

## Article

# A Comparison of Different Data Fusion Strategies' Effects on Maize Leaf Area Index Prediction Using Multisource Data from Unmanned Aerial Vehicles (UAVs)

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**Abstract:** The leaf area index (LAI) is an important indicator for crop growth monitoring. This study aims to analyze the effects of different data fusion strategies on the performance of LAI prediction models, using multisource images from unmanned aerial vehicles (UAVs). For this purpose, maize field experiments were conducted to obtain plants with different growth status. LAI and corresponding multispectral (MS) and RGB images were collected at different maize growth stages. Based on these data, different model design scenarios, including single-source image scenarios, pixel-level multisource data fusion scenarios, and feature-level multisource data fusion scenarios, were created. Then, stepwise multiple linear regression (SMLR) was used to design LAI prediction models. The performance of models were compared and the results showed that (i) combining spectral and texture features to predict LAI performs better than using only spectral or texture information; (ii) compared with using single-source images, using a multisource data fusion strategy can improve the performance of the model to predict LAI; and (iii) among the different multisource data fusion strategies, the feature-level data fusion strategy performed better than the pixel-level fusion strategy in the LAI prediction models. Thus, a feature-level data fusion strategy is recommended for the creation of maize LAI prediction models using multisource UAV images.

**Keywords:** multisource remote sensing images; leaf area index; UAV; maize



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## 1. Introduction

The leaf area index (LAI) is a key factor for indicating vegetation growth status. Obtaining LAI and its dynamic change is of great significance for crop health monitoring and yield prediction [1,2]. As an important food and feed crop globally, maize has an important role in ensuring food security [3]. Thus, it is particularly essential to achieve a rapid and nondestructive estimation of maize LAI.

The traditional LAI estimation method is destructive, time-consuming, and labor-intensive, which makes it unsuitable for use in precision agriculture [4]. Remote sensing technology has been demonstrated to be a good tool for crop physiological and biochemical parameter estimation [5,6]. In recent years, with the rapid development of unmanned aerial vehicles (UAVs) and sensor technology, UAV remote sensing technology has been widely used in agriculture. Unlike satellite and manned aerial vehicle remote sensing technology, UAV remote sensing technology can obtain high spatial and temporal resolution images at the field scale at low cost, which is critical for precision agriculture [7,8]. At present, the methods for LAI estimation using UAVs can be classified into two categories: empirical and mechanistic methods. The empirical method uses a data-driven approach to predict LAI

of the target area based on the statistical relationship obtained from the collected samples. Although this approach is easy to implement, it needs a large number of samples for model training because of the lack of machinability [9]. The mechanistic method simulates the canopy reflectance spectra by establishing the model of electromagnetic wave radiation transmission in the canopy and taking the physiological and biochemical parameters of vegetation with clear physical explanation as inputs; LAI can be predicted based on its inverse processes [10]. This method has a better mechanistic interpretation and can solve the problem of model generalizability, but due to the large number of input parameters and the complexity of the inversion process, there may also be problems with illness inversion [11,12]. While both methods have their advantages, the empirical method is more commonly used in practice at present.

Using the empirical method to predict LAI based on UAV images, Hasan et al. [13] designed a winter wheat LAI prediction model based on RGB images with partial least squares regression (PLSR). Based on hyperspectral images, Yuan et al. [14] used an artificial neural network (ANN) to build a soybean LAI prediction model. Based on multispectral (MS) images, Shi et al. [15] used support vector regression (SVR) to predict the LAI of red beans and mung beans in tea plantations. Moreover, studies have also documented that the prediction accuracy of crop growth parameters can be improved with the combination of spectral and textural information. Yang et al. [16] designed a new index to estimate rice LAI by coupling spectral and textural features from MS images. Using RGB images, Li et al. [17] estimated rice LAI using the random forest regression (RFR) method based on spectral and textural information. Zhang et al. [18] combined spectral and textural features of UAV MS images to estimate maize LAI. Although the above studies have documented that LAI can be estimated using spectral or texture information from images, they are all based on a single data source. It has been shown that fusing multisource data can combine the advantages of each data source and thus result in better prediction results for vegetation parameters [19,20]. Until recently, it has seldom been applied in the field of UAV LAI prediction.

Multisource image data fusion methods can be classified into three categories: pixel-level fusion, feature-level fusion, and decision-level fusion. Among them, pixel-level fusion is a method that couples the physical quantities of each image element to form a new image with combined characteristics during the preprocessing of remote sensing images [21]. Feature-level fusion is a method that extracts feature information based on different images separately and then fuses the feature information. Decision-level fusion is a method that inverts the target parameters based on different images and then weighs them according to the decision rules [22]. Compared with the decision-level fusion method, the feature-level fusion method and pixel-level fusion method are more commonly used for vegetation parameter inversion using remote sensing images. Among those that used UAV data, a few studies have been conducted with LAI prediction based on feature-level fusion methods. Maimaitijiang et al. [23] used UAV-acquired RGB, MS, and thermal infrared images to extract multimodal information such as spectra, texture, canopy temperature, and structure for soybean yield prediction; Zhu et al. [24] used features extracted from UAV hyperspectral, RGB, thermal infrared, and LiDAR data to investigate the effects of multisource data on the prediction accuracy of maize phenotypic parameters. Liu et al. [25] combined features of UAV MS, RGB, and TIR images to predict maize LAI. The pixel-level fusion method is currently mainly applied in studies using multisource satellite remote sensing images for vegetation parameter inversion [26] and have rarely been reported in UAV remote sensing-related studies. At the same time, there exist no studies that compare different fusion methods for LAI prediction. However, different fusion strategies will definitely have different effects on LAI prediction. Therefore, to more accurately estimate LAI and support precision management, it is important to compare the advantages and disadvantages of different image fusion methods for LAI prediction.

In this study, field experiments, with treatments including different amounts of organic fertilizer, inorganic fertilizer, and straw returned to the field, and different planting densities,

were conducted to obtain maize canopies with different LAI values. LAI and corresponding RGB and MS images were collected at different stages of maize growth. Based on these data, this study focuses on the recommended optimal strategy for LAI prediction. The purposes of this study were (i) to analyze whether both the pixel-level fusion method and feature-level fusion method could obtain a better prediction accuracy for LAI than the single-source data method using UAV data, and (ii) to recommend a better fusion strategy for LAI prediction by comparing the pixel-level fusion method and feature-level fusion method.

