Mental Health and Land Cover: A Global Analysis Based on Random Forest with Geographical Consideration

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Abstract

Nature features in living environments can help to reduce stress and improve mental health. Different land types have disproportionate impacts on mental health. However, the relationships between mental health and land cover are inconclusive. Here, we show the complex relationships between mental health and eight land types based on the random forest method and Shapley additive explanations. The accuracy of our model is 67.59%, while it usually is no more than 20% in previous studies. According to the analysis results, we estimate the average effects of eight land types. Due to their scarcity in living environments, shrubland, wetland, and bare land have larger impacts on mental health. Cropland, forest, and water could improve mental health in high population-density areas. Urban land's and grassland's impacts are mainly negative. Due to scarcity values, the current land cover composition influences people's attitudes toward a specific land type. Our research is the first study that analyzes data with geographical information by random forest and explains the result geographically. This paper provides a novel machine learning explanation method and insights to formulate better land-use policies to improve mental health.

Keywords:

Mental Health; Land Cover; Random Forest; SHAP; Geographically Weighted Connection

Introduction

Natural land cover in people's living environments positively affects human well-being and mental health [1-6], mainly driven by ecosystem service [7-9]. Ecosystem services from natural land cover can effectively benefit people [3,9-11], including recreational activities [2], air pollution reduction [12-14], and the creation of aesthetic, artistic, and scientific values for human beings [15,16]. However, 2.7% of global semi-natural or natural land has been continuously converted to other land types, specifically cropland and built-up area, from 1992 to 2015 [17]. With a decrease in natural land cover, the estimated aggregate value of ecosystem services from 1997 to 2011 has slashed by $4.3 trillion globally and annually [8]. As the benefits of the natural land cover are profound and enormous [8,9], the effects of land cover change on mental health are critical to structure land-use plans and strategies. With the continuous global development and urbanization [17], the share of natural land cover in people's living environments will keep decreasing. Due to the trade-off between economic development and desire for natural land, there is an essential need to detect whether people satisfy with the current land composition, how much alteration of land cover composition affects future mental health, and where the effects of a particular land type change are the highest.

The relationship between land cover and mental health has been long investigated [1,4,18,19]. Natural environments could reduce air pollution and stressor exposure and increase physical activity and social contact, eventually improving health and well-being [4,18,20]. Moreover, they are also the primary mediator in attenuating the negative impacts of air pollution on human health [21]. Reducing air pollution significantly benefits human well-being, especially in metropolitan areas [22]. Some findings indicate that blue-green spaces are critical to maintaining better mental status during the COVID-19 pandemic lockdown since they cut down stressor exposure [23]. A controlled laboratory study shows that the impacts of natural sounds and images on stress and mental status are positive [24]. Substantial and significant evidence shows that people in natural environments experience higher well-being and better emotions [2,25]. An empirical study indicates that individuals have significantly better mental health if they move to greener areas, and the effects last several years [6]. Furthermore, environmental degradation and the absence of green spaces are causal factors of mental health issues, according to a well-designed causation study [19]. Green space disproportionately affects human health among different socio-economic and demographic groups, so those variables must be carefully considered [26]. On the other hand, urban land cannot be simply regarded as a negative factor. People desire more urban land to support a better life if the cities are too crowded [27]. Although the relationship between land cover and mental health has long been detected and discussed, the detailed impacts remain elusive. In other words, making the value of land cover change understandable and comparable is needed to achieve a sustainable society, maintain human mental health, and formulate public policies.

To probe the comparable values and impacts of land cover on mental health, the quantitative land cover data play a distinct role in the empirical analyses. Previous studies have various land cover data, which are shares of one or several land types in each defined area [6,28-31], or greenery index, mainly normalized difference vegetation index (NDVI) [32,33]. Land cover data include several land types, which are more straightforward, but their temporal resolution is longer at least one year [34]. The NDVI can be obtained with the highest temporal resolution every eight days but only depicts greenery. Although these two types of data are widely used in previous studies, the land cover data are more suitable for the research, which does not only concentrate on greenery. The monetary values of land covers can be estimated [35,36]. For example, residents in German are willing to pay 23 Euro for a 1-ha increase in green urban areas within 1000 meters of their houses [29]. The monetary value estimation follows the marginal substitute rate (MSR) between land cover and income. The MSR strongly relies on the marginal effects of land cover and income on well-being or mental health indicators from the statistical models [36]. Most previous studies apply this method. The accuracy of statistical models dramatically affects the reliability of the estimated monetary value, and the assumption of the models is vital. Currently, the linear assumption is still widely employed since it is straightforward and effective.

The advantage of machine learning methods is their high accuracy. The goodness of fit in previous studies using traditional regression methods is no more than 20%. The relationship between mental health and land cover is mainly assumed to be linear [28,31,37], quadratic, or logarithmic [29,30,35]. On the one hand, the linear relationship is straightforward and has an evident attitude towards a specific land type. These models are based on a simple assumption that amounts of certain land types always have the same effect on mental health, no matter the current land cover status. In this case, people should live in the environment only with this land type that has the most positive effect on mental health. This is the main shortcoming of this assumption, and it is far from reality. On the other hand, the non-linear relationship is more in line with reality. Preferences for certain land types depend on the current land cover allocation [29,30,35]. It is the fundamental idea to build a non-linear model. There are two types of non-linear models. One assumes the relationship between the coverage of land types, and well-being is logarithmic [30], and the other assumes the relationship is quadratic [29,35]. In the logarithmic relationship assumption, when certain coverage keeps increasing, the effect of this land type on well-being or mental health gets down, but the direction of this attitude does not change [30]. In the quadratic relationship assumption, when the share of land cover changes, the intensity of effects on mental health will vary and even may alter the direction of the impact. Though these non-linear assumptions are better than linear ones, they still have low accuracy. The accuracy of machine learning methods, such as random forest, typically exceeds 60% [19,38]. High accuracy means that the relationships estimated by the trained model are closer to the actual situation. To make the policies based on the analysis results reliable, we should make assumptions similar to the real world. Machine learning has fewer assumptions on the relationships than previous methods [38]. Therefore, using machine learning methods is valid and reasonable.

To estimate the impacts of land cover change on mental health, relatively precise relationships between land cover and mental health are desired. This study employs 100,956 observations in an international survey from 37 countries and applies a non-parametric machine learning method, random forest, to obtain a high-fit model. However, because the random forest is typically model-agnostic, we employ effective tools to make the results understandable. A well-developed theory, Shapley value, can directly illustrate the feature value's contribution to mental health [39,40]. However, the Shapley value explanation is too local. In other words, this method cannot generate generalized knowledge. We, therefore, create a novel way, a geographically weighted connection, to link feature values and their Shapley values. According to explainable and accurate results, our research provides more information to formulate sustainable land-use policies to improve residents' mental health.

Materials and Methodology

Materials

Survey Information

Our study employs an international survey conducted by Kyushu University, Japan, from July 2015 to March 2017, covering 37 countries, including both developed and developing countries. The investigation periods for each country are generally less than one month. Moreover, to guarantee the reliability of the survey, the same questionnaires are used, while currency-related questions are based on local currencies. The population and GDP of these countries account for 68.58% of the global population and 82.67% of the worldwide GDP in 2017, respectively (**Supplementary Material Table S1**). This survey obtains individual mental health and several other demographic and socio-economic characteristics. The total number of observations that were recorded is 100,956. However, due to a lack of geographical location or records, 95,571 observations are kept. In addition, because some individuals did not provide income information, 89,273 observations are used in the calculations (Descriptive statistics of the features shown in **Supplementary Material Table S2**).

Mental Health

We include the twelve-item General Health Questionnaire (GHQ-12) in the survey to assess individual mental health. As a valid and reliable instrument, the GHQ-12 has been long and widely used in previous mental health studies, e.g., Ref. [41-43]. The GHQ-12 comprises 12 items to assess the individual mood states. Each item of the GHQ-12 has four potential answer options, encoded by the Likert method as 0, 1, 2, and 3, from negative to positive. The mental health assessment score is computed as the summed score of all 12 items. Thus, the output variable of our study is a discrete numeric variable ranging from 0 to 36. The current random forest method is designed to execute either regression or classification. The algorithm would perform the classification task using the discrete output variable, assuming the output is categorical. However, adjacent scores of the mental health assessments are related, i.e., they are ordinal rather than categorical. **Figure 1** illustrates the statistical distribution of the mental health assessment score. Most people get 24 points in the assessment, and significantly more people score 24 to 30 points than others. In this situation, if we perform the classification random forest, the classification accuracy for the people with lower or higher scores would be extremely low due to the unbalanced output distribution. Thus, we assume that the mental health assessment score is continuous.

Global Land Cover Data

As for the land cover, we use remote sensing data compiled by Tsinghua University, China (http://data.ess.tsinghua.edu.cn/), because, to the best of our knowledge, it is the dataset with the highest global resolution, at approximately 30 meters. This dataset is the 2017 global land cover. It classifies land cover into ten categories: cropland, forest, grassland, shrubland, wetland, water, tundra, urban land, bare land, and snow/ice [34]. We calculated areas of each land type surrounding our survey respondents with these data. To estimate the impact of land cover in our analysis, we use the percentages of each land type within a radius of 5,000 meters around each respondent following the previous study [29]. Eight land types are taken as the land cover data because little tundra and snow/ice are in the most analyzed area. After the random forest analysis, we will estimate the Shapley values of each land type.

Individual Income Data

Converting the impacts of land cover on mental health into monetary values is an effective way to make them understandable to the public without professional knowledge. Moreover, individual income is also an essential factor affecting mental health. In this study, we use the ratio between individual income and GDP per capita in the respondent's country (RI) as the income variable because the income in the survey is based on local currency. The main reason is that the same amounts of money might have different effects in different countries. For example, the ability and sense of 100 USD in the U.S. and Sri Lanka are not actually the same for the local people. The RI is calculated as follows:

$$RI_i = Inc_i - GDPPC_i \tag{1}$$

where RI_i is the RI of the respondent i, Inc_i is the individual income of the respondent i, and $GDPPC_i$ is the GDP per capita of the respondent i's country in the surveyed year. It must be noted that the units of Inc_i and $GDPPC_i$ are the current price of international USD. To unify the individual income data, we also convert the local currencies into the current price of international USD. We employed the official annual average exchange rate of the year during the conversion process when the survey was conducted in that country. Moreover, the survey questionnaires required the respondents to select their gross household income range rather than ask them to report their exact gross household income. Thus, we take the midpoint of the range chosen by the respondent as the gross household income. For instance, in the U.S., if respondents reported that their gross household income ranged from 50,000 to 60,000 USD per year, their household income is 55,000 USD per year in the analysis. According to previous studies [44,45], the calculation of the annual gross individual income is as follows:

$$Inc_i = \frac{GHI_i}{(Adu_i + 0.7Chi_i)^{0.5}} \tag{2}$$

where Inc_i is the annual gross individual income of the respondent i, GHI_i represents the gross annual household income of the respondent i, Adu_i represents the number of adults in the respondent i's household, and Chi_i represents the number of children in the respondent i's household. Limited by the household size and the maximum value of the selection interval, individual income rarely exceeds four times GDP per capita in the respondent's country. **Figure 2** demonstrates the statistical distribution of the RI in the respondent's country.

Other Control Variables

We add several other control variables because mental health status may differ according to people's socio-economic and demographic characteristics: age, gender, employment, educational background, emotion in the surveyed week, children number, self-reported health, self-reported personality, and evaluation of living environment. Among these control variables, employment, educational background, and self-reported personality are categorical. We use the one-hot encoding method to convert them into a series of dummy variables. Thus, every respondent has 49 features and one output variable in the analysis. The descriptions of the features are listed in **Supplementary Materials Table S3**.

Methodology

To detect influential factors on mental health and confirm the relationship between mental health and land cover, linear regression methods, such as ordinary least square (OLS) and ordered logit regression (OLR), are widely applied, e.g., Ref. [6,27,37,46]. The studies evaluate the monetary values of land cover through OLS estimation because the OLS is straightforward to explain. Additionally, the investigations employing the OLR are theoretically more reasonable since mental health evaluation is a discrete variable rather than a quantitative and continuous variable in most studies [6,37]. The OLR is a typical classification function based on logistic regression. However, these two models rely on linear assumptions and cannot directly illustrate the importance of predictors on the outcome variable. Putting another way, based on the linear assumption, a 1-unit increase in a certain land type always has the same effect on mental health, whatever the status quo. This is not consistent with the actual situation. Random forest could smoothly grasp the non-linear relationship, which bundles many different decision tree algorithms as an improved boosting method [47]. The decision tree algorithms are non-linear and closer to real-world situations [48].

The Regression Decision Tree

A single decision tree is the fundamental element of the random forest method. There are two types of trees, namely, the decision tree for either classification or regression [47,49]. **Figure 3** shows a simple example of a three-layer regression decision tree. To complete the prediction in the example tree, the algorithm passes three internodes and makes three judgments at most. As the example illustrated in **Figure 3**, we assume only three features, the unemployed dummy variable, self-reported health, and the RI, affect the output variable, mental health. The rules of each judgment and feature range splits are a critical part of machine learning training. A large amount of data is put into the algorithm to train the decision tree to decide the rules of each judgment and feature range splits. We employ a greedy approach to train regression decision trees [50]. This approach chooses the features and splits their ranges to minimize the residual sum of squares (RSS) as follows:

$$RSS = \sum_{l \in leaves} \sum_{i \in C_l} (y_i - \bar{y}_{C_l})^2 \tag{3}$$

where l is a leaf, C_l is the cases in leaf l, y_i is the observed value and $\bar{y}_{C_l}$ is the average observed value in leaf l. Unless the RSS is smaller than the defined threshold or the number of remaining cases in the end leaf is less than the defined threshold, the number of internode of trees will keep increasing [50].

