

Article

High Spatial Resolution Leaf Area Index Estimation for Woodland in Saihanba Forestry Center, China

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Abstract: Owing to advancements in satellite remote sensing technology, the acquisition of global land surface parameters, notably, the leaf area index (LAI), has become increasingly accessible. The Sentinel-2 (S2) satellite plays an important role in the monitoring of ecological environments and resource management. The prevalent use of the 20 m spatial resolution band in S2-based inversion models imposes significant limitations on the applicability of S2 data in applications requiring finer spatial resolution. Furthermore, although a substantial body of research on LAI retrieval using S2 data concentrates on agricultural landscapes, studies dedicated to forest ecosystems, although increasing, remain relatively less prevalent. This study aims to establish a viable methodology for retrieving 10 m resolution LAI data in forested regions. The empirical model of the soil adjusted vegetation index (SAVI), the backpack neural network based on simulated annealing (SA-BP) algorithm, and the variational heteroscedastic Gaussian process regression (VHGPR) model are established in this experiment based on the LAI data measured and the corresponding 10 m spatial resolution S2 satellite surface reflectance data in the Saihanba Forestry Center (SFC). The LAI retrieval performance of the three models is then validated using field data, and the error sources of the best performing VHGPR models (R^2 of 0.8696 and RMSE of 0.5078) are further analyzed. Moreover, the VHGPR model stands out for its capacity to quantify the uncertainty in LAI estimation, presenting a notable advantage in assessing the significance of input data, eliminating redundant bands, and being well suited for uncertainty estimation. This feature is particularly valuable in generating accurate LAI products, especially in regions characterized by diverse forest compositions.

Keywords: leaf area index; VHGPR; Sentinel-2; retrieval; woodland



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1. Introduction

The leaf area index (LAI) is defined as the sum of green leaf area per unit of land area [1]. It is a key parameter of vegetation structure and biophysical change [2]. In addition, it can provide dynamic information about vegetation growth and is an important input parameter of the crop growth model and decision support system [3,4]. Accurate estimation of the LAI is of great significance to the study of agriculture, ecology, environment, and climate change [5–7].

LAI estimation based on remote sensing is an effective means to obtain the vegetation LAI on a regional or global scale [8]. Numerous methods have been developed to retrieve the LAI from remote sensing data, which can be divided into three categories: (1) parametric regression methods, (2) physically-based methods, and (3) non-parametric regression methods.

The most common method of parameter regression is to establish parameterized expressions between several spectral bands and vegetation indexes (VIs) [9]. The VI method is very popular in LAI inversion because of its simplicity and fast calculation speed [10–12].

Cañete-Salinas et al. used the normalized difference vegetation index (NDVI) and the soil adjusted vegetation index (SAVI) obtained from Sentinel-2 (S2) and established the linear, quadratic, sum of sine empirical model to calibrate and verify the LAI of poplar forests in the Maule region of Chile. This study considers these empirical models of the vegetation index to be a good tool for estimating the leaf area index of large areas of poplar [13]. Similarly, Qiao et al. explored the relationships between the NDVI, enhanced vegetation index (EVI), near-infrared reflectance of vegetation (NIRv), and LAI at different phenological stages using field LAI data and MODIS-VI products from multiple samples. They found that LAI–VI relationships vary across different stages, with segmented LAI–VI relationships demonstrating significantly higher accuracy compared to single LAI–VI relationships [14]. However, these methods are usually constrained by factors like canopy structure, vegetation density, soil background, and atmospheric interferences, leading to variability in VI–LAI relationships across different regions or vegetation types and thus limiting their universality [15,16]. Moreover, taking the NDVI as a primary example, it is susceptible to saturation in densely vegetated areas. The LAI derived from the NDVI tends to be underestimated, leading to a disparity when compared with the actual conditions [17,18].

For physical methods, the radiative transfer model (RTM) establishes the relationship between the LAI, optical properties of leaves, and canopy reflectance to retrieve biophysical parameters of vegetation. However, due to the complexity of the RTM and the limited amount of observation, it is necessary to obtain more prior data in the process of solving the vegetation parameters, which leads to the ill-posed problem in the inversion process [9,19–21]. To address these challenges and enhance computational efficiency, techniques like lookup tables (LUTs) and Bayesian networks are commonly used [22–24]. For example, Xu et al. combined a Bayesian network with the PROSAIL model to estimate rice LAI, helping to improve the accuracy of crop growth parameter estimations in the RTM model [25]. J. Verrelst inverted the RTM of Sentinel-2 and Sentinel-3 satellite multiband reflectance data using a LUT to retrieve the LAI in Barrax, Spain [26]. Haizhu Pan et al. applied three different inversion methods (empirical models, neural network (NN) algorithms, and lookup table (LUT) methods based on the PROSAIL model) to retrieve winter wheat LAI based on S2 data in North China [27]. Nevertheless, the physical model has the defects of complex input parameters, a heavy calculation burden, and a tedious inversion process, which limit its application in large-scale LAI inversion. In addition, the RTM requires multi-angle observation, which is difficult for high spatial resolution sensors, thus limiting its application [28].

Non-parametric algorithms enhance their performance by optimizing weights or coefficients during data training stages. They aim to minimize prediction errors through continuous parameter adjustments [9]. A prominent subset of nonlinear regression is machine learning (ML) methods. Common ML techniques used for retrieving the LAI from remote sensing data include methods such as random forests, artificial neural networks, support vector regression, and generalized neural networks [16,29–31]. For example, Xue et al. developed the back propagation (BP) neural network model improved by the simulated annealing (SA) algorithm to estimate the LAI from Landsat data, demonstrating that the SA-BP model significantly improves estimation accuracy for a high-resolution LAI [32]. Similarly, T Dube et al. employed a random forest method to retrieve the LAI in both drought and wet seasons in Kruger National Park, South Africa, utilizing Landsat 8 imagery [33].