## 2. Materials and Methods

### 2.1. Field Experiment

The eastern part of the Inner Mongolia Autonomous Region is an important black soil area in China and an important area for maize production. Our experiment was conducted in 2022 at Dahewan Farm (123°1'33" E, 47°54'2" N) in Zalantun city. The area belongs to the temperate semi-humid continental monsoon climate zone with fertile soil and sufficient sunshine. The maize cultivar "Huaqing 6" was used in the experiment with different field treatment trials, including different amounts of inorganic fertilizer, organic fertilizer, and straw returned to the field, and different planting densities (Figure 1). The inorganic fertilizer treatment included four nitrogen application levels ( $N_1$ : 150 kg  $hm^{-2}$ ,  $N_2$ : 180 kg  $hm^{-2}$ ,  $N_3$ : 210 kg  $hm^{-2}$ , and  $N_4$ : 240 kg  $hm^{-2}$ ), three phosphate ( $P_2O_5$ ) application levels ( $P_1$ : 60 kg  $hm^{-2}$ ,  $P_2$ : 75 kg  $hm^{-2}$ , and  $P_3$ : 90 kg  $hm^{-2}$ ) and three potash ( $K_2O$ ) fertilizer levels ( $K_1$ : 75 kg  $hm^{-2}$ ,  $K_2$ : 90 kg  $hm^{-2}$ , and  $K_3$ : 105 kg  $hm^{-2}$ ); the organic fertilizer treatment had five levels ( $O_1$ : 0 kg  $hm^{-2}$ ,  $O_2$ : 22,500 kg  $hm^{-2}$ ,  $O_3$ : 37,500 kg  $hm^{-2}$ ,  $O_4$ : 45,000 kg  $hm^{-2}$ , and  $O_5$ : 52,500 kg  $hm^{-2}$ ); the treatment with straw returned to the field had five levels ( $R_1$ : 0 kg  $hm^{-2}$ ,  $R_2$ : 3000 kg  $hm^{-2}$ ,  $R_3$ : 4500 kg  $hm^{-2}$ ,  $R_4$ : 6000 kg  $hm^{-2}$  and  $R_5$ : 7500 kg  $hm^{-2}$ ); and the treatment with varying planting density had five levels ( $D_1$ : 50,000 plants  $hm^{-2}$ ,  $D_2$ : 55,000 plants  $hm^{-2}$ ,  $D_3$ : 60,000 plants  $hm^{-2}$ ,  $D_4$ : 62,000 plants  $hm^{-2}$ , and  $D_5$ : 64,000 plants  $hm^{-2}$ ). All treatments were performed with two replications. In addition, two zero-fertilizer plots ( $T_0$ : 0 kg  $hm^{-2}$ ) and two plots with a stable compound fertilizer ( $T_1$ : 750 kg  $hm^{-2}$  of stable compound fertilizer with an N- $P_2O_5$ - $K_2O$  ratio of 26-10-12) were also included in the experiment. The organic fertilizer, straw returned to the field, and varying planting density treatments received a stable compound fertilizer at an N- $P_2O_5$ - $K_2O$  ratio of 26-10-12 at 750 kg  $hm^{-2}$ . The plot size is about 30 m<sup>2</sup>. Except for the differences in treatments mentioned above, all other field management measures were the same.

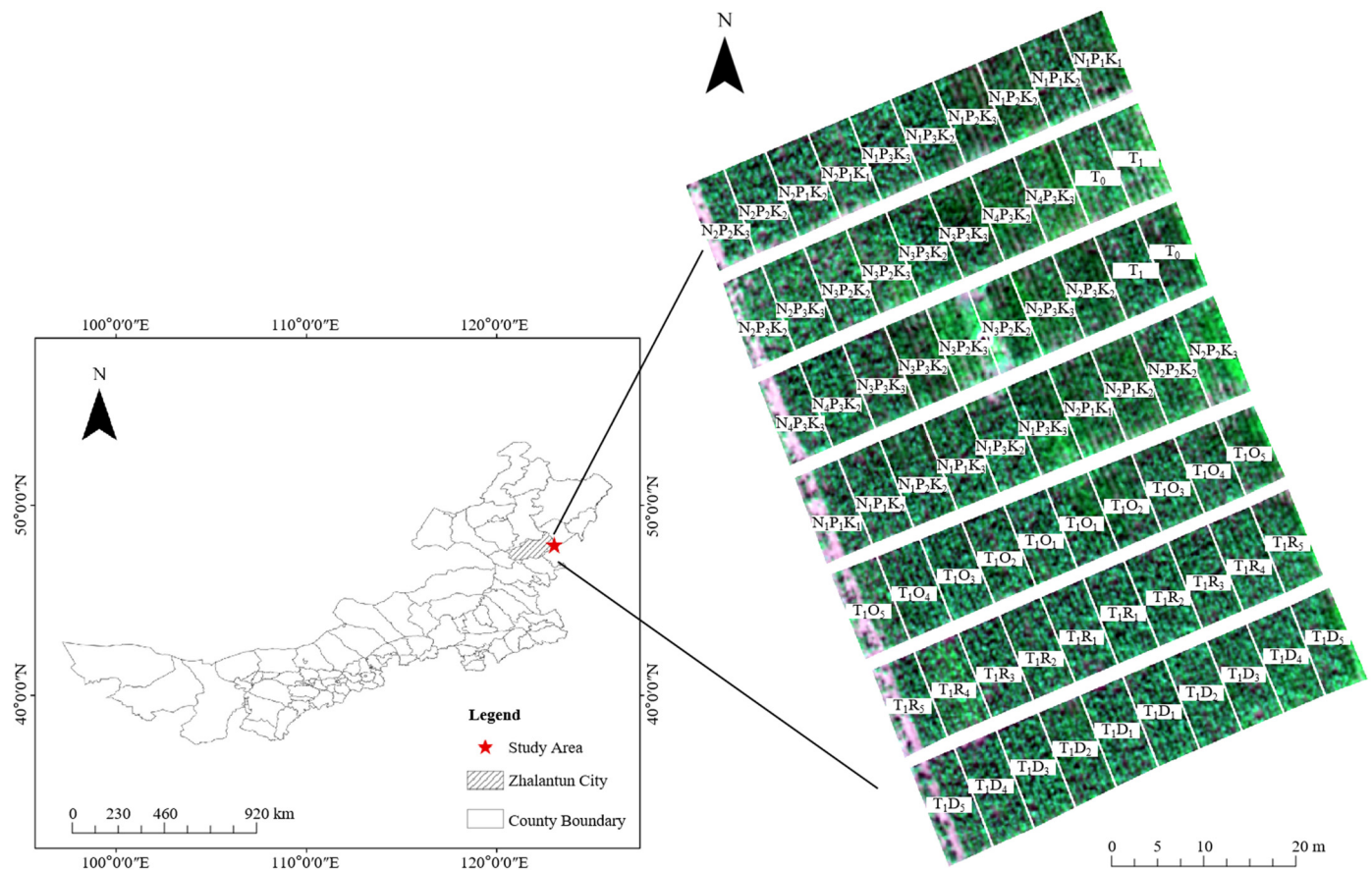
### 2.2. Data Acquisition and Processing

Field campaigns were conducted during the V4 and V9 growth stages of maize to obtain UAV images and perform field LAI measurements. These two growth stages are critical for maize water and fertilizer management.