Random Forest

In most cases, a single regression decision tree is insufficient to fit the output variables and usually causes an over-fitting analysis. To solve this issue, the random forest ensemble a bundle of decision trees and let them vote for the results [47]. The voting strategy for regression is taking the average value of all individual predictions as the random forest prediction. Bagging and bootstrapping are performed to guarantee the accuracy and reliability of the random forest [49]. Bootstrapping is the sampling technique of the random forest. Firstly, we set the number of trees in our random forest as N_{tree}. We extract N_{tree} samples with replacement from the original data, and the sample sizes are 2/3 data of the total sample. Every decision tree utilizes the bootstrapped dataset. However, at most, a predefined number of random features ($N_{features}$) are used in a single decision tree rather than all. After training, the random forest can predict the output variable by aggregating the votes from each tree. Using the bootstrapped dataset and the aggregate of votes, this process is terminologically called "bagging". Additionally, roughly 1/3 of the total sample is left out from the training process named the OOB dataset. The OOB dataset is applied to test the accuracy of the random forest through the OOB score, which is the proportion of OOB observations correctly predicted by the trained random forest. The reliable trained models have a relatively high OOB score.

In the random forest, most parts are built randomly, while only three critical parameters must be decided by the users, specifically, the minimum number of remaining observations in end leaves (N_{remain}), N_{tree} and $N_{features}$. Firstly, the minimum number of observations in the end leaves decides where the split stops because our random forest follows the greedy approach. If N_{remain} is too small, the decision tree might be too deep and too many end leaf would be generated, which could cause the model is huge and even unavailable to the computer memory. Moreover, the random forest accuracy will increase to some extent when more trees are included. However, the cost of infinitely increasing N_{tree} is a dramatic increment of calculation power and calculating time. Additionally, when N_{tree} exceeds a particular value, the marginal effect of increasing the number is minimal. Accordingly, considering the size of our dataset and computing ability, the number of trees is set to 1,000. Moreover, the number of features used in the decision trees, $N_{features}$, is another vital factor. A large $N_{features}$ might reduce the model's ability to grasp the relationship, while a small N_{try} might cause underfitting. Previous studies indicate that roughly one third of the total number is recommended [47,49,50]. Thanks to our relatively sufficient computing ability of a high-performance computer, we test the most possible $N_{features}$ values and based on 10-fold cross-validation. According to the test, the goodness of fit peaks when $N_{features}$ value is 11. We also test several possible N_{remain} values, including 2, 5, 10, 15, 20, 25, 30, 35, 40, based on 10-fold cross-validation. Although the results show that with the same $N_{features}$ and N_{tree}, the smaller N_{remain} causes a higher cross-validation score, the improvement is limited. For example, the increase of N_{remain} in the cross-validation score from 2 to 10 is not more than 1%. However, the disadvantage of the smaller N_{remain} is obvious. When we build the connection between Shapley value and values of features locally, the limited local datasets might make the connection coefficient insignificant. Due to the trade-off, we set the N_{remain} as 30. In plain language, each decision tree would randomly pick 11 features from the dataset, and each end leaf at least includes 30 observations.

Variable Importance

The random forest could estimate the importance of each feature on the output variable. The basic idea of importance estimation in the random forest is to calculate the reduction in accuracy between before and after excluding a specific feature [47]. The reduction in the accuracy of a particular feature would be higher when it is more important to successfully predict the output variable compared with other features. This reduction is similar to the partial R^2 in the OLS algorithm. There is no need to select the features in the random forest algorithm since the issues, such as multicollinearity, do not influence the accuracy of the random forest. Yet, multicollinearity is a fatal problem in the OLS.

Shapley Additive Explanations (SHAP)

Although the accuracy of random forest is high, it is challenging to understand and explain the results [40,51,52]. SHAP is an advanced approach explaining the contributions of each feature locally based on the theoretically optimal Shapley values [39]. To explain the contributions of features, each feature of the observation is a “player” in a game, and the prediction value is the payout. Shapley values help us to fairly distribute the payout among the players [39,53]. The Shapley value of a feature value is estimated as follows:

$$S_{jx} = E[\frac{1}{p!}\sum_{J} g^{j|\pi(J,j)}(x)] \tag{4}$$

where x represents a specific observation of interest, j represents a particular feature of interest, S_{jx} represents the Shapley value of the feature j of the observation x, J represents a permutation of the set of indices $\{1, 2, \ldots, p\}$corresponding to an ordering of p features included in our random forest model, $\pi(J, j)$ represents the set of the indices of the features contained in J before the j-th variable, and $g^{j|\pi(J,j)}(x)$ represents the estimated contribution value of feature j of the observation x with a specific permutation. $g^{j|\pi(J,j)}(x)$ is calculated as follows:

$$
\begin{aligned}
g^{j|\pi(J,j)}(x) = {} & E\big(f(X)\big|X^1 = x^1, \dots, X^{j-1} = x^{j-1}, X^j = x^j\big) \\
& - E\big(f(X)\big|X^1 = x^1, \dots, X^{j-1} = x^{j-1}\big)
\end{aligned}
\tag{5}
$$

where X represents a matrix of random values of features, $f()$ represents our trained random forest model, $E\big(f(X)\big|X^1 = x^1, \dots, X^{j-1} = x^{j-1}, X^j = x^j\big)$ is expected value of the predictions of X, when we set $X^1 = x^1, \dots, X^{j-1} = x^{j-1}, X^j = x^j$, and $E\big(f(X)\big|X^1 = x^1, \dots, X^{j-1} = x^{j-1}\big)$ is expected value of the predictions of X, when we set $X^1 = x^1, \dots, X^{j-1} = x^{j-1}$. It must be noted that generally, the random values are deemed to have no explaining ability. In real computation, the random dataset X is not randomly generated but randomly picked up from our dataset. In our analysis, we set the dataset size of X as 1000, approximately 1% of the total dataset, as python package makers' recommendation [40]. A bigger dataset size here would definitely increase the computation time. To estimate the Shapley values efficiently, we use 4048 random permutations of all features. Of course, more permutations lead the estimated values to the real values, but the computing time is not affordable.

The connection between Features' Values and Their SHAP Values

The explanations of SHAP values are too local. One observation's SHAP values only illustrate her/his own situation and cannot be directly used on other observations.

SHAP value is the feature value's contribution to each observation's current mental health status. For example, in one observation's living environment, the urban land takes 99.60%, and its SHAP value is -0.009. This observation's living environment is monotonous and full of urban land, which might negatively affect mental health. In another instance, the observation has 73.98% of urban land, and its SHAP value is 0.012. The impacts of a certain feature on mental health might be associated with the current status. We employ linear regression to probe the relationship between the feature value and its contribution to mental health. However, since this research is global, a huge spatial extent makes the globally unified relationship suspicious. Estimating the relationship locally is more rational. Based on the local regression, although the relationships are locally linear, globally they are non-linear.

Building a series of local datasets is the critical point. In the model training process, the location information is also included, which is the longitude and latitude of the observation. Some decision trees pick up these features. These trees divide the global extent into several zones. The observation's location belongs to zones divided by different trees. We obtain a bag of boundaries. The maximums of the boundaries in each direction are regarded as the dividing lines. Every observation is surrounded by a rectangle of dividing lines, and others within one observation's zones are the neighbors. The neighbor zones differ by location. The local relationship is estimated based on one observation and others located in its neighbor zone, so the relationship coefficients also spatially vary. The estimated process is as follows:

$$S_{jx} = \alpha_{jx} X_x^j + \beta_{jx} \tag{6}$$

where α_{jx} and β_{jx} are the slope and the intercept of the local relationship between feature j's value and its SHAP value based on x's neighbor zone, X_x^j is a vector of the feature j's values in x's neighbor zone, and S_{jx} is a vector of the SHAP values corresponding to X_x^j. According to the local relationship coefficient, we could interpret the marginal contribution of an increase in a certain feature to mental health. In order to improve the geographical continuity of the relationship and emphasize the difference between each point in the same neighbor zone, we add the geographical weights to the coefficient estimation process. We calculate the local geographical weight vector as geographically weighted regression methods [22,54] as follows:

$$\boldsymbol{W}_x = [1 - (\boldsymbol{d}_x / h_x)^2]^2 \tag{7}$$

when $\boldsymbol{W}_x$ is geographical weight vector of the elements in x's neighbor zone, $\boldsymbol{d}_x$ is a vector of distances between x and the elements in x's neighbor zone, and h_x is the furthest distance of the distance vector $\boldsymbol{d}_x$. According to this equation, the weights of the elements with the furthest distance in x's neighbor zone are always zero, while the aim observation x always has the largest weight, 1, in the regression. With the geographical weight vector, the local coefficient is estimated as follows:

$$Coef_{jx} = ({X_x^j}^T \boldsymbol{W}_x X_x^j)^{-1} {X_x^j}^T \boldsymbol{W}_x S_{jx} \tag{8}$$

where $Coef_{jx}$ is the estimated local coefficients, including α_{jx} and β_{jx}.

Monetary Values of Land Cover

To make the impacts of land cover change on mental health understandable and comparable, we estimate the monetary values of land cover. We take the marginal substitution rate (MSR) of land cover and income as the monetary values, and it is estimated as follows:

$$MSR_{jx} = \frac{\alpha_{jx}}{\alpha_{INCx}} \tag{9}$$

where MSR_{jx} is the MSR of feature j in the observation x's location, and α_{INCx} is the local relationship coefficient between the income value and its SHAP value based on the observations in x's neighbor zone. In this equation, we require the coefficients α_{jx} and α_{INCx} are significant (p value < 0.1), or the MSR would be set to zero.

$$MV_{jx} = MSR_{jx} \times GDPPC_x \tag{10}$$

where MV_{jx} is the monetary value of feature j in the observation x's location, and $GDPPC_x$ is the GDP per capita of the respondent x's country in the surveyed year. Based on these equations, the monetary values can be explained by how much income changes equals a 1% increase in a specific land cover.

Results

In this study, the trained random forest employs 1000 trees. At most, 11 features are randomly chosen in the bootstrapped datasets to train each tree. Every end leaf must have at least 30 observations. The accuracy of the random forest is 67.59%, whereas the accuracy of the OLS is only 42.66%. Moreover, the root mean square error (RMSE), mean square error (MSE), and mean absolute error (MAE) of the random forest are 3.59, 12.87, and 2.71, respectively, while the RMSE, MSE, and MAE of the OLS are 4.77, 22.77, and 3.65. In terms of accuracy, the random forest in this study significantly exceeds the linear regression. The OOB score of our model is 47.99%. Additionally, the average 10-fold cross-validation score of the random forest is 40.81%, while OLS's score is 38.19%. Although the cross-validation score is not as perfect as the accuracy, this model has the highest cross-validation score in 270 potential models with different $N_{features}$ and N_{remain}, respectively. Our model is selected based on the trade-off between accuracy and explanation. **Figure 4** demonstrates the relationship between predicted and measured mental health scores. The slope of the fit line between predicted and measured mental health scores is lower than 1. The random forest rarely exactly predicts extreme values, such as 0 and 36. Putting another way, the random forest's prediction is closer to the mean value of the output variable. As shown in **Figure 1**, extreme values are rare, so the status of the random forest is acceptable.

Figure 5 demonstrates the importance of each feature. Emotions, including sadness, pleasure and smile, and self-reported health, affect mental health the most. For example, if we do not employ the feature "Sadness" in the model, the accuracy will decrease by 22.41%. The income and land cover in respondents' living environments significantly influence mental health. The accuracy will slash by 3.13% without the income feature in the model. Moreover, the importance values of cropland, forest, grassland, shrubland, wetland, water, urban land, and bare land, are equal to 1.97%, 1.94%, 2.23%, 1.70%, 1.50%, 1.77%, 1.92%, and 1.51% reduction in the accuracy, respectively.

Figure 6 (Figure 6.a – 6.i) illustrates nine maps of spatially average SHAP value of income and land cover features. In order to make the SHAP spatial distribution readable, we use a spatially average value because the geographical scatter plots are hard to read (**Supplementary Materials Figure S1.a – S1.i**). We mean all the values in each cell with a 2.5-arc-degree side length. The observation numbers in each cell are different. **Figure**

6.a displays the spatially average SHAP value of income. In most areas, current income feature negatively contributes to mental health. A lower RI value is the main reason for negative contributions. Previous studies indicate that increased income improves human self-evaluation and emotional well-being, although some note there is a threshold for further improvement [55,56]. To most people, generally, mental health could benefit from increased income. Based on **Figure 6.a** and the current status of RI (**Figure 7.a**), it can be inferred that income positively affects mental health. However, it must be emphasized that the SHAP value of the land cover feature represents the attitudes toward current feature values. **Figures 6.b-i** demonstrate the SHAP values of the land cover feature. The observation's low mental health score due to land cover in their living environment might be various. The living environment with too more or too less a certain land type might negatively impact mental health status. For example, in terms of urban land features, too high urban land percentage means a monotone scene of the living environment, but too low value indicates a totally rural area without convenient urban services. In other words, based on the SHAP values, we can only judge whether the current land cover status (**Figure 7.a – 7.i**) positively impacts mental health, but we never know that the negative status is due to insufficiency and overplus here. Referring to the current urban land in the living environment (**Figure 7.i**), the urban land's contribution to good mental health is marginal (**Figure 6.i**), even harmful, when the living environment has more than 50% urban land. As for other land types, the maps of spatially average SHAP values indicate where the specific land type is suitable.