Gaussian process regression (GPR) is another important parameter estimation machine learning algorithm. Compared with other statistical regression tools, GPR has good numerical performance and stability and only needs a relatively small training data set. In addition, it can use a very flexible kernel function to identify the relevant bands and observations and establish the relationship with variables [34–36]. However, GPR assumes that the variance in the noise process is independent of the input data, which is inconsistent with the actual situation and limits the accuracy of the method [37]. Scholars have proposed many improved schemes for GPR, which are applied to different scenarios. Among them, the variational heteroscedastic Gaussian process (VHGPR) performs well in the

application of land surface parameter estimation [38–40]. Compared with GPR, the VHGP takes into account the nonlinearity and heteroscedasticity in the practical application of remote sensing parameter estimation, which improves the inversion accuracy of the parameters [41]. Several studies have demonstrated that the VHGP is effective in LAI retrieval. J. Verrelst et al. systematically compared a variety of parametric, nonparametric, and physically-based retrieval methods using simulated S2 data at an agricultural site in Spain and evaluated the ability of various retrieval methods to estimate LAI [9]. They found that kernel-based machine learning regression algorithms (VHGPs) are most suitable for the estimation of agricultural LAI. J. Estévez et al. combined RTM with the VHGP and used S2 bottom-of-atmosphere (BOA) L2A and S2 top-of-atmosphere (TOA) L1C as input to retrieve a variety of crop traits, including the LAI [37]. Their experimental results in a farmland site in Munich, Germany, show that the hybrid inversion model can be directly applied to TOA radiation or reflectance data.

Many of the above studies relied on all bands of S2 but paid limited attention to the specific utilization of S2 10 m spatial resolution band data independently. The 10 m spatial resolution reflectance offers more detailed information, and is capable of capturing finer features and details of smaller objects, thus reducing uncertainty in subsequent applications [42]. This is particularly crucial for monitoring heterogeneous surfaces such as urban vegetation and agricultural crops [43,44]. The aim of this paper is to achieve high-accuracy LAI estimation at 10 m spatial resolution using S2 data. The VHGP model is first applied for woodland LAI estimation. The results are compared with the SAVI empirical model and the SA-BP neural network model alongside field observations. The outcomes derived from this research contribute valuable insights and advancements in the accurate assessment of high-spatial-resolution LAI in regions characterized by dense vegetation and intricate landscapes, particularly for forested areas.

2. Data

2.1. Study Area

Saihanba Forestry Center (SFC) in Chengde, Hebei Province, China, was selected as the experiment area. The longitude and latitude range of the study area is 116.78°E–117.65°E, 42.06°N–42.60°N, with an average altitude of 1500 m. This research area belongs to the cold temperate continental monsoon climate, with an average annual temperature of -1.5°C , an average annual precipitation of 438 mm, an average evaporation of 1230 mm, an average annual frost-free period of 60 days, and snow cover time of 7 months. The SFC is in the typical artificial forest zone, with rich vegetation species, and it is also one of the birthplaces of the Luanhe River and the Liaohe River. The growing season for vegetation in this area is mainly from May to September. The forest vegetation in the study area can be divided into natural coniferous forest, mixed coniferous forest, and broad-leaved forest. The SFC was established in 1962, with a total management area of 95,000 hectares, including 75,000 hectares of woodland and 80% forest coverage. *Larix principis-rupprechtii* plantations are the main forest type in the SFC, and the other types are hardwood deciduous forests, *Betula platyphylla* plantations, *Pinus tabulaeformis* plantations, *Pinus sylvestris* var. *mongolica* plantations, and *Picea asperata* plantations.

The land classification map of the study area is as follows (Figure 1, the land classification map was generated by Gao et al. using the random forest classification model) [45]:

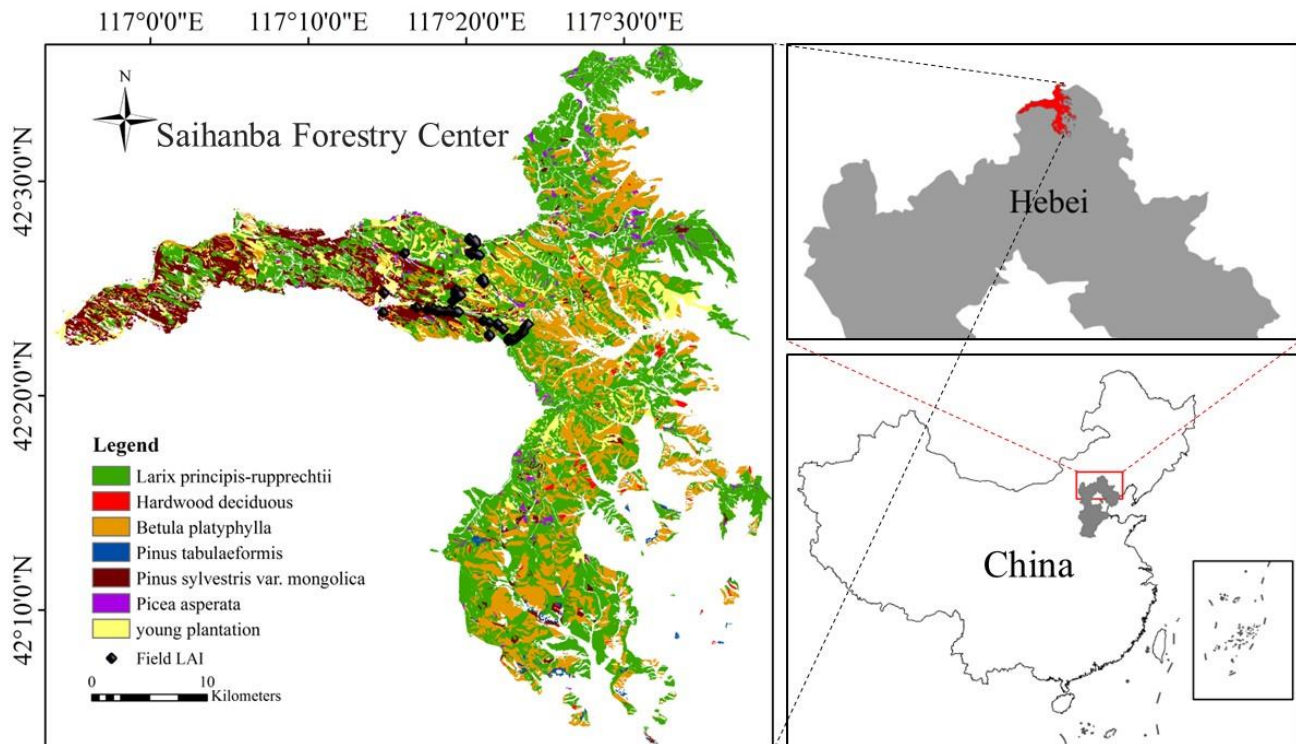


Figure 1. Land classification map and location of the Saihanba Forestry Center (SFC).

