and “flow”. A large amount of land occupied by cities will lead to a series of ecological and environmental problems and even lead to disasters, such as urban heat islands and geological disasters. Similarly, land cover patterns affect many aspects of the city, such as improving the climate. The geographical location and spatial distribution of a city is a very meaningful problem that needs to be studied. George D. Bathrellos et al. [55] studied the suitability of evaluating a city by using multiple hazard maps. Therefore, the choice of location and condition of urban expansion needs to consider many factors. In the evaluation of urban suitability, policy becomes an important factor that cannot be ignored. This paper provides a method for evaluating the influence of policy.

This study seeks to consider the impact of policies on land cover change, mainly examining arable land and construction land. Other factors such as economics, population, geographical location, etc. still need to be considered. The economy is clearly a significant factor. The mode of land cover can be seen in Figure 5 and Figure 6. The more developed areas near Wuhan have seen greater land cover change. The impact of population growth on land cover is not necessarily significant because, often, populous areas are larger, and as mobility increases, the population can move further away from the city. Land cover type depends primarily on economic factors such as local land use mode and policy.

4.6. Limitations

This study considers the land cover mode in relation to policy influence but does not consider other factors such as the economy and population. More factors should be considered for a more comprehensive examination of this topic in the future. At the same time, data acquisition was limited. With the passage of time, more and more information will be recorded in BDI, and a greater number of detailed search terms will be included. These limitations provide a focus for future research.