The connection between the current land feature value and its SHAP value is desired since the SHAP value cannot inform us that increasing or decreasing specific features would improve mental health. **Figure 8** demonstrates nine maps of spatially average local coefficient of income feature and land cover features on mental health, based on **Equations 6 - 8**. If a local dataset's coefficient is insignificant, it would be set to zero. According to **Figure 8.a**, in most zones, a higher RI value is associated with a larger contribution to mental health, while in some metropolitan areas, such as Hong Kong, Beijing, and Washington D.C., the higher RI is negatively related to the SHAP value. The increase in income does not always contribute more to mental health. Previous studies show that the relationship between income and human well-being might not be monotonical [55,57], i.e., there is a turning point in the relationship. In fact, if the increased income cannot fulfill more mental needs, the effects of this increase are limited [58-60]. Furthermore, the higher income is usually accompanied by high levels of responsibility and heavy workload, which might even worsen the situation [61]. Therefore, the connection between income and its contribution to mental health is negative in these metropolitan areas.

Figure 8.b shows the local coefficients between cropland status and its SHAP value. Referring to the current status of cropland (**Figure 7.b**), in the place with too much cropland, an increase in the cropland has negative impacts on mental health, whereas, in the region with rare cropland, more cropland could contribute more to mental health. The reason for people's preference is due to scarcity value. According to **Figures 7.c, 8.c, 7.e, 8.e, 7.f, 8.f, 7.g, 8.g, 7.h, 8.h, 7.i,** and **8.i,** forest, shrubland, water, wetland, urban land, and bare land have similar situations as cropland. Grassland is an exemption, illustrated by **Figures 7.d** and **8.d**: the relationship between grassland and its contribution to mental health is negative in most places, and the degree of positive connection is relatively low, which is counterintuitive. Two reasons cause this problem. Firstly, this research uses

remote sensing data. In the remote sensing process, grassland is easier to be misclassified especially when close to cropland and shrubland [34]. Especially, sporadic grass is more likely to be misclassified, so the low accuracy of grassland in urban areas might mislead the model's results. Secondly, a large area of grassland is for grazing rather than improving mental health in rural areas.

Figure 9 illustrates the spatially average monetary values of eight land types, according to **Equation 9**. As shown in **Figure 9.a**, the monetary values of cropland are higher in metropolitan areas such as New York, London, Paris, Tokyo, among others. Forest's and water's monetary values (**Figures 9.b** and **9.e**) are also higher in the big cities. Grassland's and urban land's monetary values (**Figures 9.c** and **9.g**) are positive where the contribution of an increase in income is negative. In most places, their monetary values are favorable due to shrubland's, wetland's, and bare land's scarcity values (**Figures 9.d**, **9.f**, and **9.i**). It must be noted that shrubland, wetland, and bare land are very rare in most living environments (as shown in **Figures S1.e**, **S1.f**, and **S1.h**). A slight increase in wetland, shrubland, or bare land is difficult. This is the reason for their extraordinary monetary value, consistent with previous studies [8].

Discussion

Our main findings are that mental health and land cover relationships are non-linear and various. Increases in each land type positively impact mental health when the percentages of these land types are low. Accordingly, it could be implied that people who prefer to live in environments with high diversity and extremely monolithic landscapes might lead to poor mental health. Furthermore, it is the first study that uses SHAP and random forest to grasp the relationship between land cover and mental health. To make the results understandable, we employ geographically local technology to connect the current land cover status to its SHAP values. This study provides one more way to explain the machine learning model. Based on the links between SHAP value and current status, the monetary values of land cover are estimated, although the numbers of significant monetary values of land cover are limited. Our results show that a slight increase in shrubland, wetland, and bare land in most regions could improve people's mental health. Cropland, forest, and water are mainly desired in metropolitan areas and places with too less cropland, forest, and water. Moreover, the model's accuracy is relatively high, indicating the reliability of the results. The accuracy, RMSE, MSE, and MEA are 67.59%, 3.59, 12.87, and 2.71, respectively, exceeding most previous studies.

Previous studies focus more on the impacts of green space on human well-being or mental health in the city [6,28,29,31,37]. The coverage percentage of green space positively affects mental health [6,31,37]. In our study, almost all natural land types are positively related to mental health when their percentages are low. Wetland is the most preferred, as it provides the most ecosystem service [7,8], and it is scarce in the living environment. Bare land's average SHAP values and monetary values are high. According to the figure in the data provider's article [34], the large area of bare land is generally desert, while it might be sports play yards in the cities. Shrubland's situation is similar to wetland's and bare land's, and it positively impacts mental health when they are scarce. Forest and cropland's effects are various. In metropolitan areas, increased cropland and forest percentage would improve mental health. People cannot enter the large aggregated forest to have various nature experiences, and they are also associated with the possibility of crime [62,63]. The high percentage of urban land is negatively associated with mental health. Living in cities naturally is necessary [64-66]. However, the adverse effects of large amounts of non-urban land types on mental health indicate that people living in rural areas are likely to have mental disorders and need more assistants. Therefore, in land use, the percentage of urban land should be carefully treated and balanced.

The biggest contribution of this study is providing a new way to employ a machine learning method, random forest, to analyze the data with geographic information. The random forest method is good at grasping non-parametric relationships, improving the model's accuracy and making the explanation more reliable. Directly adding geographical locations to the analysis in the random forest model makes the analysis take geographical context into account because the model deems that the neighbor observations are similar. However, this does not work in traditional regression methods, such as OLS, as the coefficients of longitude and latitude are hard to explain. Currently, the widely used approaches to explain the random forest result are partial dependence plot [67], accumulated local effects [68], and Shapley value [39,40]. Among these three methods, the Shapley value has the most solid theoretical foundation [53]. However, the Shapley value explanation is entirely local. In other words, one observation’s explanation cannot be directly used on other observations. For this reason, building reasonable connections between the Shapley value and the feature value is critical in the studies. Links created by geographically weighted regression methods are spatially continuous. The relationship coefficients of each location do not suddenly change and are more similar if they are closer, which is more consistent with the real world. This connection method makes the relationship between the feature values and their contribution more understandable.

There are several limitations and issues worthy of note. First, the land cover variables are the percentages of eight land types in the buffers with a 5-km radius surrounding the living locations of respondents. There is an assumption that the quality of land cover does not influence the effects of those land types on mental health. For example, there may be no difference between a well-designed urban park and grassland in the pasture. Furthermore, the impacts of the distance to a certain land type are ignored. Secondly, this study only uses global cross-sectional data, so it cannot detect the difference within individuals when land cover changes. Global research using panel data to probe the effects within individuals is still desired. Third, the number of respondents in each country is not the same or proportional to the country's population. The countries with more respondents have more substantial impacts on the results. Thus, the results might be prejudiced, though this database is one of the biggest databases in this field. In future studies, the long panel data should be used to investigate the impacts of land cover within individuals. Moreover, the model's cross-validation accuracy is not ideal, which might make the SHAP values inaccurate. Further improvement of the model is needed. Effective explaining methods and tools should be developed to make the machine learning results understandable.

Conclusion

The relationships between land cover in living environments and mental health are more complex than linear assumptions. An unsuitable increase in a specific land type might not improve residents' mental health. Among eight land types, shrubland, wetland, and bare land have the highest effects on mental health due to their scarcity in living environments. Cropland's, forest's, and water's impacts are high, mainly in metropolitan areas. The impacts of urban land and grassland are mainly negative. Our study illustrates the heterogeneity of the effects of eight land types on mental health to provide more information for governments and the public. Furthermore, this research offers one example of analyzing data with geographical information by random forest and explaining the result geographically.

Data Availability

The fully reproducible codes are publicly available at https://github.com/MichaelChaoLi-cpu/MentalHealthAndLandCover . Data are available from the corresponding author on reasonable request.

Acknowledgment

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Figure:

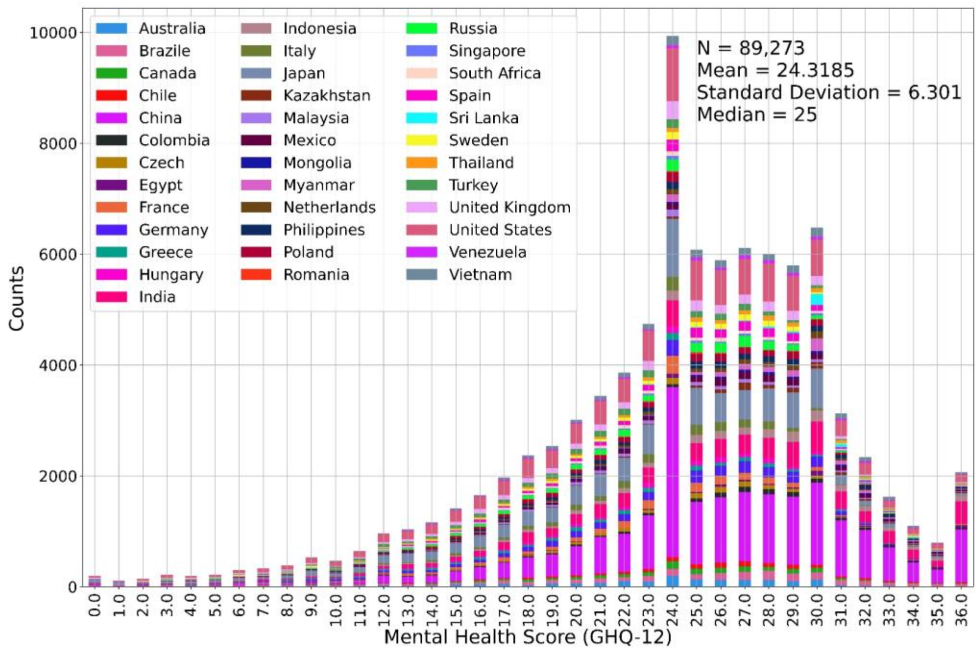

Figure 1: The Statistical Distribution of Mental Health Assessment

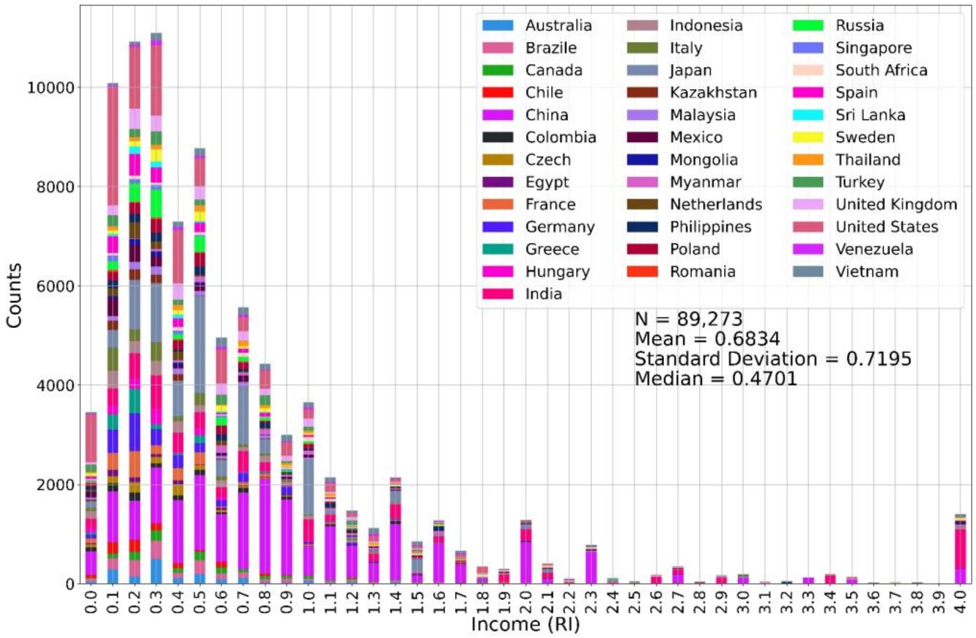

Figure 2: The Statistical Distribution of DIG

(Note: In this figure, the column of 4.0 represents the count of RI no less than 4.0.)