2.2. Field Data

The Beijing Normal University State Key Laboratory of Remote Sensing Science conducted a comprehensive field observation experiment in the Luanhe River Basin from 7 June to 12 September 2018 and obtained the ground measurement data of the LAI in the SFC [46–48]. The LAI measurement targets included forest land and grassland. The main measuring instruments were LAI2000, LAIPhoto, and TRAC. In order to ensure the consistency of the LAIs measured from different sources, they were all adjusted to the true LAI. In the field experiment, since the measured quadrats were homogeneous, scaling was based on their central position, and as the measurements covered a $25\text{ m} \times 25\text{ m}$ area, the data were adapted to correspond to a $10\text{ m} \times 10\text{ m}$ area for each point. Finally, 58 high-quality field LAI points with contemporaneous high-quality S2 data were used in this study.

2.3. Sentinel-2 Data

In 2015 and 2017, the European Space Agency (ESA) launched two Sentinel-2 satellites to establish the European Operational earth monitoring system. Compared with other multispectral missions such as MODIS and Landsat, the Sentinel-2 multispectral instrument (MSI) has finer spatial resolution (10, 20, and 60 m), more comprehensive spectral sampling (including the red edge band), and a more frequent revisit period (5 days). S2 further improves the temporal, spatial, and spectral resolution of remote sensing data, which has great potential in vegetation monitoring. In this research, four 10 m bands (blue, green, red, NIR) were used for the construction of LAI inversion models. Table 1 is the band information of Sentinel-2 MSI.

Table 1. Sentinel-2 (S2) MSI band settings.

Band	Description	Wavelength (μm)	Resolution (m)
1	Coastal aerosol	0.433–0.453	60
2	Blue *	0.458–0.523	10
3	Green *	0.543–0.578	10
4	Red *	0.650–0.680	10

Table 1. Cont.

Band	Description	Wavelength (μm)	Resolution (m)
5	Vegetation red edge	0.698–0.713	20
6	Vegetation red edge	0.733–0.748	20
7	Vegetation red edge	0.773–0.793	20
8	NIR *	0.785–0.900	10
8A	Narrow NIR	0.855–0.875	20
9	Water vapor	0.935–0.955	60
10	SWIR–cirrus	1.365–1.385	60
11	SWIR-1	1.565–1.655	20
12	SWIR-2	2.100–2.280	20

Bands marked with an asterisk (*) are utilized for LAI estimation in this study.

2.4. Matching Sentinel-2 Reflectance and Field LAI

To ensure the accuracy of the LAI estimation, it was crucial to establish a temporal correspondence between Sentinel-2 satellite reflectance data and the field-measured LAI [49]. A matching window with a five-day interval tolerance was employed under the assumption that the woodland LAI would remain relatively stable over this five-day period. Note that some remote sensing images participated in matching with actual measurement points, but due to their large cloud coverage, they were not used for subsequent LAI distribution map estimation. The time of the image data and measured data used is shown in Figure 2.

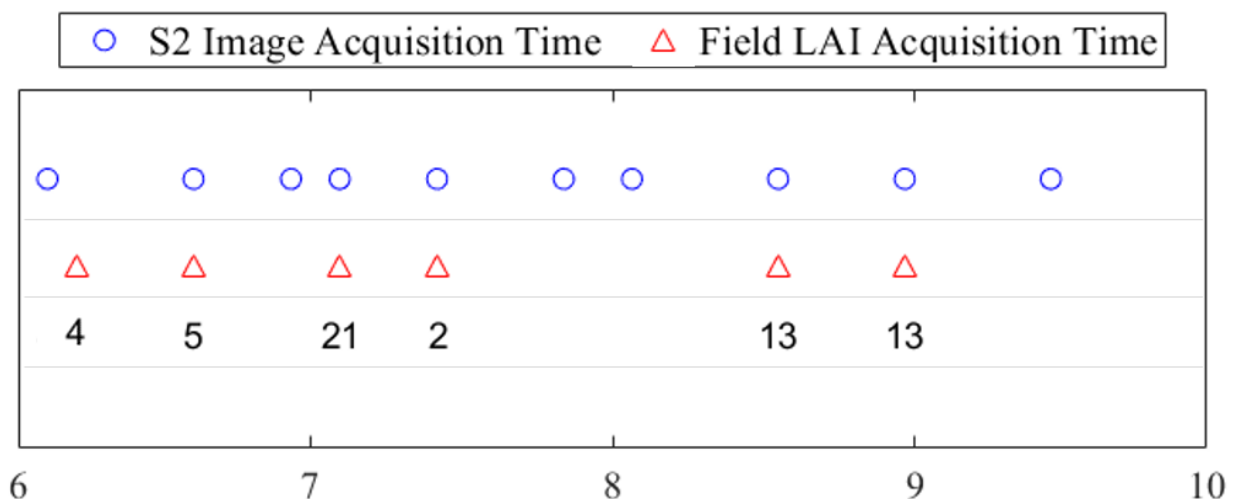


Figure 2. The involved Sentinel-2 image and field LAI in 2018. The horizontal axis represents the month, and the numbers under the triangle represent the number of the measured LAI.

3. Methods

3.1. Principle of Involved Models

3.1.1. Gaussian Process Regression

Gaussian process regression is a nonparametric model that uses the Gaussian process a priori for data regression analysis [50]. Compared with other machine learning methods, GPR has great advantages in modeling, but in the general Gaussian regression process, the noise variance of all signals is consistent, which is not consistent with reality [51]. As an improvement scheme for GPR, the VHGP can retain the advantages of GPR and add changeable noise to the regression process so as to achieve better regression results [40].

Specifically, the Gaussian process is a random process consisting of an infinite number of random variables that obey a Gaussian distribution defined on a continuous domain [51]. GPR regards the functional space corresponding to the regression model as a Gaussian

process, which establishes the relationship between the input r (reflectance) and output y (LAI):

$$y = f(r, w) + \varepsilon_n, f \sim GP(0, k_\theta(r, r')), \varepsilon_n \sim \mathcal{N}(0, \sigma^2) \quad (1)$$

where r is the surface spectral reflectance, w is the regression model parameters, $k_\theta(r, r')$ is a covariance function parameterized by θ , ε_n is the Gaussian noise with a variance of σ^2 , and θ and σ^2 are hyperparameters.