5. Conclusions

Through the interpretation of remote sensing data, this study obtained four sets of data on land cover in Hubei Province, incorporating the land use transfer matrix, the single land use dynamic degree and the comprehensive land use dynamic degree for various types of land cover change. By determining the relationship between the BDI and land cover change, we found that the ratio of land cover change to BDI was the lowest in Wuhan for farmland and construction land. The area around Wuhan is the highest, and the ratio decreases as the distance increases. Based on the above research results, the following suggestions are proposed: 1) as Wuhan has a large population and little land change, the expansion of urban boundaries should be strictly restricted; 2) we should strengthen economic development and promote a balanced economy between east and west. Enshi Tujia and Miao Autonomous Prefecture and other places in the region are economically underdeveloped and should be given stronger support; 3) backward areas can develop economies of scale industrial chains, similar to Shiyan city’s commercial vehicle base; and 4) changes in land cover are strictly controlled to avoid damaging environmental health, such as urban heat islands and natural disasters.
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References
1. Han, L.J.; Zhou, W.Q.; Li, W.F. Fine particulate (PM2.5) dynamics during rapid urbanization in Beijing, 1973–2013. Sci. Rep. 2016, 6, 23604.
2. Ayanlade, A. Seasonality in the daytime and night-time intensity of land surface temperature in a tropical city area. Sci. Total Environ. 2016, 557, 415–424.
3. Foley, J.A.; DeFries, R.; Asner, G.P.; Barford, C.; Bonan, G.; Carpenter, S.R.; Chapin, F.S.; Coe, M.T.; Daily, G.C.; Gibbs, H.K.; et al. Global Consequences of Land Use. Science 2005, 309, 570–574.
4. Yan, H.M.; Liu, F.; Liu, J.Y.; Xiao, X.M.; Qin, Y.W. Status of land use intensity in China and its impacts on land carrying capacity. J. Geogr. Sci. 2017, 27, 387–402.
5. Hütt, C.; Waldhoff, G.; Bareth, G. Fusion of Sentinel-1 with Official Topographic and Cadastral Geodata for Crop-Type Enriched LULC Mapping Using FOSS and Open Data. ISPRS Int. J. Geo Inf. 2020, 9, 120.
6. Foody, G.M. Status of land cover classification accuracy assessment. Remote Sens. Environ. 2002, 80, 185–201.
7. Salazar, E.; Henriquez, C.; Sliuzas, R. and Qiense, J. Evaluating Spatial Scenarios for Sustainable Development in Quito, Ecuador. ISPRS Int. J. Geo Inf. 2020, 9, 141.
8. Adams, J.B.; SABOL, D.E.; KAPOS, V.; ALMEIDA, R.; ROBERTS, D.A.; SMITH, M.O.; GILLESPIE, A.R. Classification of multispectral images based on fractions of endmembers: Application to land-cover change in the Brazilian Amazon. Remote Sens. Environ. 1995, 52, 137–154.
9. Anand, V.; Oinam, B. Future land use land cover prediction with special emphasis on urbanization and wetlands. Remote Sens. Lett. 2020, 11, 225–234.
10. Don, A.; Schumacher, J.; Freibauer, A. Impact of tropical land-use change on soil organic carbon stocks—a meta-analysis. Glob. Chang. Biol. 2011, 17, 1658–1670.
11. Bhaduri, B.; Harbor, J.; Engel, B.; Grove, M. Assessing watershed-scale, long-term hydrologic impacts of land-use change using a GIS-NPS model. Environ. Manag. 2000, 26, 643–658.
12. Rashford, B.S.; Adams, R.M.; Wu, J.J.; Voldseth, R.A.; Guntenspergen, G.R.; Werner, B.; Johnson, W.C. Impacts of climate change on land-use and wetland productivity in the Prairie Pothole Region of North America. Reg. Environ. Chang. 2016, 16, 515–526.
13. Selwood, K.E.; McGeoch, M.A.; Mac, N.R. The effects of climate change and land-use change on demographic rates and population viability Prairie Pothole Region of North America. Biol. Rev. 2014, 90, 837–853.
14. Sterling, S.M.; Ducharme, A.; Polcher, J. The impact of global land-cover change on the terrestrial water cycle. Nat. Clim. Chang. 2013, 3, 385–390.
15. Fedeski, M.; Gwilliam, J. Urban sustainability in the presence of flood and geological hazards: The development of a GIS-based vulnerability and risk assessment methodology. Landsc. Urban Plan. 2007, 83, 50–61.
16. Bathrellos, G.D.; Gaki-Papanastassiou, K.; Skilodimou, H.D.; Papanastassiou, D.; Chousianitis, K.G. Potential suitability for urban planning and industry development by using natural hazard maps and geological-geomorphological parameters. Environ. Earth Sci. 2012, 66, 537–548.
17. Brion, H. Combating Land Degradation and Desertification: The Land-Use Planning Quandary. Land 2019, 8, 27.
18. Liu, J.Y.; Kuang, W.H.; Zhang, Z.X.; Xu, X.L.; Qin, Y.W.; Ning, J.; Zhou, W.C.; Zhang, S.W.; Li, R.D.; Yan, C.Z.; et al. Spatiotemporal characteristics, patterns, and causes of land-use changes in China since the late 1980s. *J. Geogr. Sci.* 2014, 24, 195–210.

19. Long, H.L.; Zou, J.; Liu, Y.S. Differentiation of rural development driven by industrialization and urbanization in eastern coastal China. *Habitat Int.* 2009, 33, 454–462.

20. Xu, G.; Zhang, H.F.; Chen, B.Z.; Zhang, H.R.; Innes, J.L.; Wang, G.Y.; Yan, J.W.; Zheng, Y.H.; Zhu, Z.C.; Myneni, R.B. Changes in Vegetation Growth Dynamics and Relations with Climate over China’s Landmass from 1982 to 2011. *Remote Sens.* 2014, 6, 3263–3283.

21. Liu, Y.L.; Lei, H.M. Responses of Natural Vegetation Dynamics to Climate Drivers in China from 1982 to 2011. *Remote Sens.* 2015, 7, 10243–10268.

22. Yang, Y.J.; Wang, K.; Liu, D.; Zhao, X.Q.; Fan, J.W. Effects of land-use conversions on the ecosystem services in the agro-pastoral ecotone of northern China. *J. Clean. Prod.* 2020, 249, 119360.