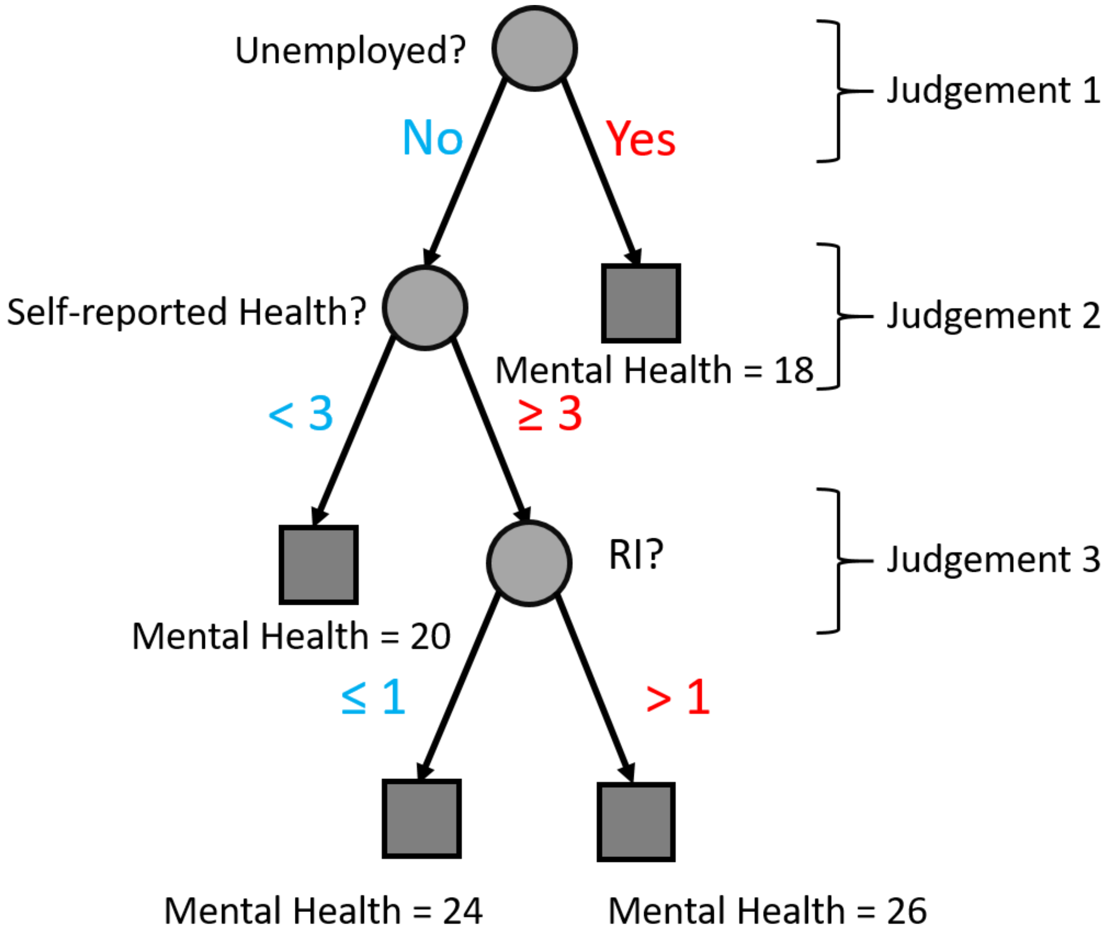

Figure 3: Example of a Regression Decision Tree

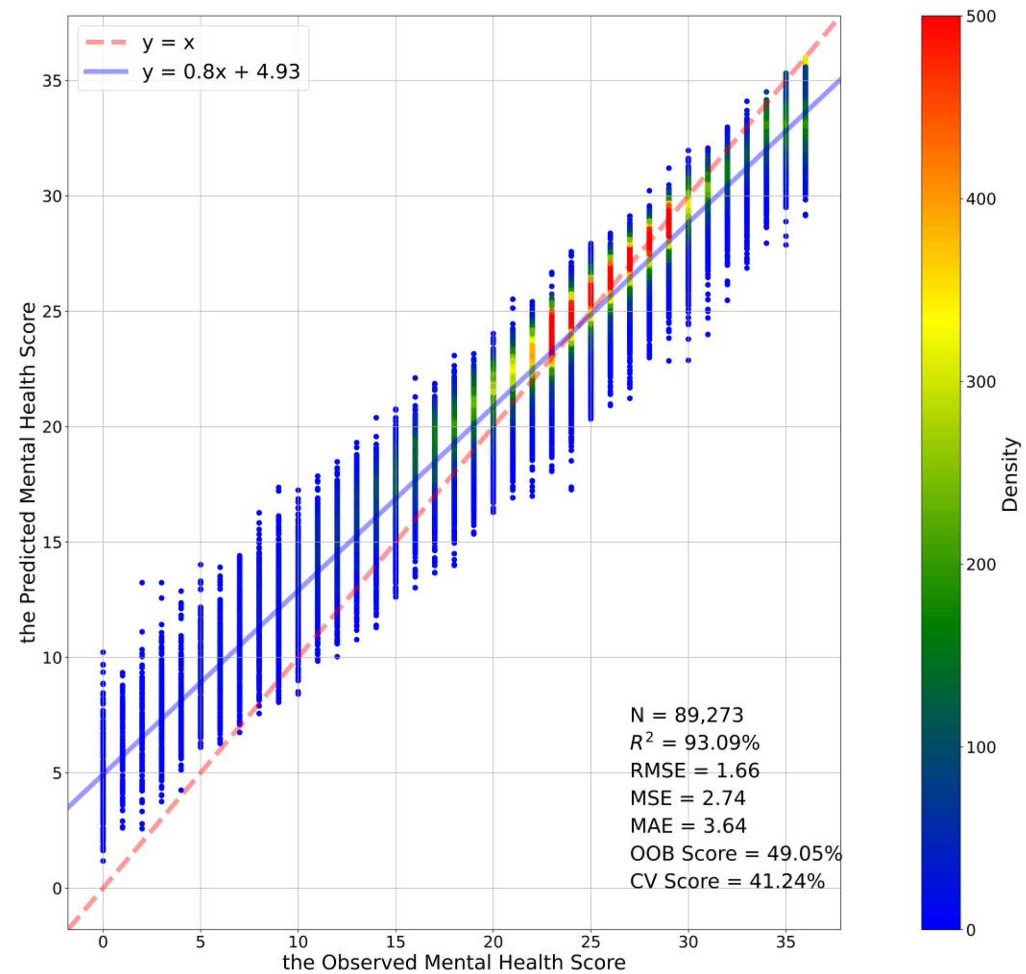

Figure 4: The Density Plots between the Measured and Predicted Mental Health Score

(The red dashed line is the 1:1 line. The blue line is the regression line.)

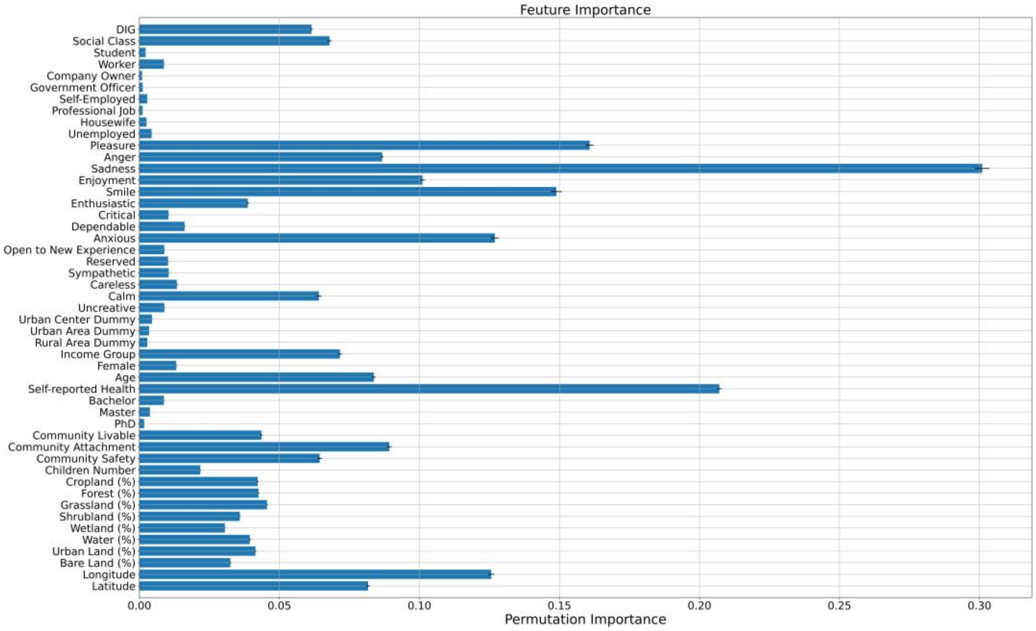

Figure 5: Feature Importance

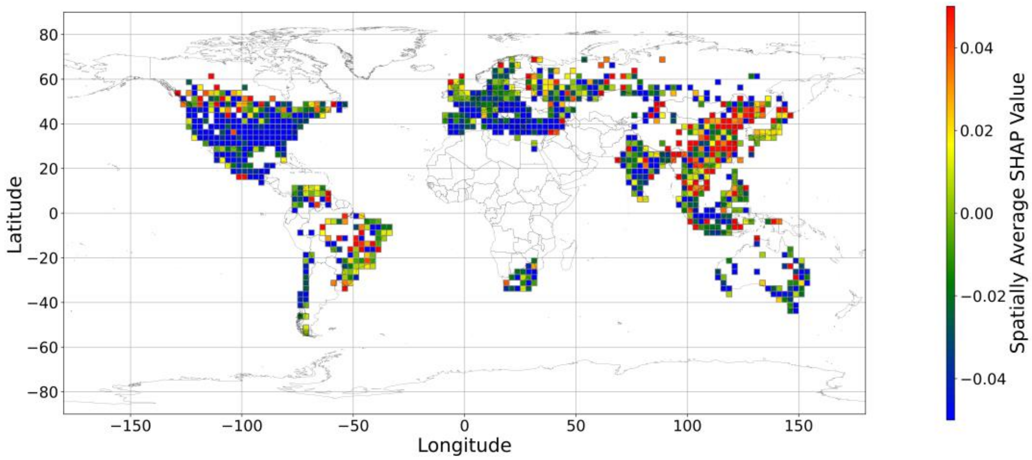

Figure 6.a: The Spatially Average SHAP Values of Income

(Note: Cell size is 2.5° × 2.5°)

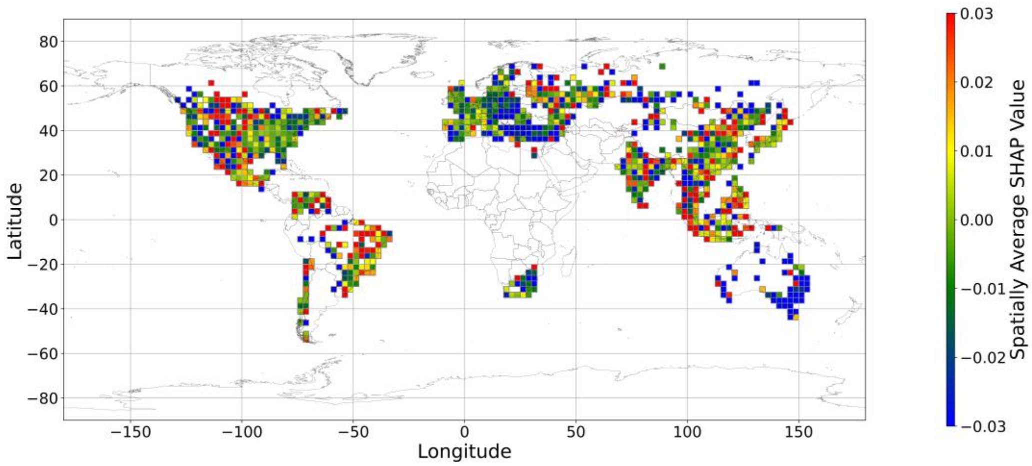

Figure 6.b: The Spatially Average SHAP Values of Cropland

(Note: Cell size is 2.5° × 2.5°)

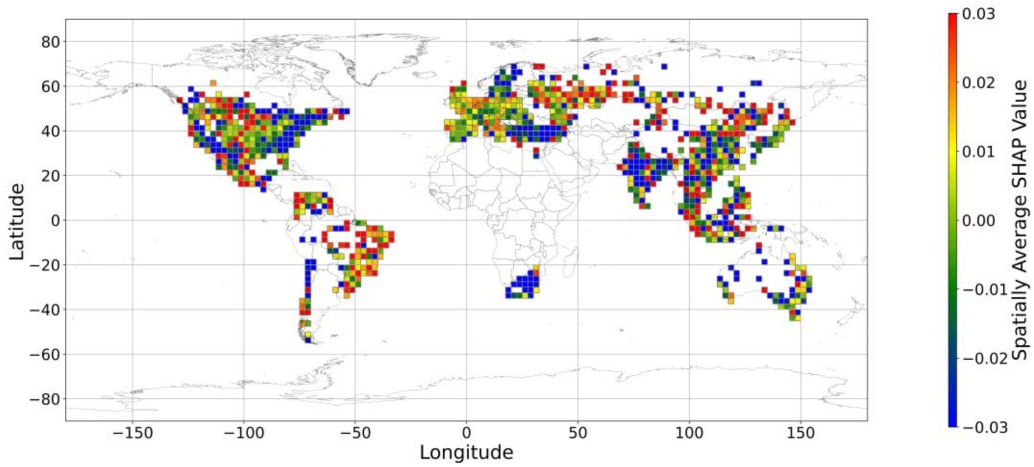

Figure 6.c: The Spatially Average SHAP Values of Forest

(Note: Cell size is 2.5° × 2.5°)