The Gaussian process is a stochastic process that satisfies that any finite subset of random variable set obeys multivariate Gaussian distribution [52]. In Gaussian process regression, the following hypothesis exists: If two values of r are similar (i.e., close to each other), then the correlation of the corresponding $f(r)$ is also similar. Therefore, a covariance matrix K_{rr} is introduced to describe the relationship between different values of r . Under the condition of Equation (1), the samples extracted from the position set of $f(r)$ followed a joint multivariate Gaussian distribution with zero mean and covariance matrix K_{rr} decided by $k_\theta(r, r')$. $k_\theta(r, r')$ is the kernel function of Gaussian distribution, and the form of kernel function used in this study was squared exponential:

$$k_\theta(r, r') = \exp\left(\frac{-\|r_i - r_j\|^2}{2\sigma^2}\right) \quad (2)$$

If new test data r_* are introduced outside the training data set, Equation (1) will produce the following joint prior distribution among the observations:

$$\begin{bmatrix} y \\ y_* \end{bmatrix} \sim \mathcal{N}\left(0, \begin{bmatrix} K_{rr} + \sigma^2 I_n & k_{r*} \\ k_{r*}^\top & k_{**} + \sigma^2 \end{bmatrix}\right) \quad (3)$$

where k_{r*} is the covariance between r_* and r , and I_n is the $n \times n$ identity matrix.

The prediction mean and variance of y_* are given by the following formula:

$$\mu_* = k_{r*}^\top (K_{rr} + \sigma^2 I_n)^{-1} y \quad (4)$$

$$\sigma_*^2 = k_{**} + \sigma^2 - k_{r*}^\top (K_{rr} + \sigma^2 I_n)^{-1} k_{r*} \quad (5)$$

where μ_* is the estimated LAI by GPR, and σ_*^2 is the posterior variance of the estimated LAI.

The VHGPR introduces a noise sequence with variable variance, which allows the noise to change steadily during the regression process [38].

$$y = f(r, w) + \varepsilon_n, f \sim GP(0, k_\theta(r, r')), \varepsilon_n \sim \mathcal{N}(0, e^{g(r)}) \quad (6)$$

$$g(r) \sim GP(\mu_0, k_g(r, r')) \quad (7)$$

This form of noise distribution means that the VHGPR is not easy to analyze and is unable to obtain a closed-form solution directly. Thus, a complex method called marginal variational (MV) approximation is introduced in the VHGPR to improve the efficiency and prevent overfitting. Meanwhile, MV approximation guarantees the computational efficiency of the model and provides an analytical expression for the Kullback–Leibler divergence between the proposed distribution and the true posterior distribution [53]. By minimizing the proposed distribution and hyperparameters, the true posterior estimation is generated while simultaneously performing model selection. More details can be found in the research of Lázaro-Gredilla et al. [38,39].

3.1.2. Backpack Neural Network Based on Simulated Annealing Algorithm

To facilitate comparison with the VHGPR, the SA-BP model (an enhanced version of the widely recognized base model) was used. This improvement enhances convergence performance of the BP neural network while retaining the ability to manage nonlinear

problems and complex input data without prior knowledge of the target being required [32]. The BP neural network model stands out for its simplicity, stability, high accuracy, and robust fault tolerance, making it adept for parameter retrieval. Despite its benefits, the model's reliance on gradient descent introduces issues like slow convergence and susceptibility to local minimax [54]. To overcome these problems, scholars integrated the simulated annealing algorithm into the iteration process of the BP neural network, enhancing the search for global optima by limiting the search range of the network's weights and thus speeding up the convergence to optimal values and improving the model's efficiency and accuracy. For more detailed information, please refer to [32].

3.2. Method Implementation and Verification

In this study, the kernel function of the VHGPB was preset to a squared exponential, and the hyperparameters in the model were changed iteratively without deliberately assigning initial values. The SA-BP neural network has three layers, including an input layer, an output layer, and a hidden layer. The Sigmoid function is used as the transfer function, and the output layer uses a linear transfer function. The initial temperature of the SA algorithm was 100, the termination temperature was 0.01, and the cooling decay parameter was 0.95. Based on the weight range of the independent pre-trained BP neural network model, the weight interval was set to $[-3, 3]$.

In the comparison experiment, 75% of the field-measured LAI data and the corresponding S2 reflectance data were randomly selected as the training data set, and the remaining 25% were used as the verification data set. This dataset was uniformly applied to two different models: the VHGPB and the SA-BP models, ensuring a consistent and fair comparison of their performance. In addition to these advanced machine learning models, a traditional SAVI-based exponential empirical model was incorporated as a control group. The formula is as follows:

$$LAI = 0.17 \times e^{3.24 \times SAVI} \quad (8)$$

The key metrics used in this validation process were the determinant coefficient (R^2) and the root mean square error (RMSE). These statistical measures allowed for a quantitative assessment of the accuracy and predictive power of each model, providing a clear understanding of their performance in estimating the LAI.

4. Result

4.1. Validation with Field Data

Figure 3a shows the validation results of the VHGPB model with field observation. In the SFC area, the 10 m spatial resolution LAI estimated using the VHGPB aligned well with field observations, exhibiting an impressive R^2 of 0.8696 and a low RMSE of 0.5078. Additionally, Figure 3b,c incorporates the results from the commonly used SAVI method and the SA-BP method. The SAVI exponential empirical model exhibited the least favorable performance among the three LAI estimation models, displaying an acceptable R^2 of 0.7908 but a notably high RMSE of 1.1996. This discrepancy can be attributed to the underestimation of the SAVI when the LAI value exceeded 3, primarily due to model saturation in the presence of lush vegetation. In contrast, the SA-BP model avoided the saturation issue related to the VI methods. Although the accuracy of the SA-BP was satisfactory (R^2 of 0.8095 and RMSE of 0.568), it still fell short of the accuracy achieved by the VHGPB model.