#### 2.2.1. UAV Data Acquisition

A self-designed tail-seat vertical takeoff and landing fixed-wing UAV equipped with an Altum MS camera (MicaSense, Washington, DC, USA) and a Sony RX1RII digital camera (Sony, Tokyo, Japan) was used to acquire maize RGB images and MS images, respectively (Figure 2). Compared to fixed-wing UAVs and rotary-wing UAVs, the vertical takeoff and landing fixed-wing UAV combines the advantages of low requirements for takeoff and landing of rotary-wing UAVs and the long working time and fast speed of fixed UAVs. The central wavelength and bandwidth of the Altum camera are shown in Table 1. The image size is 2064 × 1544 pixels. Sony RX1RII has an image size of 7952 × 5340 pixels. In order to ensure the reliability of the data, the flight time was from 10:00 to 12:00 on a sunny and windless day. The flight height was 150 m for the acquisition of both types of images. For the MS camera, a 75% forward overlap and 75% side overlap were set, and for the RGB camera, the forward overlap was set to 72%, and the side overlap was set

to 75%. The spatial resolution of the acquired RGB images was 2.3 cm, and the spatial resolution of the MS images was 8.8 cm. For MS images, digital number (DN) values were converted to reflection values with the help of a white panel image taken before UAV take-off. Meanwhile, 46 ground control points (GCPs) were uniformly distributed in the field, and the longitude and latitude information of GCPs was measured based on the GEO7X (Trimble, Sunnyvale, CA, USA) global positioning system (GPS) with a centimeter-level error.



N<sub>1</sub>: 150 kg hm<sup>-2</sup>, N<sub>2</sub>: 180 kg hm<sup>-2</sup>, N<sub>3</sub>: 210 kg hm<sup>-2</sup>, N<sub>4</sub>: 240 kg hm<sup>-2</sup>; P<sub>1</sub>: 60 kg hm<sup>-2</sup>, P<sub>2</sub>: 75 kg hm<sup>-2</sup>, P<sub>3</sub>: 90 kg hm<sup>-2</sup>; K<sub>1</sub>: 75 kg hm<sup>-2</sup>, K<sub>2</sub>: 90 kg hm<sup>-2</sup>, K<sub>3</sub>: 105 kg hm<sup>-2</sup>; O<sub>1</sub>: 0 kg hm<sup>-2</sup>, O<sub>2</sub>: 22,500 kg hm<sup>-2</sup>, O<sub>3</sub>: 37,500 kg hm<sup>-2</sup>, O<sub>4</sub>: 45,000 kg hm<sup>-2</sup>, O<sub>5</sub>: 52,500 kg hm<sup>-2</sup>; D<sub>1</sub>: 50,000 plant hm<sup>-2</sup>, D<sub>2</sub>: 55,000 plant hm<sup>-2</sup>, D<sub>3</sub>: 60,000 plant hm<sup>-2</sup>, D<sub>4</sub>: 62,000 plant hm<sup>-2</sup>, D<sub>5</sub>: 64,000 plant hm<sup>-2</sup>; R<sub>1</sub>: 0 kg hm<sup>-2</sup>, R<sub>2</sub>: 3000 kg hm<sup>-2</sup>, R<sub>3</sub>: 4500 kg hm<sup>-2</sup>, R<sub>4</sub>: 6000 kg hm<sup>-2</sup>, R<sub>5</sub>: 7500 kg hm<sup>-2</sup>

**Figure 1.** Location and treatments of the study area.



**Figure 2.** The tail-seat vertical takeoff and landing fixed-wing UAV platform used in this study.

**Table 1.** Information for the visible to near-infrared bands of the Altum MS camera.

| Band Name     | Central Wavelength (nm) | Bandwidth (nm) |
|---------------|-------------------------|----------------|
| Blue          | 475                     | 20             |
| Green         | 560                     | 20             |
| Red           | 668                     | 10             |
| Red edge      | 717                     | 10             |
| Near-infrared | 840                     | 40             |

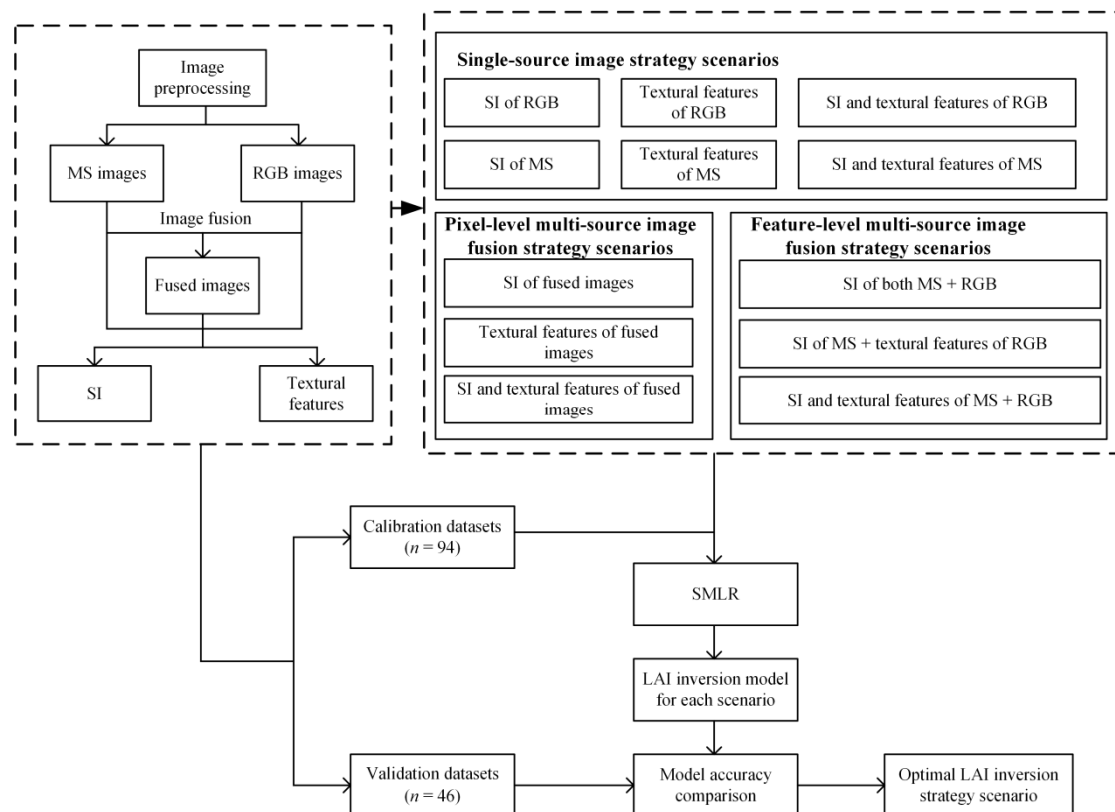
For UAV image processing, first, RGB and MS images were mosaicked using the Pix4Dmapper (Pix4D, Lausanne, Switzerland). Second, ArcGIS (Esri, Redlands, CA, USA) was used to perform geometrical correction of the mosaicked RGB images using GCPs. Third, the mosaicked MS image was geo-corrected based on the corrected RGB image.