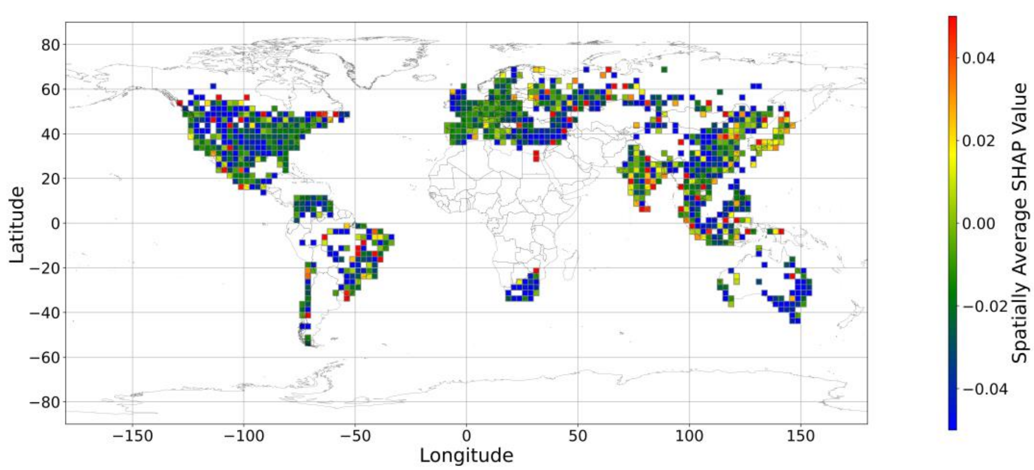

Figure 6.d: The Spatially Average SHAP Values of Grassland

(Note: Cell size is 2.5° × 2.5°)

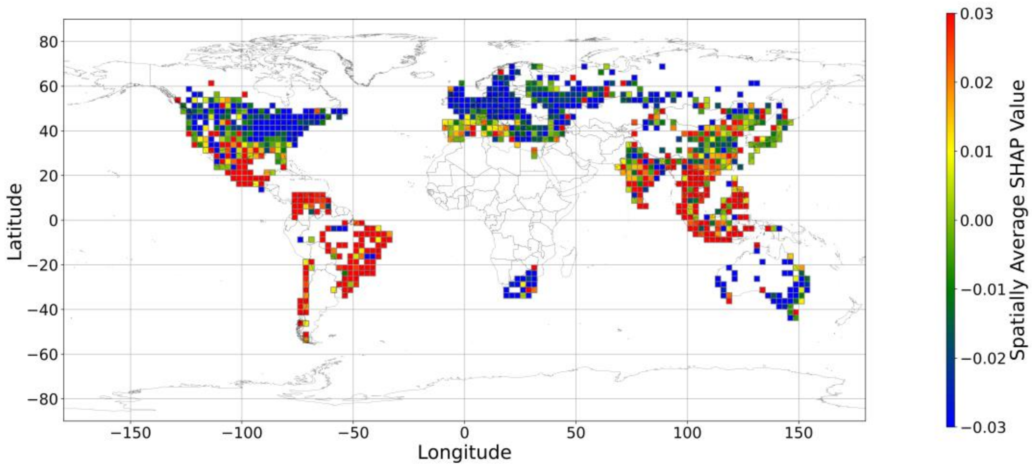

Figure 6.e: The Spatially Average SHAP Values of Shrubland

(Note: Cell size is 2.5° × 2.5°)

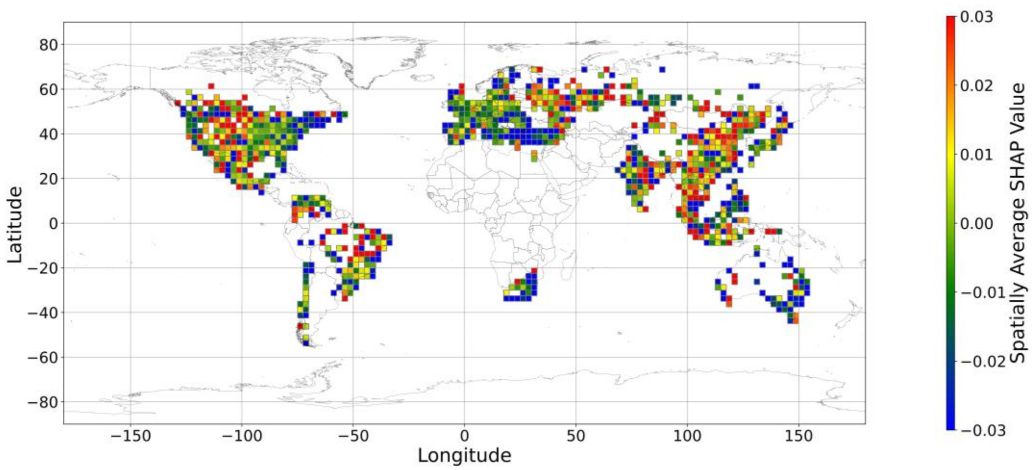

Figure 6.f: The Spatially Average SHAP Values of Water

(Note: Cell size is 2.5° × 2.5°)

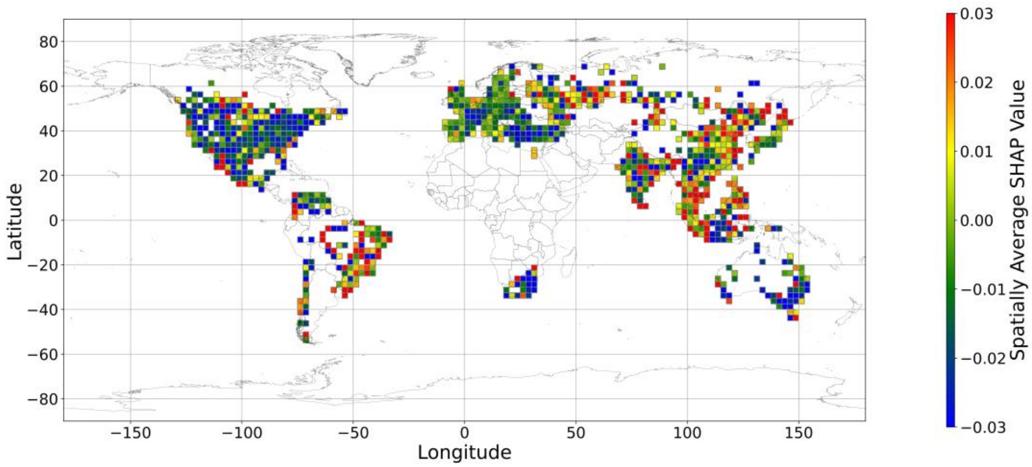

Figure 6.g: The Spatially Average SHAP Values of Wetland

(Note: Cell size is 2.5° × 2.5°)

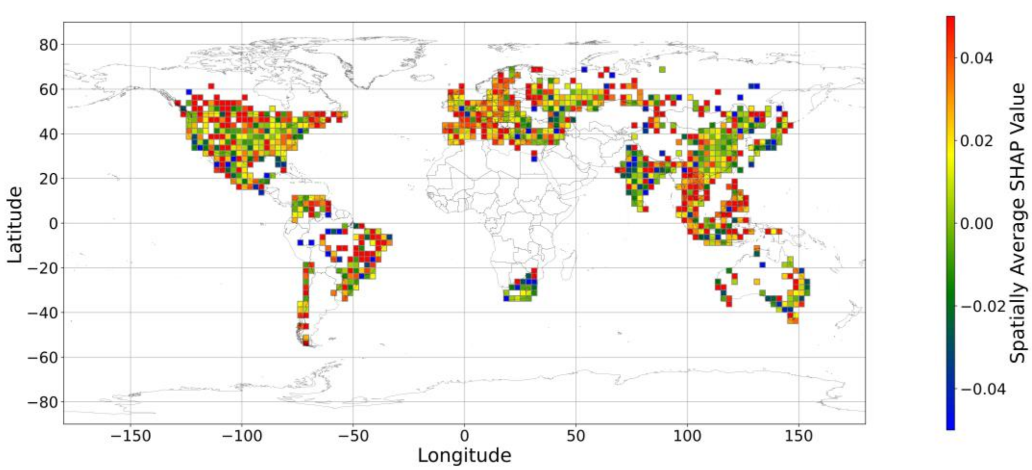

Figure 6.h: The Spatially Average SHAP Values of Urban Land

(Note: Cell size is 2.5° × 2.5°)

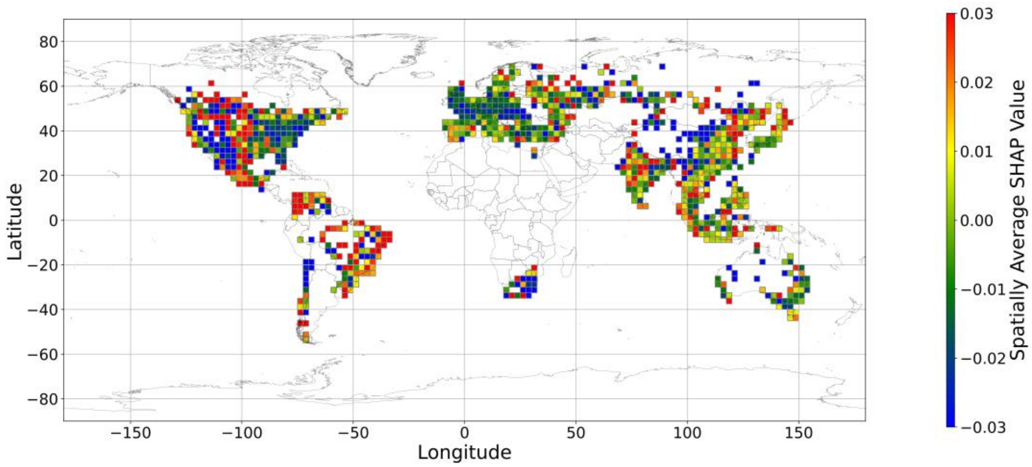

Figure 6.i: The Spatially Average SHAP Values of Bare Land

(Note: Cell size is 2.5° × 2.5°)