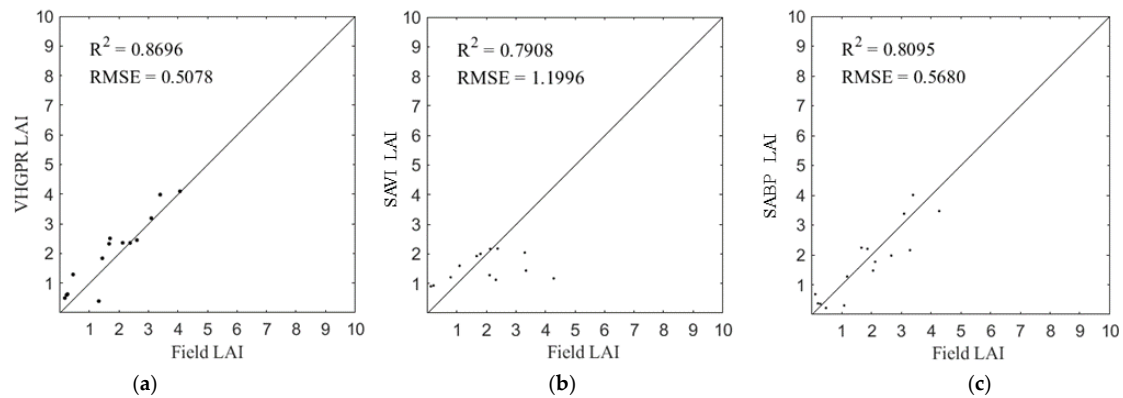


Figure 3. Distribution of the correlation relationship between the field LAI and the estimated LAI by the VHGP (a), SAVI (b) and SA-BP (c).

4.2. SFC LAI Distribution Map Generated by VHGP

The LAI distribution maps for the SFC in 2018 were generated utilizing the VHGP model and S2 reflectance data (Figure 4). The LAI estimation results effectively captured the vegetation growth patterns in the SFC, providing a comprehensive depiction of the spatial distribution characteristics and temporal changes in vegetation. Notably, the month of July exhibited the peak prosperity of forest vegetation, aligning with the observed variations in forest LAI within the study region. The LAI map on Julian day 208, representing the peak prosperity across all maps, revealed that *Larix principis-rupprechtii* exhibited optimal growth, with the highest LAI values. However, some distinct lower values were observed in specific research areas. For instance, the LAI values of *Betula platyphylla* and *Pinus tabulaeformis* were relatively lower compared to those of *Larix principis-rupprechtii* in the primary research area. In the western region, characterized by a mix of *Pinus sylvestris* var. *mongolica*, *Larix principis-rupprechtii*, young plantations, and a small number of *Picea asperata*, the LAI values were lower than the central part, where *Larix principis-rupprechtii* was predominant. Compared with other tree species, the growth period of *Betula platyphylla* started the earliest and had obvious green indication on the 185th day. However, there was no obvious difference between *Betula platyphylla* and other tree species at the end of the growth period.

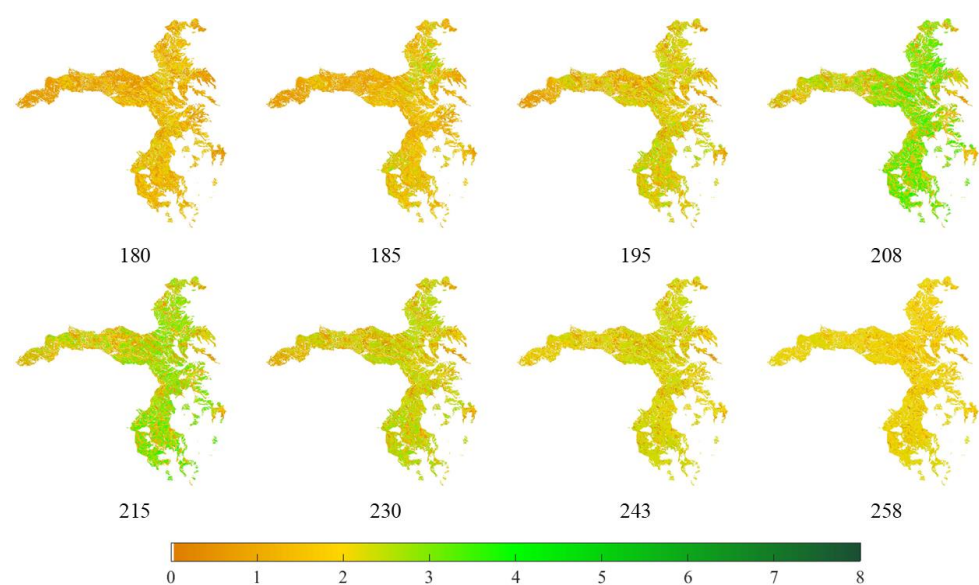


Figure 4. LAI maps generated by the VHGP in the SFC in 2018. Each LAI map is marked with the corresponding day of the year (DOY).

4.3. Uncertainties and Relative Uncertainties of SFC LAI Distribution Map

Since the VHGPB was developed within the Bayesian framework, it provides the estimation uncertainty in addition to the leaf area index estimation. Relative uncertainty can be calculated from this uncertainty graph: absolute and relative uncertainty represented by the standard deviation (SD) around the average estimate ($CV = SD / \text{average estimate}$ in %). These two error maps can provide additional information about retrieving model performance on a per-pixel basis.

In the associated uncertainties of the LAI maps (Figure 5), lower SD values represent more reliable LAI estimates, whereas higher values, in light blue and green, reflect higher uncertainty. After integrating the error distribution map (Figures 5 and 6) and the statistical table (Table 2), a series of related uncertainty maps for 2018 exhibited the following main characteristics: (1) Overall uncertainty was relatively high in the early and late growing seasons and (2) uncertainty was high near ridges and water bodies. These characteristics can be attributed to the following reasons: (1) The LAI ground survey data dates were predominantly concentrated in the mid-growing season, when vegetation flourishes, in contrast to the early and late growing seasons, when the sparse vegetation canopy is susceptible to shrub or grassland vegetation, thereby increasing uncertainty. (2) Most of the water bodies in the SFC are wetland landforms, significantly impacting the accuracy of LAI retrieval and resulting in heightened uncertainty. However, the forest vegetation near the ridge is sparse, and the vegetation in open-air areas primarily consists of grassland and shrub, contributing to the uncertainty in the inversion results.