### 2.2.2. Field-Measured Data

After the UAV was flown, areas with uniform maize growth were selected as representative sample points in each plot, and their locations were measured using the above-mentioned GEO 7X in NRTK mode. Then, the LAI 2200 Plant Canopy Analyzer (LI-COR Inc., Lincoln, NE, USA) was used to measure maize LAI according to the manual of the instrument. During this process, the distance between two adjacent rows was divided into four equal parts, and LAI was measured at each position and averaged [27].

### 2.3. Data Analysis

To analyze the effects of different modeling strategies on LAI prediction, this study included different scenarios based on RGB and MS image use. For each scenario, stepwise multiple linear regression (SMLR) was used to create the LAI prediction model. The results were compared and analyzed to show the advantages and disadvantages of each modeling strategy. The details of modeling are shown in Figure 3.

**Figure 3.** Main flow for different modeling strategies.

### 2.3.1. Different Prediction Strategy Scenarios

To compare the effects of different prediction strategies on LAI prediction, scenarios were designed and can be classified into three categories: (1) Single-source data strategy scenarios. This category included six scenarios: (i) spectral information (SI) of MS; (ii) SI of RGB; (iii) textural features of RGB; (iv) textural features of MS; (v) SI and textural features of MS; and (vi) SI and textural features of RGB. (2) Pixel-level multisource data fusion strategy scenarios. This category included three scenarios: (i) textural features of pixel-level fused images; (ii) SI of pixel-level fused images; and (iii) SI and textural features of pixel-level fused images. (3) Feature-level multisource data fusion strategy scenarios. This category included three scenarios: (i) SI of both MS + RGB; (ii) SI of MS + textural features of RGB; and (iii) SI and textural features of both MS + RGB.

Notably, the pixel-level fused image was obtained by the fusion method proposed by Selva et al. [28]. According to their study, the acquired RGB and MS images were fused according to Equations (1)–(5).

$$\hat{h}s_n = h s_{nexp} + g_n \cdot (X_n - \tilde{X}_{nexp}) \quad (1)$$

$$g_n = \frac{\text{cov}(h s_{nexp}, \tilde{X}_{nexp})}{\text{var}(\tilde{X}_{nexp})} \quad (2)$$

$$X_n = \sum_{m=1}^M w_{nm} \cdot HS_m + b_n \quad (3)$$

$$\bar{m} = \underset{m}{\operatorname{argmax}} \operatorname{corr}(h s_{nexp}, \tilde{HS}_{mexp}) \quad (4)$$

$$w_{nm} = \begin{cases} 1, & \text{if } m = \bar{m} \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

where  $\hat{h}s_n$  indicates the  $n$ th band of the fused high spatial resolution image;  $h s_{nexp}$  indicates the  $n$ th band of the interpolated MS image at high spatial resolution;  $g_n$  indicates a gain factor;  $\tilde{X}_{nexp}$  indicates the  $n$ th band of  $\tilde{X}_n$  interpolated at high spatial resolution;  $\tilde{X}_n$  indicates the  $n$ th band of  $X_n$  downsampled to a low spatial resolution;  $HS_m$  indicates the  $m$ th band of the original RGB image;  $\tilde{HS}_{mexp}$  indicates the  $m$ th band of the RGB image downsampled to a low spatial resolution, and then interpolated to a high spatial resolution;  $\bar{m}$  indicates the band in  $\tilde{HS}_{mexp}$  which has the best relationship with  $h s_{nexp}$ ;  $w_{nm}$  and  $b_n$  indicate the weight and the constant, respectively.  $b_n$  was set to 0 according to Selva et al. [28].

### 2.3.2. Image Feature Extraction

A spectral index effectively indicates the growth of vegetation by combining specific spectral bands to reduce the effects of background factors and enhance vegetation information [29]. UAV images are also rich in texture information which can indicate vegetation growth status apart from spectral information [30]. Therefore, in this study, first, for each type of image (RGB, MS, and fused images), the mean value of all pixels within a circular area (a radius equal to the row spacing) centered at the measured sampling point were calculated to correspond to the LAI value at that point. Then, commonly used spectral indices of MS/fused images (Table 2) and RGB images (Table 3) were calculated. Notably, for RGB image data, it has been shown that the normalized visible band has a better estimation capability than the original visible band [31]. Thus, the bands were normalized before being used for the calculation of the spectral indices of RGB images. In addition, the

textural features of the three types of images were also extracted, including mean (mea), variance (var), homogeneity (hom), contrast (con), dissimilarity (dis), entropy (ent), second moment (sec), and correlation (cor). During these processes, the gray-level co-occurrence matrix (GLCM) method was used to calculate the textural features of each band using ENVI 5.6 (Exelis VIS, Boulder, CO, USA).