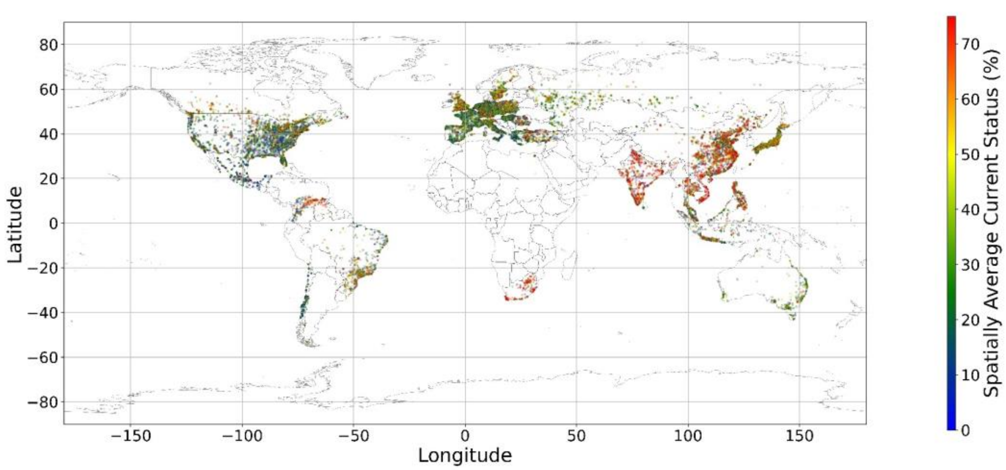

Figure 7.a: The Spatial Scatter Plot of the Income's Current Status

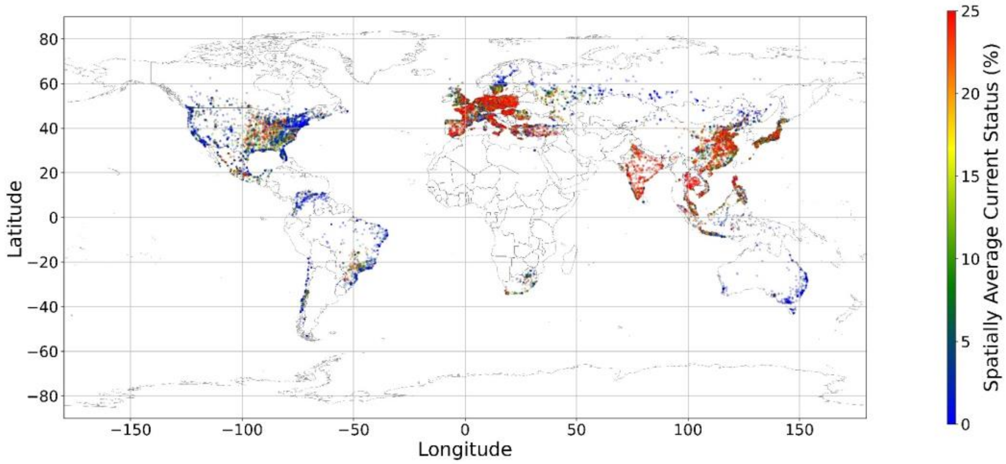

Figure 7.b: The Spatial Scatter Plot of the Cropland's Current Status

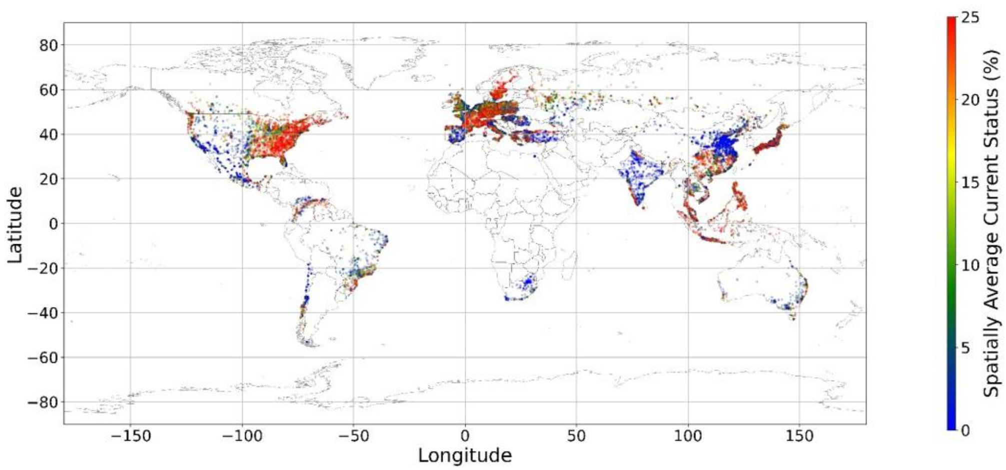

Figure 7.c: The Spatial Scatter Plot of the Forest's Current Status

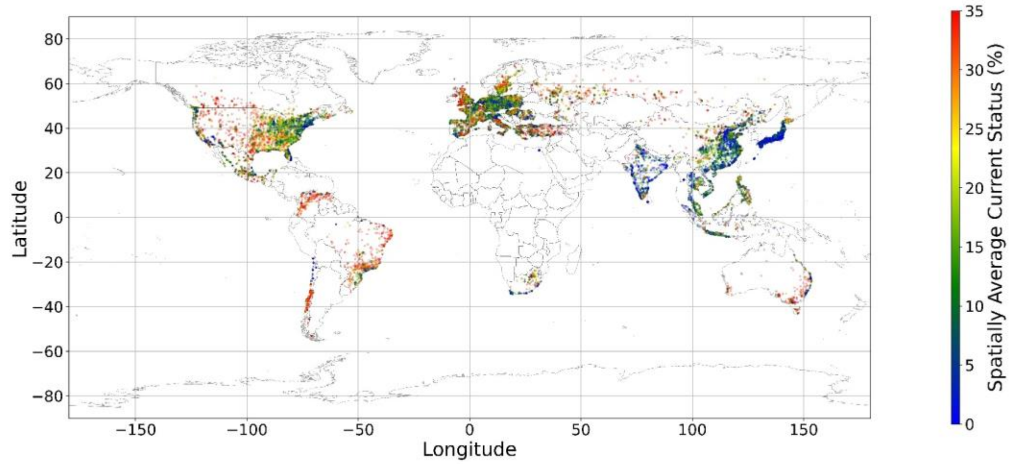

Figure 7.d: The Spatial Scatter Plot of the Grassland's Current Status

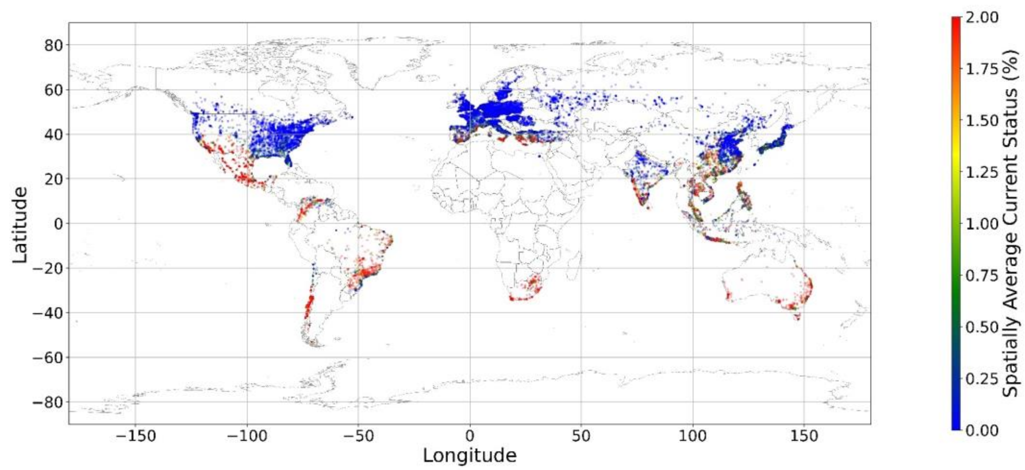

Figure 7.e: The Spatial Scatter Plot of the Shrubland's Current Status

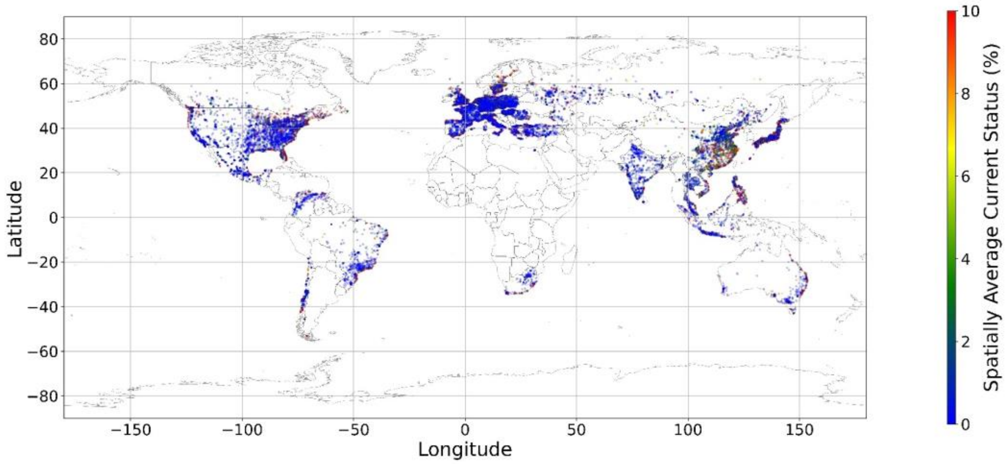

Figure 7.f: The Spatial Scatter Plot of the Water's Current Status

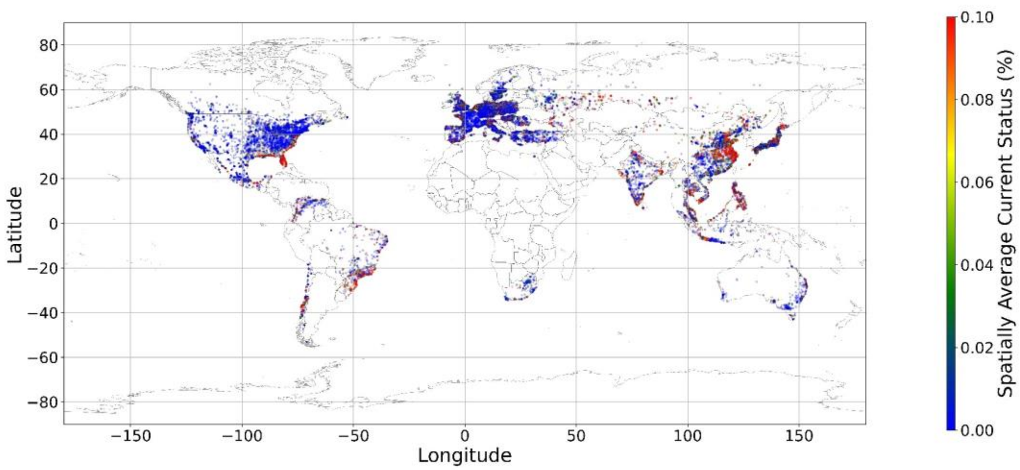

Figure 7.g: The Spatial Scatter Plot of the Wetland's Current Status

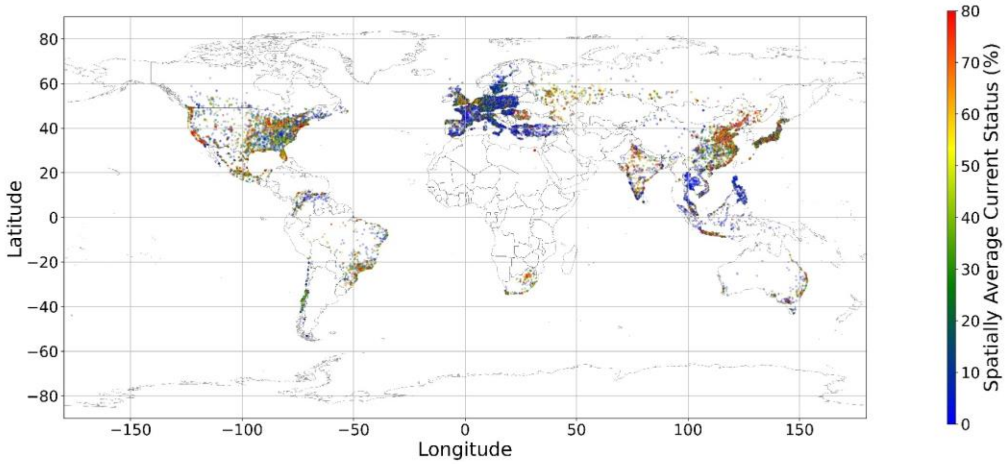

Figure 7.h: The Spatial Scatter Plot of the Urban Land's Current Status

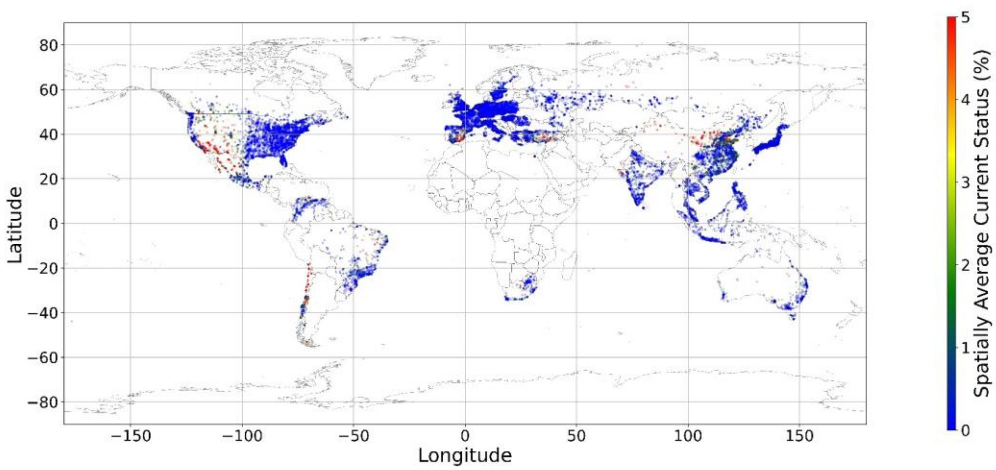

Figure 7.i: The Spatial Scatter Plot of the Bare Land's Current Status

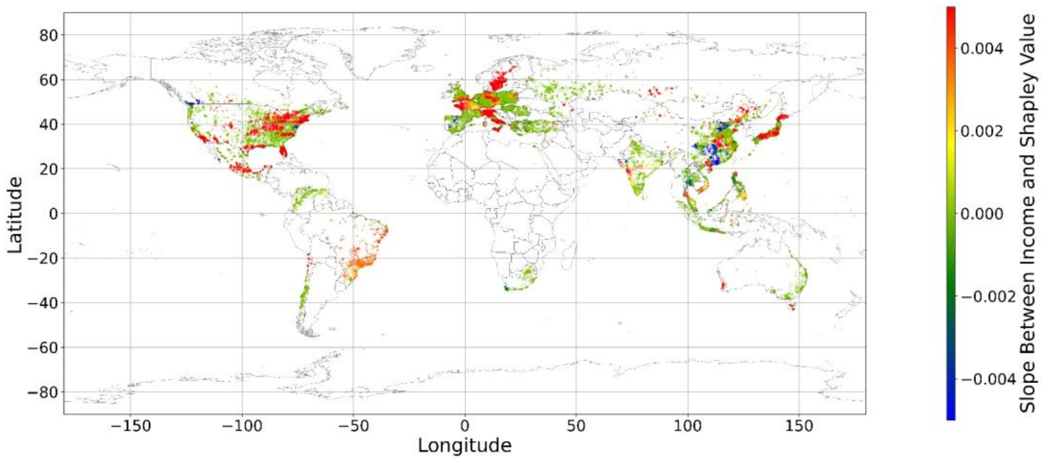

Figure 8.a: The Spatial Scatter Plot of the Local Coefficient between Income and Its SHAP Value