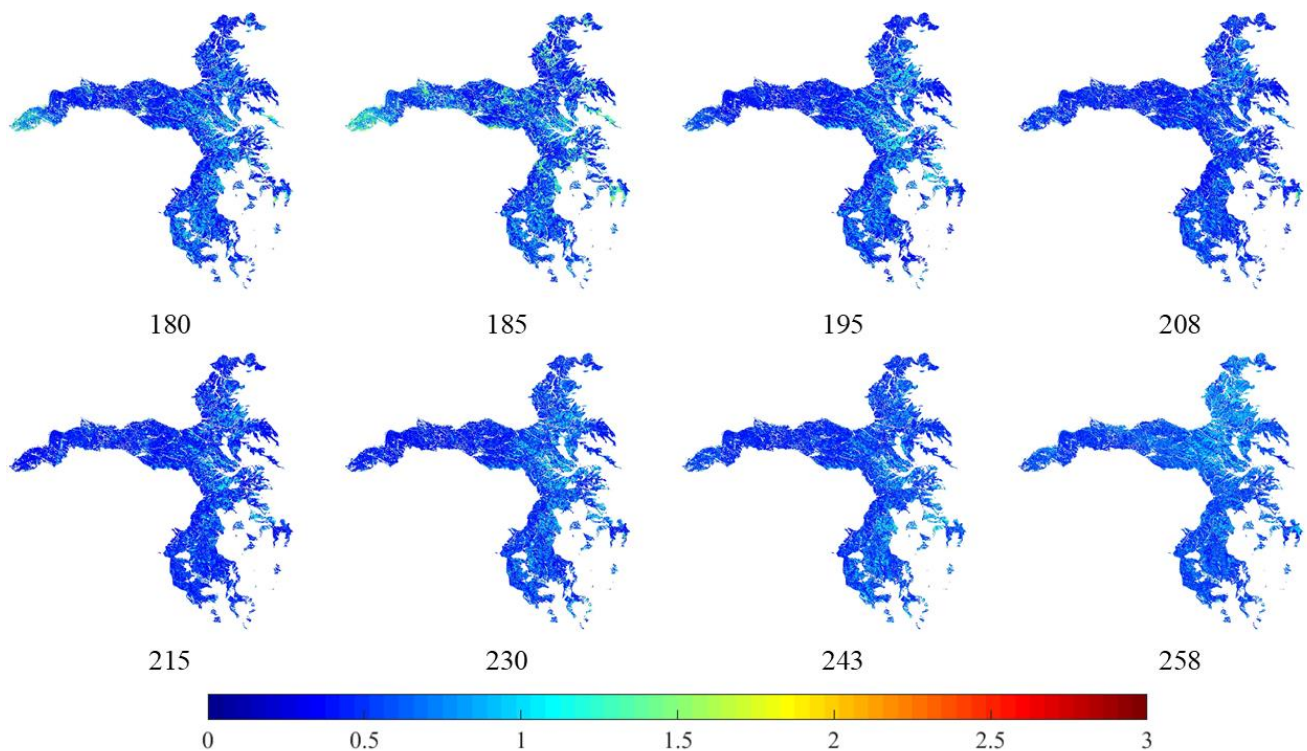


Figure 5. Associated uncertainties of LAI maps in 2018 (expressed as standard deviation (SD) around the mean of LAI estimates (μ)).

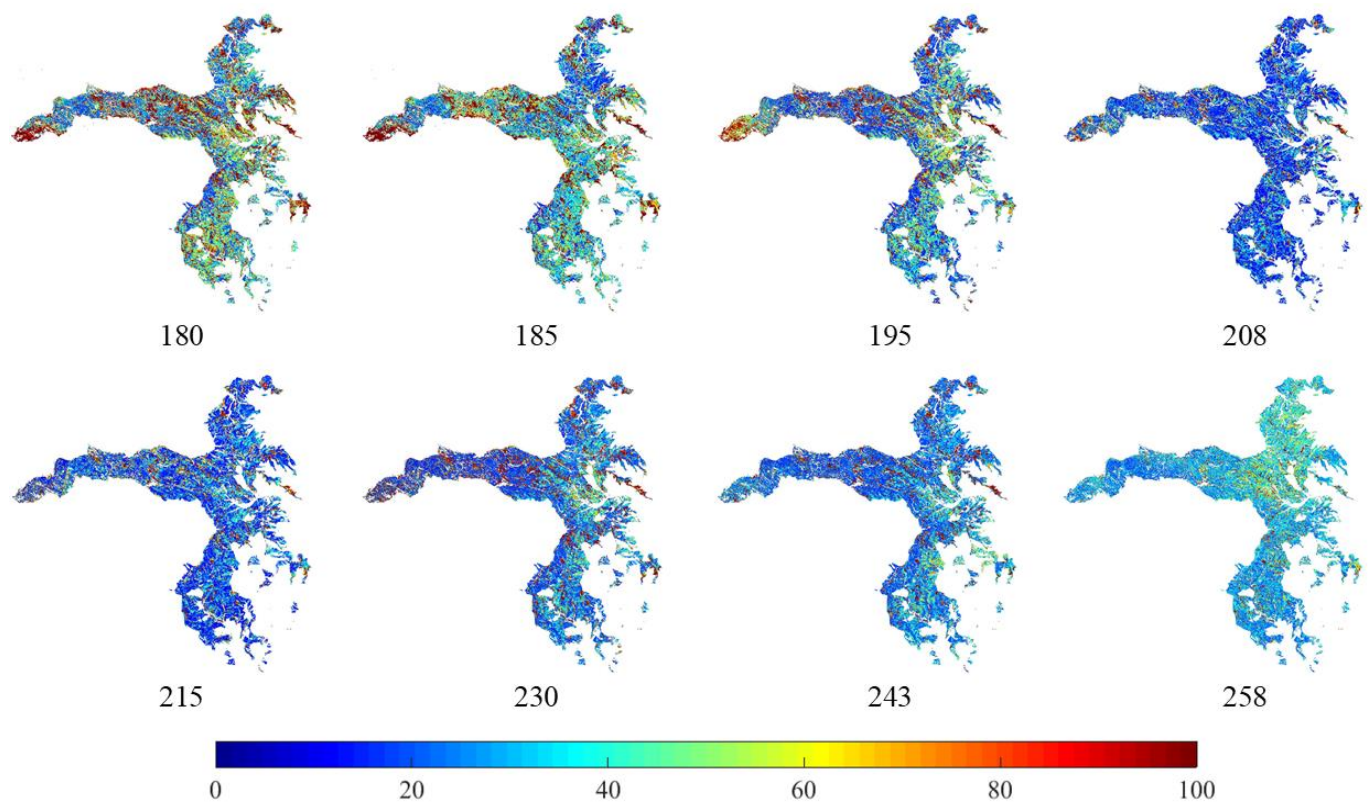


Figure 6. Relative uncertainties of LAI maps in 2018 (expressed as coefficient of variation: $(CV = \frac{SD}{\text{LAI}} * 100)$ in %).