23. Li, S.H.; Peng, S.Y.; Jin, B.X.; Zhou, J.S.; Li, Y.X. Multi-scale relationship between land use/land cover types and water quality in different pollution source areas in Fuxian Lake Basin. *PeerJ* 2019, 7, e7283.

24. Li, F.; Sun, W.W.; Yang, G.; Weng, Q.H. Investigating Spatiotemporal Patterns of Surface Urban Heat Islands in the Hangzhou Metropolitan Area, China, 2000–2015. *Remote Sens.* 2019, 11, 1533.

25. Li, P.X.; Cao, H. Simulating Uneven Urban Spatial Expansion under Various Land Protection Strategies: Case Study on Southern Jiangsu Urban Agglomeration. *ISPRS Int. J. Geo Inf.* 2019, 8, 521.

26. Chen, Y.; Chen, Z.G.; Xu, G.L.; Tian, Z.Q. Built-up land efficiency in urban China: Insights from the General Land Use Plan (2006–2020). *Habitat Int.* 2016, 51, 31–38.

27. Liu, Y.S.; Li, J.T.; Yang, Y.Y. Strategic adjustment of land use policy under the economic transformation. *Land Use Policy* 2018, 74, 5–14.

28. Zhang, W.W.; Li, H. Characterizing and Assessing the Agricultural Land Use Intensity of the Beijing Mountainous Region. *Sustainability* 2016, 8, 1180.

29. Huang, X.K.; Zhang, L.F.; Ding, Y.S. The Baidu Index: Uses in predicting tourism flows –A case study of the Forbidden City. *Tour. Manag.* 2017, 58, 301–306.

30. Sun, S.L.; Wei, Y.J.; Tsui, K.L.; Wang, S.Y. Forecasting tourist arrivals with machine learning and internet search index. *Tour. Manag.* 2019, 70, 1–10.

31. Yang, X.; Pan, B.; Evans, J.A.; Lv, B. Forecasting Chinese tourist volume with search engine data. *Tour. Manag.* 2015, 46, 386–397.

32. Su, K.; Xu, L.; Li, G.Q.; Ruan, X.W.; Li, X.; Deng, P.; Li, X.M.; Li, Q.; Chen, X.X.; Xiong, Y.; et al. Forecasting influenza activity using self-adaptive AI model and multi-source data in Chongqing, China. *Ebiomedicine* 2019, 47, 284–292.

33. Liu, K.K.; Wang, T.; Yang, Z.C.; Huang, X.D.; Milinovich, G.J.; Lu, Y.; Jing, Q.L.; Xia, Y.; Zhao, Z.Y.; Yang, Y.; et al. Using Baidu Search Index to Predict Dengue Outbreak in China. *Sci. Rep.* 2016, 6, 38040.

34. Li, K.; Liu, M.L.; Feng, Y.; Ning, C.Y.; Ou, W.D.; Sun, J.; Wei, W.D.; Liang, H.; Shao, Y.M. Using Baidu Search Engine to Monitor AIDS Epidemics Inform for Targeted intervention of HIV/AIDS in China. *Sci. Rep.* 2016, 6, 38040.

35. Chen, S.X.; Liu, X.J.; Wu, Y.S.; Xu, G.X.; Zhang, X.B.; Mei, S.J.; Zhang, Z.; O’Meara, M.; O’Gara, M.C.; Tan, X.R.; et al. The application of meteorological data and search index data in improving the prediction of HFMD: A study of two cities in Guangdong Province, China. *Sci. Total Environ.* 2019, 652, 1013–1021.

36. Liu, Y.; Peng, G.; Hu, L.Y.; Dong, J.C.; Zhang, Q.Q. Using Google Trends and Baidu Index to analyze the impacts of disaster events on company stock prices. *Ind. Manag. Data Syst.* 2020, 120, 350–365.

37. Dong, J.C.; Dai, W.; Liu, Y.; Yu, L.A.; Wang, J. Forecasting Chinese Stock Market Prices using Baidu Search Index with a Learning-Based Data Collection Method. *Int. J. Inf. Tech. Decis.* 2019, 18, 1605–1629.