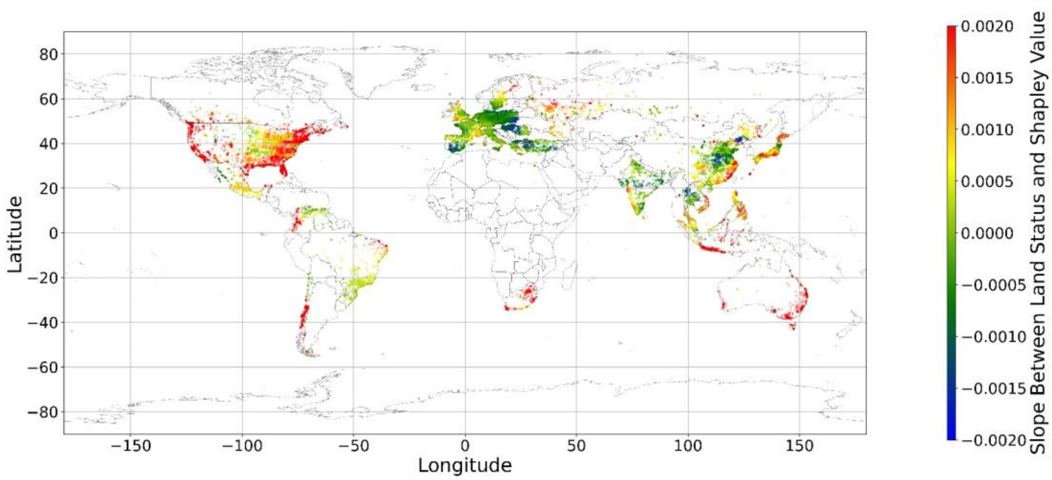

Figure 8.b: The Spatial Scatter Plot of the Local Coefficient between Cropland and Its SHAP Value

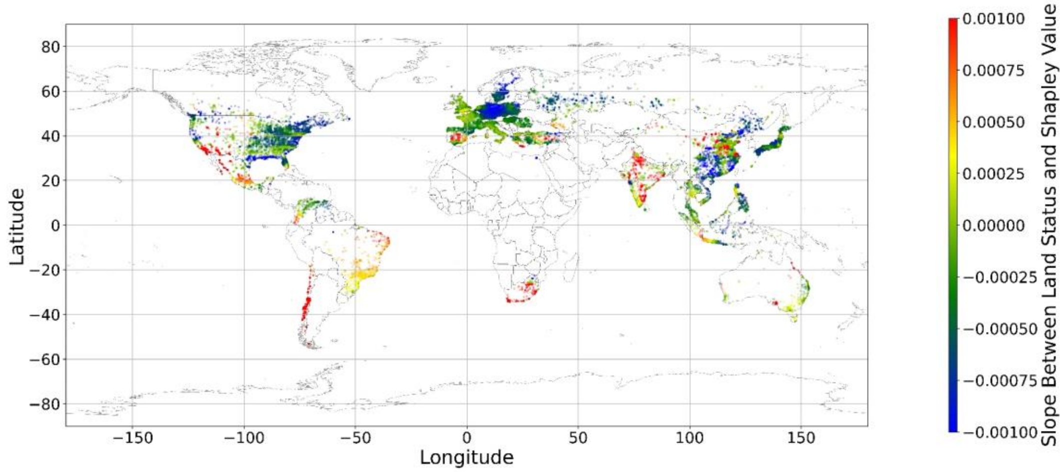

Figure 8.c: The Spatial Scatter Plot of the Local Coefficient between Forest and Its SHAP Value

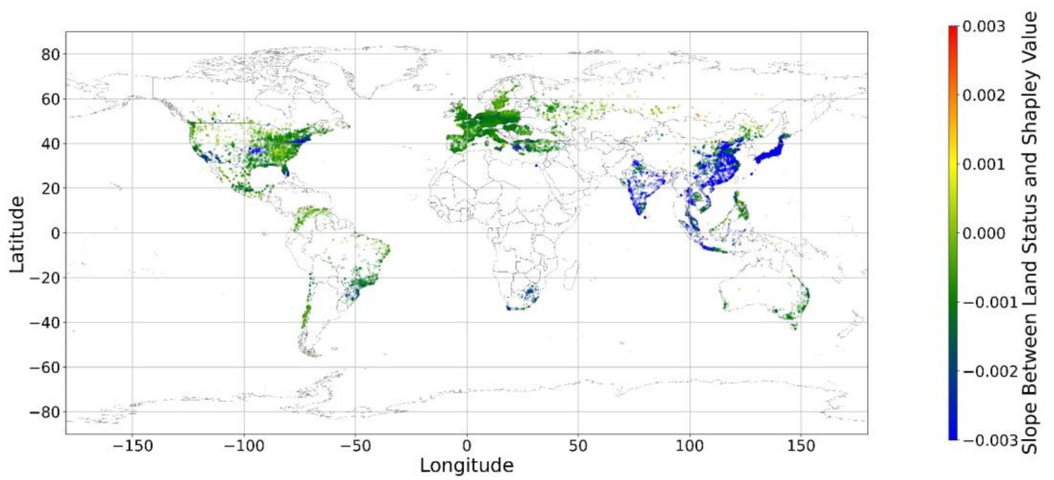

Figure 8.d: The Spatial Scatter Plot of the Local Coefficient between Grassland and Its SHAP Value

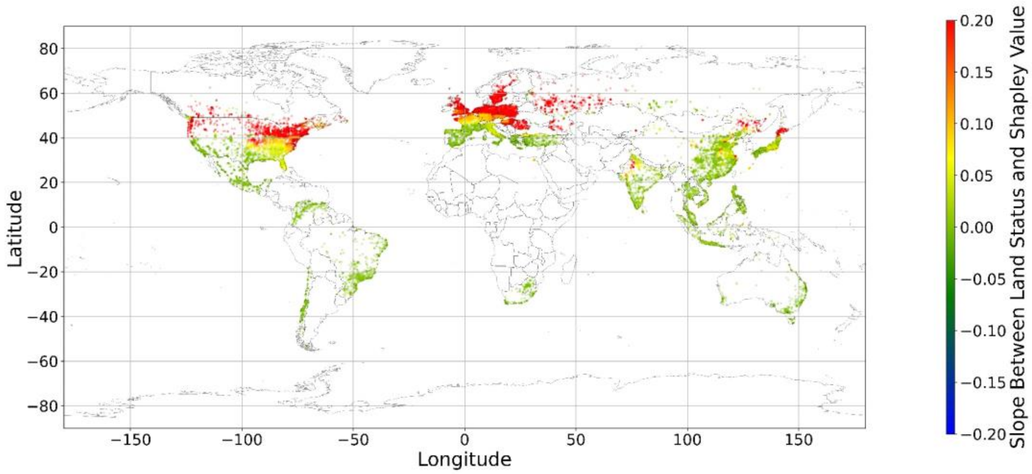

Figure 8.e: The Spatial Scatter Plot of the Local Coefficient between Shrubland and Its SHAP Value

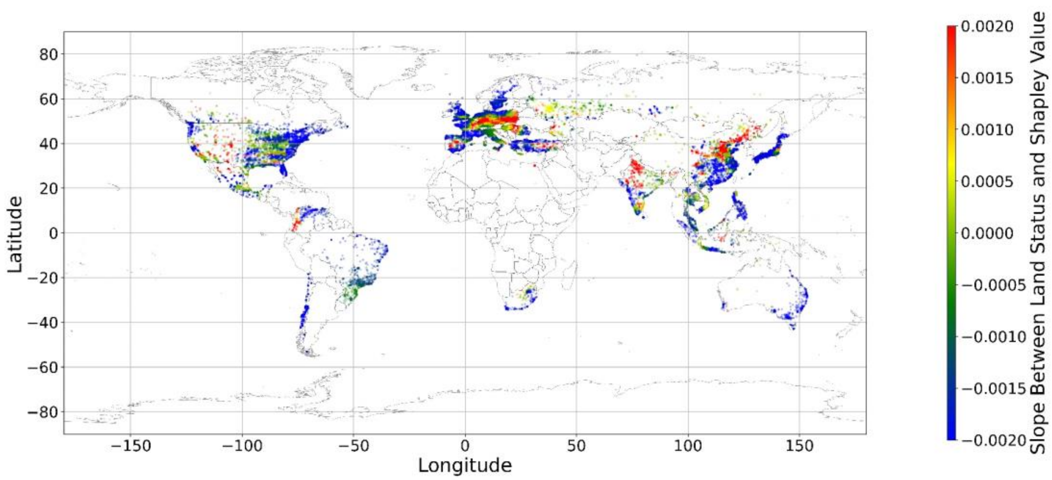

Figure 8.f: The Spatial Scatter Plot of the Local Coefficient between Water and Its SHAP Value

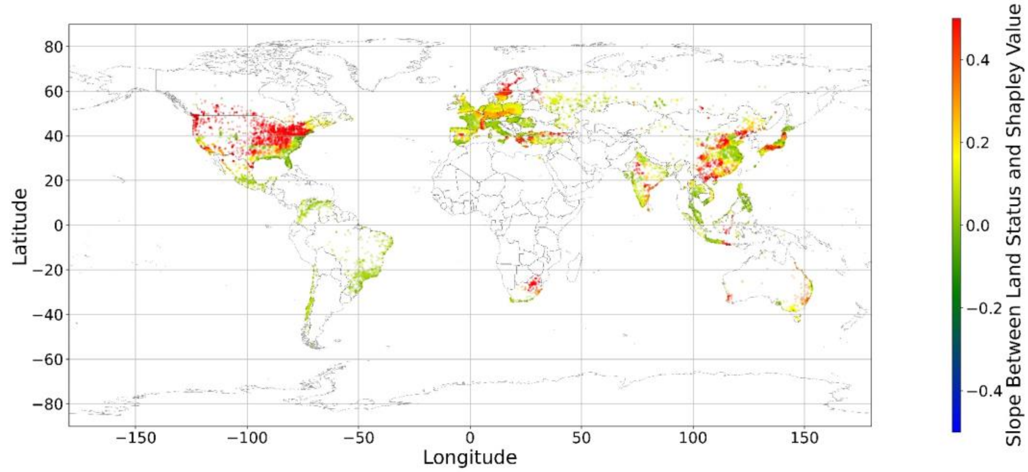

Figure 8.g: The Spatial Scatter Plot of the Local Coefficient between Wetland and Its SHAP Value

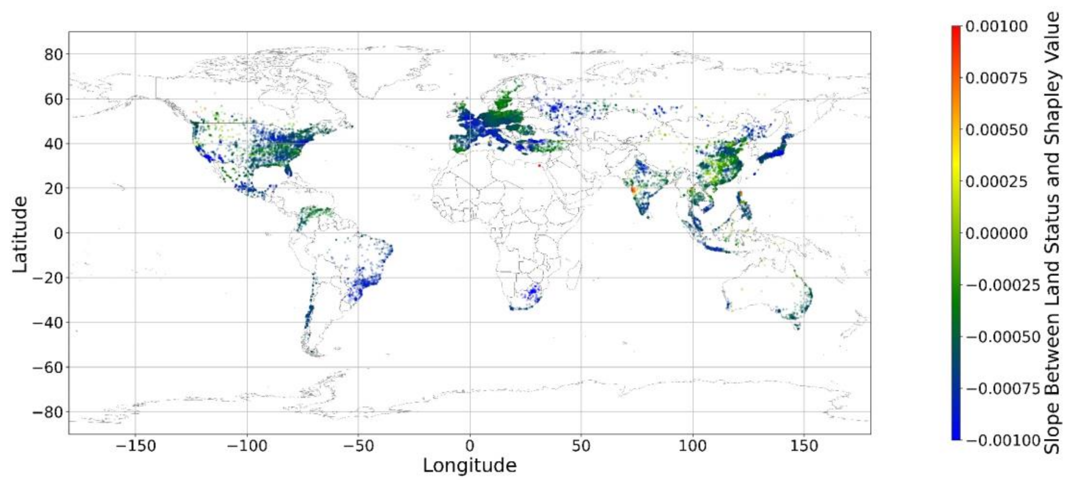

Figure 8.h: The Spatial Scatter Plot of the Local Coefficient between Urban Land and Its SHAP Value

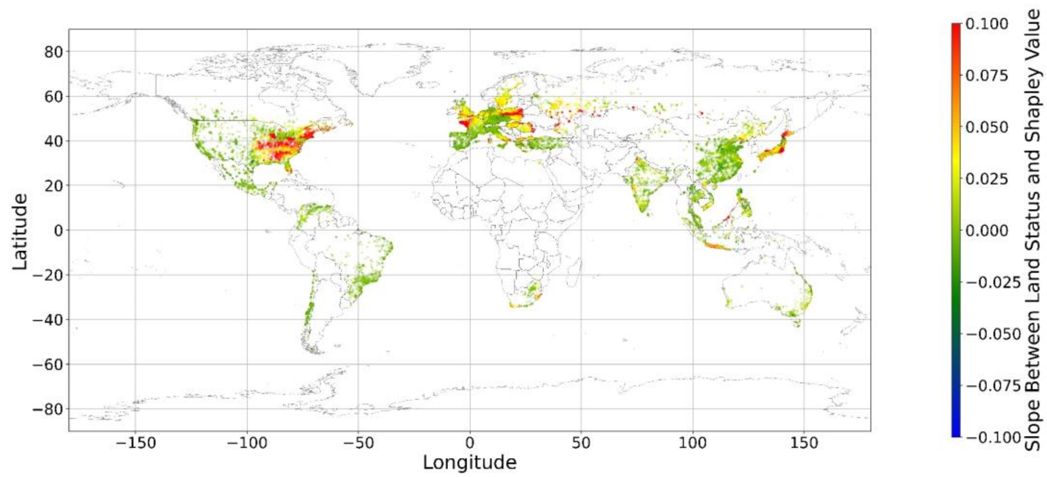

Figure 8.i: The Spatial Scatter Plot of the Local Coefficient between Bare Land and Its SHAP Value

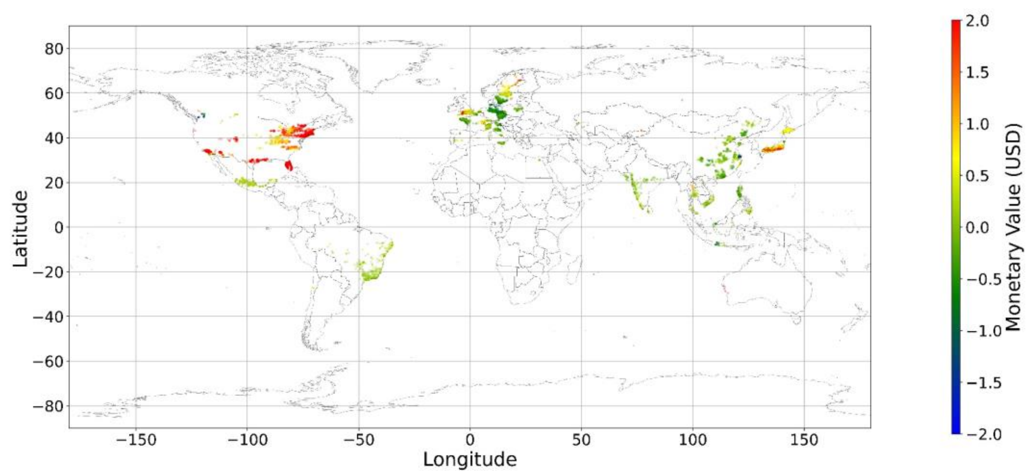

Figure 9.a: The Spatial Scatter Plot of the Monetary Value of Cropland (Note: Zero has been removed.)