Table 2. Average error of different time.

DOY	Mean SD	Mean CV (%)
180	0.1212	10.2851
185	0.1360	10.0728
195	0.1176	7.5763
208	0.1104	5.0239
215	0.1059	5.2505
230	0.1170	6.7886
243	0.1167	6.6019
258	0.1269	8.5541

Due to the inherent calculation method, the CV value was obviously higher in the early and late growing seasons, as well as in regions with smaller LAI values. In addition, certain areas exhibited consistently high CV values across all growth stages. In order to further explore the causes of these anomalies, some typical areas with high CV were selected randomly and compared with the corresponding land cover map (LC), the false color synthesis map (FCS), the LAI distribution map, the SD distribution map, and the NDVI distribution map.

As shown in Figure 7, there was a noticeable boundary in the CV map, distinguishing the estimated abnormal area from the surrounding regions of A and B. Combined with the NDVI distribution map and the LAI distribution map, it can be seen that the vegetation in these areas was relatively sparse. Meanwhile, these areas appeared light blue in the FCS, indicating a non-vegetative surface. The reason for this misclassification is in the masking of the results map based on the 30 m land cover map. In line C, certain areas exhibited significantly higher relative errors. These areas were characterized by spruce vegetation, which was sparse, with low LAI and NDVI values. The error is attributed to the limited availability of *Picea asperata* plantation field data in the modeling process, resulting in

unsatisfactory estimation accuracy for spruce. In line D, combined with different maps, the vegetation in this area was relatively sparse, and the corresponding CV value was particularly high. This is due to the inherent calculation of the CV and the poor estimation ability of the model for sparse vegetation. Finally, in rows E and F, especially in row E, the CV values of the VHGP estimates were significantly higher than those of other vegetation types in young forest vegetation areas. The lesser attention given to young forest during the collection of measured points, coupled with the absence of similar training points in the VHGP model, contributed to the lower reliability in estimating the LAI for young plantations. As a result, the CV values were exceptionally high in these cases.

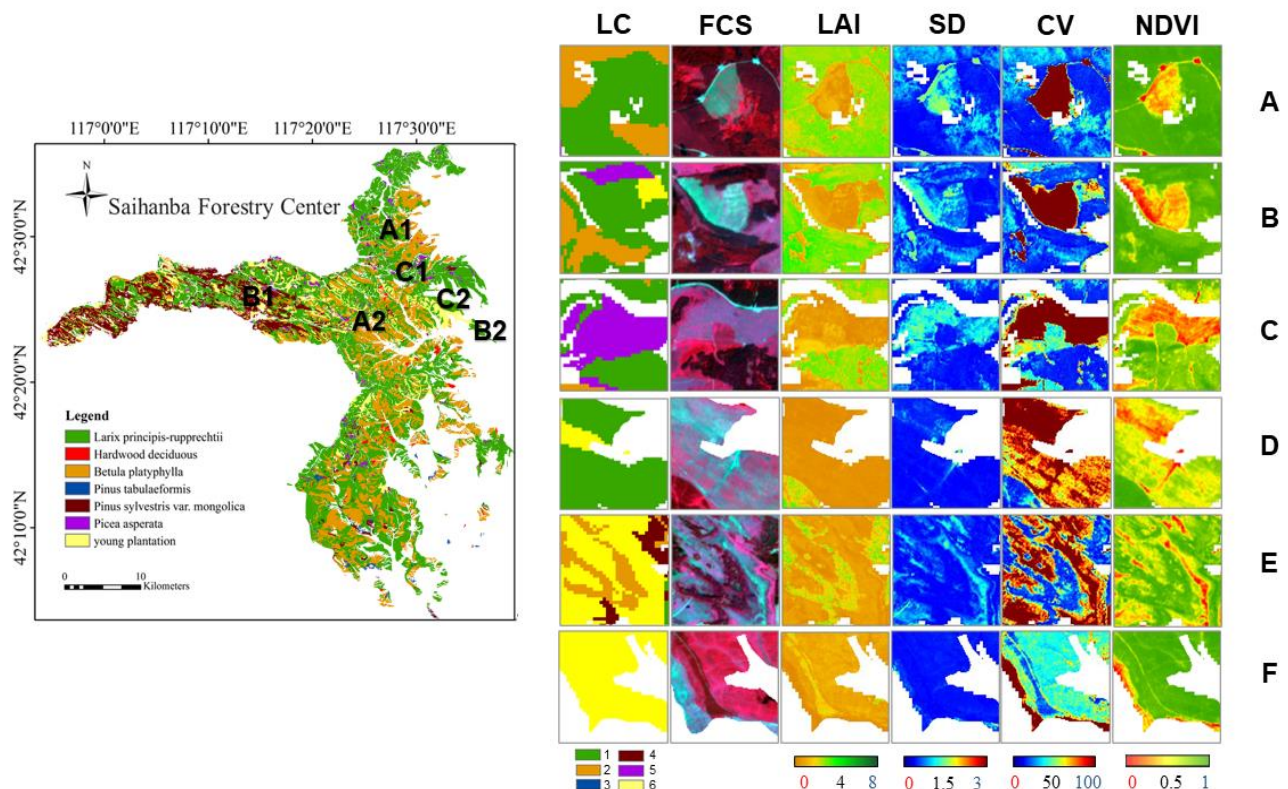


Figure 7. Local validation comparison map. LC, FCS, LAI SD, CV, and NDVI mean the false color land cover map, synthesis map, LAI distribution map, SD distribution map, and NDVI distribution map, respectively. The LC legend 1~6 corresponds to *Larix principis-rupprechtii* plantations, *Betula platyphylla* plantations, *Pinus tabulaeformis* plantations, *Pinus sylvestris* var. *mongolica* plantations, *Picea asperata* plantations, and young plantations, respectively; A–F represents six different typical areas.