**Table 2.** Spectral indices used in this study for MS and fused images.

| SI          | Full Name                                               | Formula                                           | Source |
|-------------|---------------------------------------------------------|---------------------------------------------------|--------|
| RVI         | Ratio Vegetation Index                                  | $NIR/R$                                           | [32]   |
| GRVI        | Green Ratio Vegetation Index                            | $NIR/G - 1$                                       | [33]   |
| DVI         | Difference Environmental Vegetation Index               | $NIR - R$                                         | [34]   |
| RESR        | Red-Edge Simple Ratio                                   | $RE/R$                                            | [35]   |
| NDVI        | Normalized Difference Vegetation Index                  | $(NIR - R)/(NIR + R)$                             | [36]   |
| NDRE        | Normalized Difference Red Edge Index                    | $(NIR - RE)/(NIR + RE)$                           | [37]   |
| EVI         | Enhanced Vegetation Index                               | $2.5(NIR - R)/(NIR + 6R - 7.5B + 1)$              | [38]   |
| MSAVI       | Modified Soil-Adjusted Vegetation Index                 | $(2NIR + 1 - \sqrt{(2NIR + 1)^2 - 8(NIR - R)})/2$ | [39]   |
| OSAVI       | Optimized Soil-Adjusted Vegetation Index                | $1.16(NIR - R)/(NIR + R + 0.16)$                  | [40]   |
| GNDVI       | Green Normalized Difference Vegetation Index            | $(NIR - G)/(NIR + G)$                             | [41]   |
| TVI         | Triangular Vegetation Index                             | $60(NIR - G) - 100(R - G)$                        | [42]   |
| SAVI        | Soil-Adjusted Vegetation Index                          | $1.5(NIR - R)/(NIR + R + 0.5)$                    | [43]   |
| RENDVI      | Red Edge Normalized Difference Vegetation Index         | $(RE - R)/(RE + R)$                               | [44]   |
| MCARI       | Modified Chlorophyll Absorption Ratio Index             | $((RE - R) - 0.2(RE - G))(RE/R)$                  | [45]   |
| TCARI       | Transformed Chlorophyll Absorption in Reflectance Index | $3((RE - R) - 0.2(RE - G)(RE/R))$                 | [46]   |
| TCARI/OSAVI | Combined Spectral Index                                 | $TCARI/OSAVI$                                     | [47]   |
| VARI        | Visible Atmospherically Resistant Index                 | $(G - R)/(G + R - B)$                             | [48]   |
| RDVI        | Re-normalized Difference Vegetation Index               | $(NIR - R)/\sqrt{(NIR + R)}$                      | [49]   |
| MSR         | Modified Simple Ratio                                   | $(NIR/R - 1)/\sqrt{(NIR/R + 1)}$                  | [50]   |
| NGI         | Normalized Green Index                                  | $G/(NIR + G + RE)$                                | [51]   |

$B$ ,  $G$ ,  $R$ ,  $RE$ , and  $NIR$  indicate the bands of the MS and fused image.

**Table 3.** Spectral indices used in this study for RGB images.

| SI    | Full Name                               | Formula                               | Source |
|-------|-----------------------------------------|---------------------------------------|--------|
| GBRI  | Green–Blue Ratio Index                  | $g/b$                                 | [13]   |
| GRRI  | Green–Red Ratio Index                   | $g/r$                                 | [52]   |
| BRRI  | Blue–Red Ratio Index                    | $b/r$                                 | [53]   |
| ExG   | Excess Green                            | $2g - r - b$                          | [54]   |
| ExR   | Excess Red                              | $1.4r - g$                            | [55]   |
| ExGR  | Excess Green Minus Excess Red           | $ExG - ExR$                           | [56]   |
| NGRDI | Normalized Green–Red Difference Index   | $(g - r)/(g + r)$                     | [57]   |
| RGBVI | Red–Green–Blue Vegetation Index         | $(g^2 - br)/(g^2 + br)$               | [58]   |
| CIVE  | Color Index of Vegetation               | $0.441r - 0.811g + 0.385b + 18.78745$ | [59]   |
| MExG  | Modified Excess Green                   | $1.262g - 0.884r - 0.311b$            | [60]   |
| GLA   | Green Leaf Algorithm                    | $(2g - r - b)/(2g + r + b)$           | [61]   |
| VARI  | Visible Atmospherically Resistant Index | $(g - r)/(g + r - b)$                 | [62]   |
| NGBDI | Normalized Green–Blue Difference Index  | $(g - b)/(g + b)$                     | [63]   |

$r$ ,  $g$ , and  $b$  indicate the normalized bands of the RGB image;  $r = R/(R + G + B)$ ,  $g = G/(R + G + B)$ , and  $b = B/(R + G + B)$ .

### 2.3.3. Model Design for Each Scenario

To analyze the effects of different strategies for designing an LAI prediction model and clearly show which variables are used in the model, the study used SMLR. SMLR is a linear regression model with multiple independent variables [64], which reduces the covariance problem by introducing variables into the model one by one; each time a variable is introduced, the variables already selected are tested one by one to ensure that

only significant variables are included in the regression equation. Before model design, the collected data were divided into calibration datasets ( $n = 94$ ) and validation datasets ( $n = 46$ ) at a ratio of 2:1. The calibration dataset was used to design the LAI prediction model, and validate the model based on the validation dataset. The adjusted determination coefficient ( $R^2_{adj}$ ), root mean square error ( $RMSE_{cal}$ ), and Akaike information criterion (AIC) during model calibration, and the determination coefficient ( $R^2$ ) and root mean square error ( $RMSE_{val}$ ) during model validation were used to evaluate model performance. Notably, all scenarios were based on the same calibration and validation datasets during the design of the LAI prediction model. In this study, SPSS (IBM, New York, USA) was used to implement SMLR modeling. Additionally, before designing the multiple linear models, the conditions were examined to make sure they satisfy the assumptions, such as linearity, equal variance, independence, and normality.

### 3. Results and Analysis

#### 3.1. LAI in the Field

The statistical analysis results of LAI obtained in the field experiment are shown in Table 4. The data show a large variation for both growth stages, indicating that different maize canopy LAI values were obtained in this study through the different experimental treatments. Overall, the LAI values ranged from 0.37 to 3.19, covering a wide range during these two maize growth stages, which are critical periods for fertilizer management; thus, the results can support the comparative analysis of different LAI prediction strategies. We should note that, as the aim of this study is to compare the performance of different strategies for LAI prediction model designing, the LAI values for each treatment are not shown herein for clarity.

**Table 4.** Statistical analysis results of LAI in the maize field experiment.

| Growth Stage | Number of Samples | Min. Value | Max. Value | Average Value | Standard Deviation | Variance | Coefficient of Variation (%) |
|--------------|-------------------|------------|------------|---------------|--------------------|----------|------------------------------|
| V4 stage     | 70                | 0.37       | 2.20       | 0.83          | 0.34               | 0.11     | 40.96                        |
| V9 stage     | 70                | 1.61       | 3.19       | 2.31          | 0.34               | 0.12     | 14.72                        |

#### 3.2. Comparison of the Original Image and Pixel-Level Fused Image

The RGB and MS images were fused in this study, and the images before and after fusion are shown in Figure 4. The fused image not only has the textural information from the RGB image but also has the spectral information from the MS image. Overall, a good pixel-level fused image was obtained, which ensures accurate assessments based on the pixel-level fused images in this study.