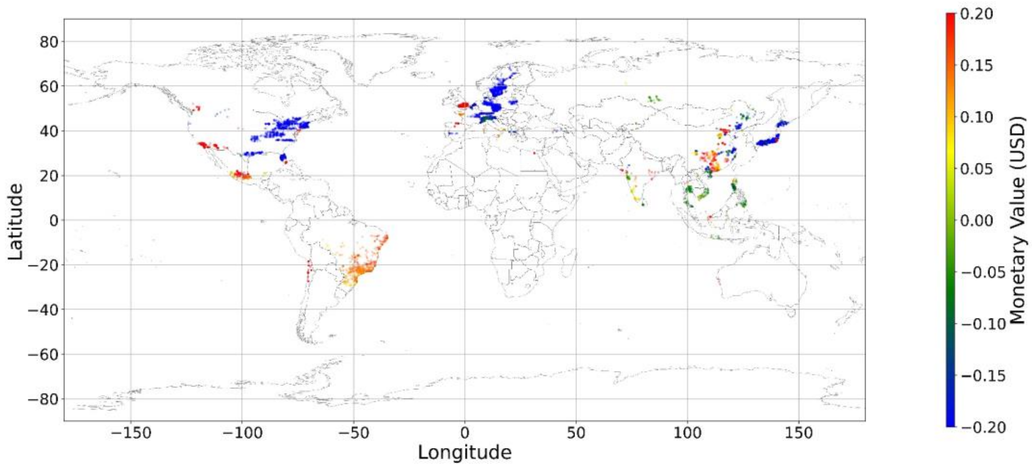

Figure 9.b: The Spatial Scatter Plot of the Monetary Value of Forest

(Note: Zero has been removed.)

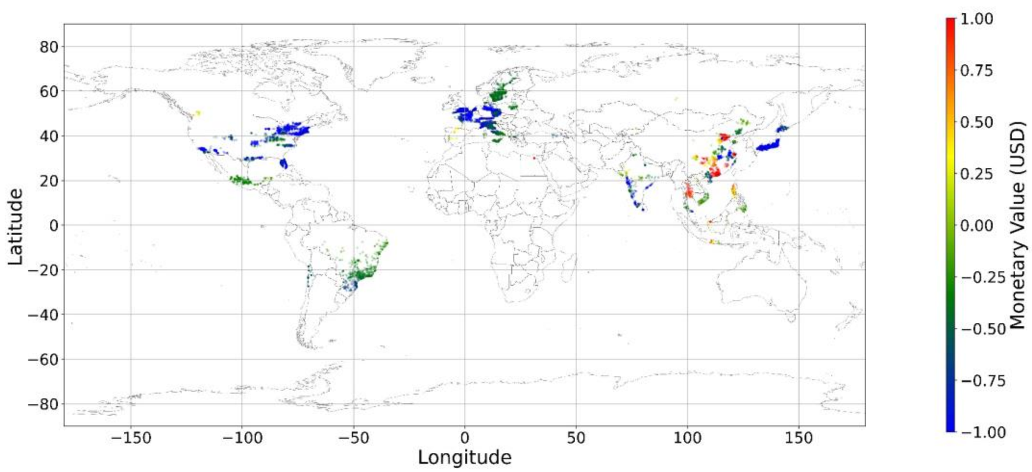

Figure 9.c: The Spatial Scatter Plot of the Monetary Value of Grassland

(Note: Zero has been removed.)

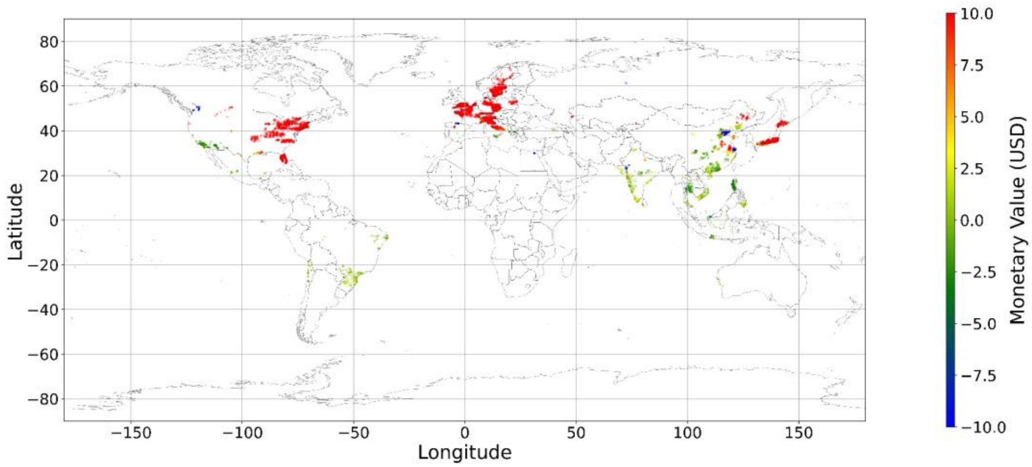

Figure 9.d: The Spatial Scatter Plot of the Monetary Value of Shrubland

(Note: Zero has been removed.)

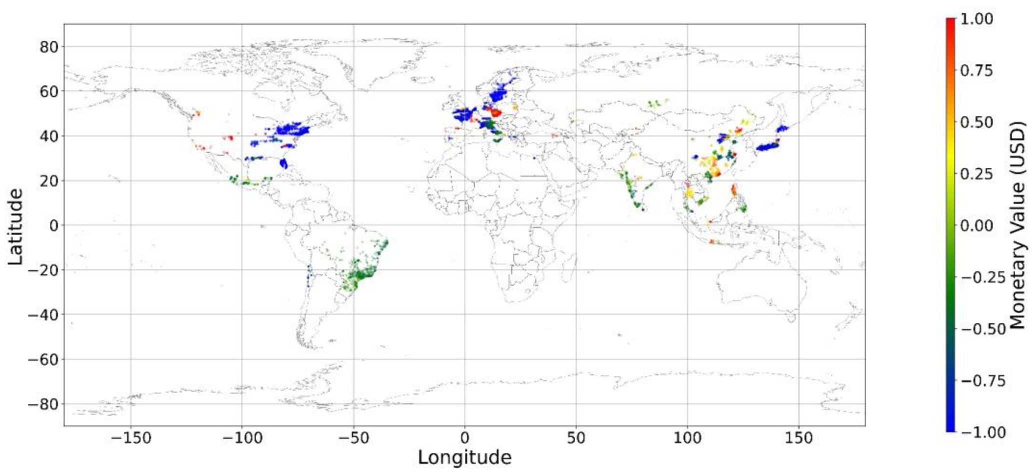

Figure 9.e: The Spatial Scatter Plot of the Monetary Value of Water

(Note: Zero has been removed.)

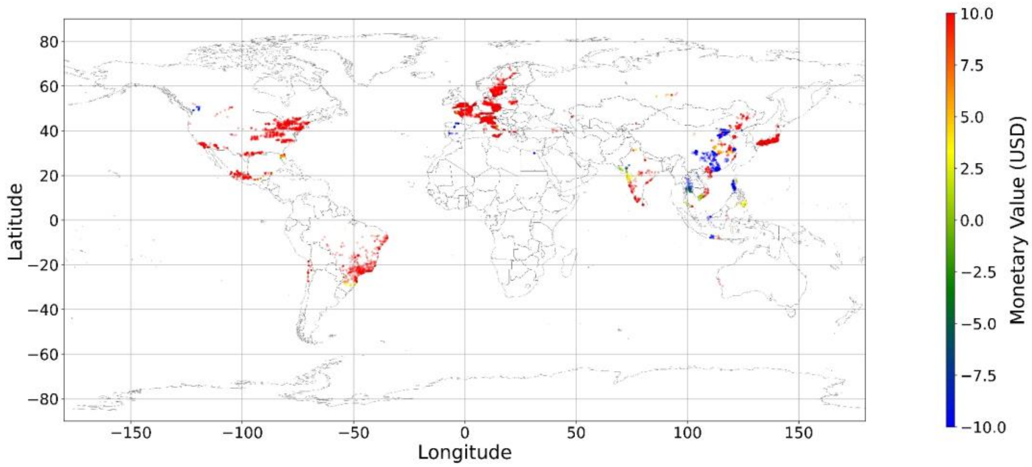

Figure 9.f: The Spatial Scatter Plot of the Monetary Value of Wetland

(Note: Zero has been removed.)

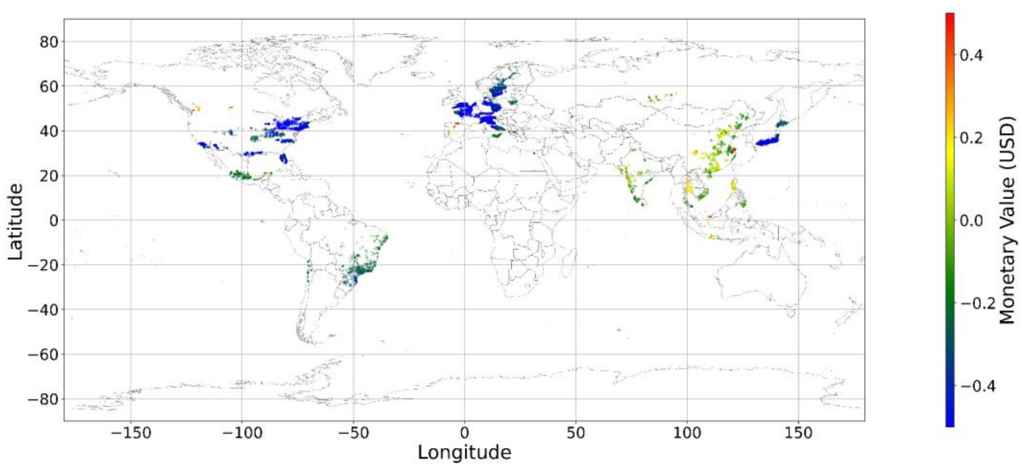

Figure 9.g: The Spatial Scatter Plot of the Monetary Value of Urban Land

(Note: Zero has been removed.)

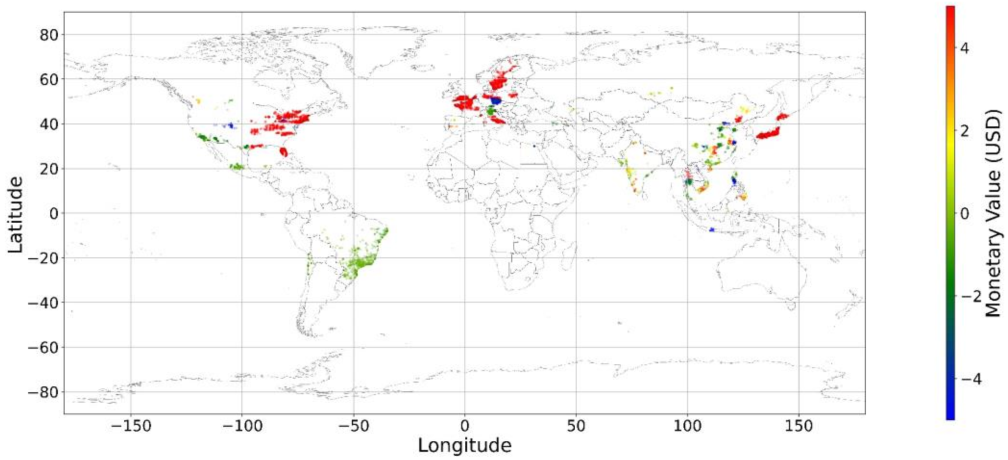

Figure 9.i: The Spatial Scatter Plot of the Monetary Value of Bare Land

(Note: Zero has been removed.)

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