5. Discussion

5.1. Errors from Field LAI Data

At present, the measurement of LAI data mainly depends on human resources. Different instruments, subjective human factors, and the distribution of sampling points can collectively influence the experimental outcomes [4,55]. The LAI measured in this experiment was mainly concentrated in the central part of the study area. Relative to the study area, the distribution of the LAI was relatively small and concentrated [46–48]. Although the six major vegetation types in the study area accounted for a proportion of these samples, the total number of survey points was limited, and most of the test areas consisted of mixed forests. Consequently, the overall accuracy of the LAI distribution map may have been somewhat affected.

5.2. Advantage of VHGP Methods

The SA-BP neural network retains several advantages over the BP neural network model, including nonlinear mapping, robust fault tolerance, and strong adaptability. It incorporates the simulated annealing algorithm to expand the weight update space of the neural network, addressing the limitation of BP neural networks being prone to local minima issues [32,56]. The advantage of the VHGP model is that it can judge the importance of input data eliminate unimportant bands, and it has unique advantages in large-scale mapping. In addition, the VHGP can provide uncertainty estimates and relative uncertainty estimates of prediction results, which is very useful for error source analysis and mapping applications [57]. Although the accuracy difference between the two is not particularly obvious, the VHGP is superior in LAI model inversion and product generation due to its error estimation ability.

5.3. Further Work for LAI Estimated by VHGP

The initial methodological choice for this research, which primarily relied on machine learning approaches such as the SA-BP and the VHGP, was driven by their proven effectiveness in handling high-dimensional data and complex nonlinear relationships inherent in remote sensing applications. The primary objective of this study was to explore and validate the potential of the SA-BP and the VHGP models in accurate LAI estimation in the SFC with field data. The topography effect was not considered, which is a main drawback of this study. The VHGP used in this experiment depended on the field data and performed well in the overall area of the SFC but was poorly popularized in areas with different latitudes or large differences in terrain distribution. As shown in the experiment, the variance and coefficient of variation were large in areas with complex surface distribution and high elevation area. For these problems, the following solutions may work: (1) Combine the VHGP with LUT-based RTM to form an LAI estimation model that does not depend on the measured data [16,58,59]. This method leverages the scientific rigor of RTMs and the adaptability of machine learning to various data conditions and thereby can potentially reduce the necessity for extensive spatial and temporal field data. (2) Incorporate topographic factors (such as slope, aspect, elevation, etc.) into the model to improve the model estimation accuracy in rugged terrain areas [60,61]. (3) Introduce a 10 m resolution land cover map to further improve the calculation ability of the model on complex terrain [62].

5.4. Evaluation of LAI Time Series Distribution Maps

In this study, only a few clear and a few cloudy images were selected to generate the final LAI distribution map. The spatial resolution of the LAI distribution maps obtained in the study was 10 m, while the temporal resolution was low. Moreover, the uneven distribution of the dynamic time information may have caused a certain degree of misjudgment and bias in the analysis, such as the growth peak value and the starting and ending points of the growing season. The commonly used method to obtain spatio-temporal continuous high-resolution LAI is to combine high-temporal-resolution information from coarse resolution data with high-spatial-resolution information from low-temporal-resolution data, such as the spatial and temporal adaptive reflectance fusion model (STARFM) [63] or the ensemble Kalman filter assimilation (EnKF) [64]. These algorithms are used in the production of the LAI, abedlo, NPP, NDVI, and other surface parameters [56,65–68]. The spatial resolution of the LAI based on S2 retrieval is 10 m, which is different than the commonly used coarse resolution data, such as MODIS data (500 m), glass data (1 km), and so on. Combining the LAI generated by S2 data with these coarse resolution data will yield a more obvious scale effect, reduce the advantage of the high resolution of the S2 data to a certain extent, and bring more uncertainty [69,70]. At present, a feasible method is to combine Landsat satellite with MODIS and other coarse resolution data to generate 30 m continuous time series LAI background field data and then combine the time series inversion method with S2 data to generate the final 10 m high-spatial-temporal-resolution LAI data [71]. However,

this approach presents certain challenges, such as the introduction of observation error from multiple satellites, and the accumulation of error from various models in parameters estimation [72].

6. Conclusions

This paper focused on the inversion of LAI using only a few 10 m resolution bands of S2. Although Sentinel-2 data offer the advantages of remarkable resolution and a short return cycle, existing LAI retrieval methods often fall short of harnessing the full potential of the 10 m resolution bands, leading to the acquisition of only 20 m resolution LAI results. The study considered the applicability of the VHGP method to retrieve the LAI from S2 data with only blue, green, red, and NIR bands and compared the results with the SAVI empirical model and the SA-BP model. Among them, the accuracy of the VHGP was better than the SAVI and the SA-BP models, with an R^2 of 0.8696 and an RMSE of 0.5078. The SA-BP method demonstrated an observable upper limit in its estimation values, influenced by the maximum value of the training sample. In contrast, the VHGP exhibited resilience to this limiting factor, solidifying its position as the superior method. This finding emphasizes the robustness and versatility of the VHGP, especially in comparison to existing approaches. Then, based on the VHGP method, the study further generated LAI distribution maps, an SD distribution map, and a CV distribution map of cloud-free S2 images in 2018 and, combined with the landcover map and the false color synthesis map, analyzed the error sources and characteristics of the VHGP. The results show that the VHGP method can generate 10 m LAI from S2 data quickly and accurately, and can reflect the accuracy and deviation of the model estimation results. It is a feasible 10 m LAI inversion scheme.

Nevertheless, the study acknowledges the challenge posed by the limited availability of field data, which impacted the method's overall robustness. To address this limitation, future research endeavors should focus on enriching the diversity and depth of training data. Potential strategies include integrating simulated RTM data or supplementing the dataset with coarse resolution LAI products during the training phase. This approach would contribute to overcoming the current limitations and further enhancing the performance of the VHGP.

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