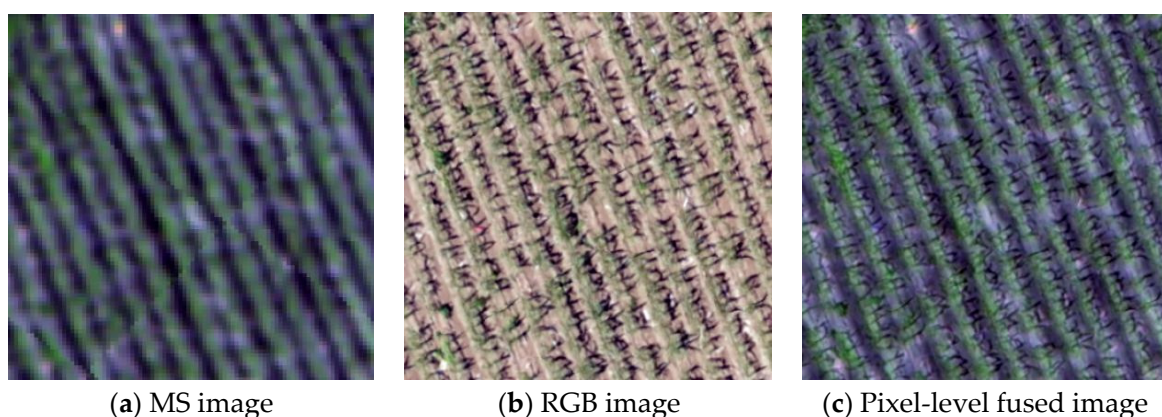


**Figure 4.** Comparison of images before and after fusion.

### 3.3. Results of LAI Inversion for the Single-Source Image Strategy Scenarios

The results of the LAI prediction models designed using a single-source data strategy are shown in Table 5. In summary, regardless of whether it was based on MS images or RGB images, the strategies that used both SI and textural features to design the model performed better than the strategies that used only SI or textural features. In addition, the LAI prediction model designed with SI and textural features of MS images had the best performance, which is also shown in Figure 5. We should note that, for each section, we only gave figures for best results for concision.

**Table 5.** LAI prediction results based on single-source image strategy scenarios.

| Strategy                        | Model                                                                           | Calibration |                     |         | Validation |                     |
|---------------------------------|---------------------------------------------------------------------------------|-------------|---------------------|---------|------------|---------------------|
|                                 |                                                                                 | $R^2_{adj}$ | RMSE <sub>cal</sub> | AIC     | $R^2$      | RMSE <sub>val</sub> |
| SI of MS                        | $y = 13.55 * NDRE - 6.293 * NDVI + 0.491$                                       | 0.838       | 0.315               | −211.26 | 0.897      | 0.283               |
| Textural features of MS         | $y = 0.154 * nir\_mea - 0.225 * re\_mea + 0.184 * b\_mea + 0.743$               | 0.817       | 0.332               | −198.62 | 0.881      | 0.303               |
| SI and textural features of MS  | $y = 14.944 * NDRE - 6.424 * NDVI + 4.603 * re\_ent - 0.028 * nir\_con - 9.202$ | 0.859       | 0.291               | −221.89 | 0.899      | 0.273               |
| SI of RGB                       | $y = -66.07 * BRRI - 137.778 * ExR - 39.775 * GBRI + 123.845$                   | 0.819       | 0.332               | −199.42 | 0.875      | 0.316               |
| Textural features of RGB        | $y = -0.348 * R\_mea + 0.335 * B\_mea + 11.235 * G\_sec + 2.698$                | 0.826       | 0.325               | −203.29 | 0.902      | 0.289               |
| SI and textural features of RGB | $y = 13.619 * BRRI - 0.093 * B\_mea + 12.116 * G\_sec - 8.27$                   | 0.833       | 0.319               | −207.01 | 0.903      | 0.283               |

$R$ ,  $G$ , and  $B$  indicate the Red, Green, and Blue bands of the RGB image;  $b$ ,  $re$ , and  $nir$  indicate the blue, red-edge, and near-infrared bands of the MS image, respectively;  $B_*$ ,  $G_*$ , and  $R_*$  indicate the \* textural values of the bands in the RGB image, respectively; and  $b_*$ ,  $re_*$ , and  $nir_*$  indicate the \* textural values of the bands in the MS image, respectively.

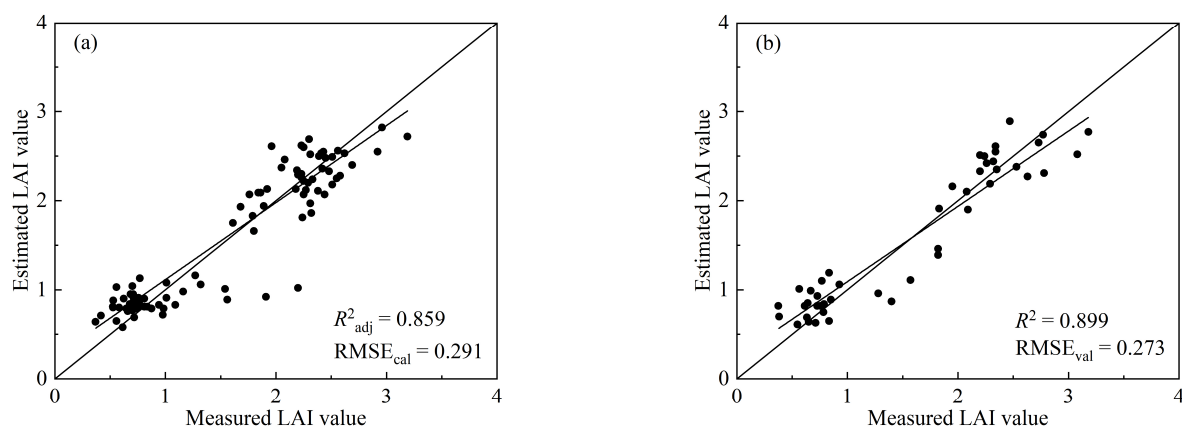


**Figure 5.** Results obtained from the model created with the SI and textural features of MS images to predict LAI. (a) Calibration; (b) validation.

For the MS image, when the designed LAI prediction model used both SI and textural features, two spectral indices ( $NDVI$  and  $NDRE$ ) and two textural features ( $re\_ent$  and  $nir\_con$ ) were selected as independent variables in the model. While the  $R^2_{adj}$ ,  $RMSE_{cal}$ , and AIC of the model were 0.859, 0.291, and −221.89 during calibration, the validation values of  $R^2$  and  $RMSE_{val}$  were 0.899 and 0.273. Considering the accuracy of the models, the SI model was followed, with  $NDVI$  and  $NDRE$  selected as independent variables. The  $R^2_{adj}$ ,  $RMSE_{cal}$ , and AIC of the model were 0.838, 0.315, and −211.26 during calibration, while the  $R^2$  and  $RMSE_{val}$  were 0.897 and 0.283 during validation. The LAI model designed

with only textural features performed the worst, with *nir\_mea*, *re\_mea*, and *b\_mea* selected as independent variables. It had an  $R^2_{adj}$  of 0.817,  $RMSE_{cal}$  of 0.332, and AIC of  $-198.62$  during calibration, and an  $R^2$  of 0.881 and  $RMSE_{val}$  of 0.303 during validation.