38. Wang, J.X.; Lu, C.F.; Tang, J.; Ge, L.; Huang, Z.L.; Zhou, S.L. Time Series and Spatial Characteristics of Public Attention towards Huangyan Island Based on Baidu Index. *J. Coast. Res. Spec. Issue* 2019, 91, 281–285.

39. Fang, J.C.; Wu, W.S.; Lu, Z.; Cho, E.H. Using Baidu Index to Nowcast Mobile Phone Sales in China. *Sing. Econ. Rev.* 2019, 64, 83–96.

40. Pan, B.; Wu, D.C.; Song, H.Y. Forecasting hotel room demand using search engine data. *J. Hosp. Tour. Tech.* 2012, 3, 196–210.

41. Wang, Q.X.; Zhao, M. Research on the City Network of Guangdong, Hongkong and Macao from the Perspective of Information Flow: Analysis based on Baidu Index. *J. Reg. City Plan.* 2018, 29, 281–293.
42. Thapa, R.B.; Murayama, Y. Drivers of urban growth in the Kathmandu valley, Nepal: Examining the efficacy of the analytic hierarchy process. *Appl. Geogr.* 2010, *30*, 70–83.
43. Timothy, S.; Heimlich, R.; Houghton, R.A. Use of US croplands for biofuels increases greenhouse gases through emissions from land-use change. *Science* 2008, *319*, 1238–1240.
44. Allan, J.D. Landscapes and riverscapes: The influence of land use on stream ecosystems. *Ann. Rev. Ecol. Evol. Syst.* 2004, *35*, 257–284.
45. Novovič, O.; Brdar, S.; Mesaroš, M.; Crnojević, V. and Papadopoulos, A.N. Uncovering the Relationship between Human Connectivity Dynamics and Land Use. *ISPRS Int. J. Geo Inf.* 2020, *9*, 140.
46. National Bureau of Statistics of the People’s Republic of China. Available online: http://data.stats.gov.cn/index.htm (accessed on 10 February 2020).
47. International Scientific & Technical Data Mirror Site, Computer Network Information Center, Chinese Academy of Sciences. Available online: http://www.gscloud.cn/ (accessed on 10 February 2020).
48. Baidu Search Index. Available online: http://index.baidu.com/v2/index.html#/ (accessed on 10 February 2020).
49. Wu, L.N.; Yang, S.T.; Liu, X.Y.; Luo, Y.; Zhou, X.; Zhao, G.H. The response of land use change to human activities in the Beiluo river basin since 1976. *ACTA Geogr. Sin.* 2014, *69*, 54–63. (In Chinese)
50. Li, X.F.; Liu, L.M.; Qi, X.; Zhang, J.X.; Zhao, T.B.; Wang, Y.; Liu, X.F.; Zhou, Y.B. Dynamic change and driving force of land use in ecological fragile area in northwest Shanxi. *J. Appl. Ecol.* 2014, *25*, 2659–2667. (In Chinese)
51. China Internet Network Information Centre. Available online: http://www.cnnic.net.cn/ (accessed on 10 February 2020).
52. Shiyan Government of Hubei Province. Available online: http://www.shiyan.gov.cn/xwzx_2477/syyw_2479/200309/t20030924_237747.shtml (accessed on 10 February 2020).
53. Suizhou Government of Hubei Province. Available online: http://www.gov.cn/gongbao/content/2000/content_60479.htm (accessed on 10 February 2020).
54. Bathrellos, G.D.; Skilodimou, H.D. Land Use Planning for Natural Hazards. *Land* 2019, *8*, 128.
55. Bathrellos, G.D.; Skilodimou, H.D.; Chousianitis, K.; Youssef, A.M.; Pradhan, B. Suitability estimation for urban development using multi-hazard assessment map. *Sci. Total Environ.* 2017, *575*, 119–134.

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