For the RGB image, when the designed LAI prediction model used both SI and textural features, one spectral index (*BRRI*) and two textural features (*B\_mea* and *G\_sec*) were selected as independent variables in the model. While the  $R^2_{adj}$ ,  $RMSE_{cal}$  and AIC of the model were 0.833, 0.319, and  $-207.01$  during calibration, the validation values of  $R^2$  and  $RMSE_{val}$  were 0.903 and 0.283 (Table 5). Different from the MS image, the prediction model designed with only textural features performed better than the model designed with only SI. This may be because the RGB image has a higher spatial resolution and lower spectral information than the MS image, making the textual features of the image more important than SI for LAI prediction. For the model designed with only textural features, *R\_mea*, *B\_mea*, and *G\_sec* were selected as the independent variables. The calibration  $R^2_{adj}$ ,  $RMSE_{cal}$ , and AIC of the model were 0.826, 0.325, and  $-203.29$ , while the validation  $R^2$  and  $RMSE_{val}$  were 0.902 and 0.289. For the LAI prediction model with SI, *BRRI*, *ExR* and *GBRI* were selected as the independent variables. The  $R^2_{adj}$ ,  $RMSE_{cal}$ , and AIC were 0.819, 0.332, and  $-199.42$  during calibration, and the  $R^2$  and  $RMSE_{val}$  were 0.875 and 0.316 during validation.

### 3.4. Results of LAI Inversion for Pixel-Level Data Fusion Strategy Scenarios

The results of the LAI prediction models designed using the pixel-level data fusion scenarios are shown in Table 6. The model designed with both SI and textural features had the best accuracy, with two spectral indices (*NDRE* and *NDVI*) and three textural features (*g\_cor*, *r\_var*, and *b\_var*) selected as independent variables. It had calibration  $R^2_{adj}$  of 0.870,  $RMSE_{cal}$  of 0.277, and AIC of  $-229.20$ , and validation  $R^2$  of 0.894 and  $RMSE_{val}$  of 0.284 (Figure 6). The performance of the model designed using only textural features followed, with *nir\_mea*, *b\_mea*, *g\_cor*, and *g\_mea* selected as the independent variables. It had calibration  $R^2_{adj}$  of 0.861,  $RMSE_{cal}$  of 0.288, and AIC of  $-223.82$ , and validation  $R^2$  of 0.898 and  $RMSE_{val}$  of 0.280. The LAI prediction model designed with only SI had the worst performance. For this model, *NDVI* and *NDRE* were selected as the independent variables, with calibration  $R^2_{adj}$  of 0.837,  $RMSE_{cal}$  of 0.316, and AIC of  $-210.65$ , and validation  $R^2$  of 0.896 and  $RMSE_{val}$  of 0.285.

**Table 6.** LAI prediction results based on pixel-level data fusion strategy scenarios.

| Strategy                              | Model                                                                                        | Calibration |              |           | Validation |              |
|---------------------------------------|----------------------------------------------------------------------------------------------|-------------|--------------|-----------|------------|--------------|
|                                       |                                                                                              | $R^2_{adj}$ | $RMSE_{cal}$ | AIC       | $R^2$      | $RMSE_{val}$ |
| SI of fused image                     | $y = 13.463 * NDRE - 6.228 * NDVI + 0.483$                                                   | 0.837       | 0.316        | $-210.65$ | 0.896      | 0.285        |
| Textural features of fused image      | $y = 0.093 * nir\_mea + 0.232 * b\_mea + 4.07 * g\_cor - 0.312 * g\_mea - 1.169$             | 0.861       | 0.288        | $-223.82$ | 0.898      | 0.280        |
| SI + textural features of fused image | $y = 8.399 * NDRE - 3.523 * NDVI + 2.925 * g\_cor - 1.564 * r\_var + 2.089 * b\_var - 0.757$ | 0.870       | 0.277        | $-229.20$ | 0.894      | 0.284        |

*b*, *g*, *r*, and *nir* indicate the blue, green, red, and near-infrared bands; *b\_\**, *g\_\**, *r\_\**, and *nir\_\** indicate the \* textural values of the bands in the fused image, respectively.

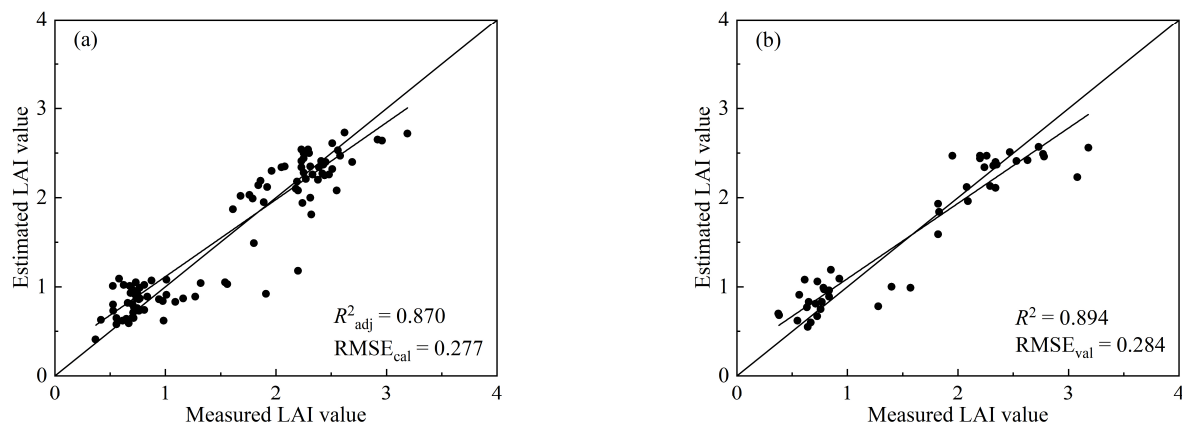


**Figure 6.** Results obtained from the model created with the SI and textural features of pixel-level fused images to predict LAI. (a) Calibration; (b) validation.

### 3.5. Results of LAI Inversion for Feature-Level Data Fusion Strategy Scenarios

The results of the LAI prediction models designed using the feature-level data fusion scenarios are shown in Table 7. The LAI prediction model designed using SI and textural features of both MS + RGB images had the best accuracy, with two spectral indices (*NDRE* and *NDVI*) and two textural features (*re\_ent* and *nir\_con*) from the MS image, and one spectral index (*GBRI*) and two textural features (*R\_mea* and *G\_sec*) from the RGB image selected as the independent variables. It had calibration  $R^2_{adj}$  of 0.883,  $RMSE_{cal}$  of 0.261, and AIC of  $-236.61$ , and validation  $R^2$  of 0.905 and  $RMSE_{val}$  of 0.263 (Figure 7). The performance of the LAI prediction model created with the SI of the MS image and textural features of the RGB image followed. For this model, two spectral indices of the MS image (*NDRE* and *NDVI*) and one textural feature (*G\_cor*) of the RGB image were selected as the independent variables, with calibration  $R^2_{adj}$  of 0.849,  $RMSE_{cal}$  of 0.303, and AIC of  $-216.46$ , and validation  $R^2$  of 0.890 and  $RMSE_{val}$  of 0.292. For the LAI prediction model with the SI of both the MS and RGB images, two spectral indices (*NDRE* and *NDVI*) and one spectral index (*BRRI*) of the RGB image were selected as the independent variables; the  $R^2_{adj}$ ,  $RMSE_{cal}$ , and AIC were 0.844, 0.308, and  $-213.44$  during calibration, and the  $R^2$  and  $RMSE_{val}$  were 0.902 and 0.277 during validation.

**Table 7.** LAI prediction results based on feature-level data fusion strategy scenarios.

| Strategy                             | Fitting Model                                                                                                                        | Calibration |              |           | Validation |              |
|--------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------|-------------|--------------|-----------|------------|--------------|
|                                      |                                                                                                                                      | $R^2_{adj}$ | $RMSE_{cal}$ | AIC       | $R^2$      | $RMSE_{val}$ |
| SI of MS + RGB                       | $y = 10.08 * NDRE - 4.389 * NDVI + 3.734 * BRRI - 2.369$                                                                             | 0.844       | 0.308        | $-213.44$ | 0.902      | 0.277        |
| SI of MS + textural features of RGB  | $y = 12.793 * NDRE - 5.693 * NDVI + 3.53 * G_{cor} - 1.839$                                                                          | 0.849       | 0.303        | $-216.46$ | 0.890      | 0.292        |
| SI and textural features of MS + RGB | $y = 11.61 * NDRE - 3.485 * NDVI + 5.849 * re_{ent} + 16.185 * G_{sec} - 0.074 * R_{mea} - 0.036 * nir_{con} - 3.013 * GBRI - 8.056$ | 0.883       | 0.261        | $-236.61$ | 0.905      | 0.263        |

*R* and *G* indicate the red and green bands of the RGB image, respectively; *re* and *nir* indicate the red-edge and near-infrared bands of the MS image, respectively; *G\_\** and *R\_\** indicate the \* textural values of the bands in the RGB image, respectively; *re\_\** and *nir\_\** indicate the \* textural values of the bands in the MS image.

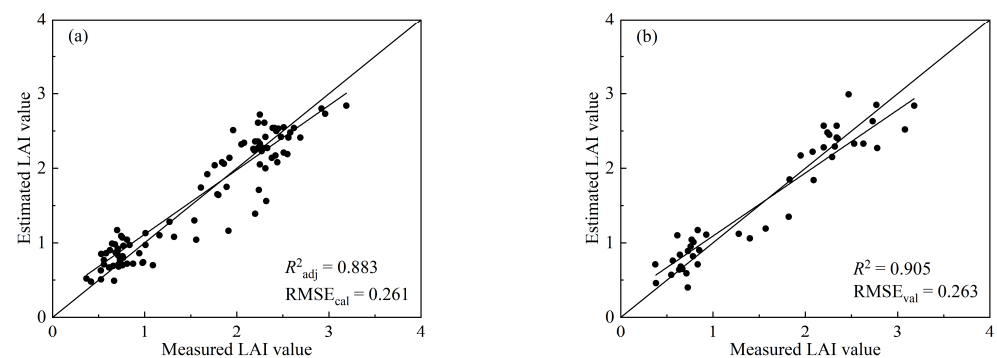


**Figure 7.** Results obtained from the model created with the SI and textural features of both MS + RGB images to predict LAI. (a) Calibration; (b) validation.

## 4. Discussion

### 4.1. Comparison with Previous Studies

In this study, UAV RGB, MS, and fused images were used to make single-source data, pixel-level fusion data, and feature-level fusion data scenarios for creating LAI prediction models based on the SMLR method. The  $R^2_{adj}$  of models varied from 0.817 to 0.883 and the RMSE varied from 0.261 to 0.332 during calibration, while the  $R^2$  varied from 0.875 to 0.905 and the RMSE varied from 0.263 to 0.316 during validation. Considering previous studies of LAI prediction, Zhang et al. [18] designed a maize LAI estimation model with the SVR method using spectral and textural features of UAV MS images, and the model had  $R^2$  values of 0.877 during validation. Combining spectral and textural indices extracted from UAV MS images, Sun et al. [65] used the SVR method to design a maize LAI prediction model, with an  $R^2$  of 0.806 during calibration and an  $R^2$  of 0.813 during validation. Liu et al. [25] combined features extracted from UAV MS, RGB, and TIR images to predict maize LAI with the PLSR method; the  $R^2$  of calibration was 0.78 and the  $R^2$  of validation was 0.70. Compared with the above studies, the results of the prediction models created in this study under different scenarios are within a reasonable range.

Moreover, due to limitations created by time and weather conditions, the timeframe for crop growth status monitoring is short. Thus, for large areas, an efficient means for UAV image acquisition is urgently needed. In this study, we adopted a self-designed tail-seat vertical takeoff and landing fixed-wing UAV platform to acquire UAV images. As mentioned before, the UAV platform uses the rotor-wing mode to takeoff and land and the fixed-wing mode to acquire data, which has the advantage of flexibility without the need for an aircraft runway and can also acquire data more efficiently than rotor-wing UAV platforms. The results of this study support the application of our designed vertical takeoff and landing fixed-wing UAV for crop status monitoring.

### 4.2. Optimal LAI Prediction Strategy

In this study, different LAI prediction strategies were compared, including single-source image-based, pixel-level multisource data fusion, and feature-level multisource data fusion strategies. The results indicate that (1) compared with using only SI or textural features, the LAI prediction model created with a combination of SI and textural features had the best performance. The results validate the accuracy of previous relevant studies [16,66]. This may be because SI always has saturation problems at medium to high LAI levels [67], while textural features can describe the spatial geometric information of plants. Combining these data sources with spectral information could solve the saturation problem to a certain extent and improve the LAI prediction accuracy. (2) Compared with LAI prediction models created using single-source images, the results of LAI prediction models created with multisource image fusion strategies performed better. This is probably because data fusion can combine the advantages of high spatial resolution in RGB images and multiple bands containing red-edge, and near-infrared bands in MS images,

which is critical for LAI prediction. Furthermore, this study documented that the LAI prediction models created with the pixel-level fusion strategy performed better than the models created with single-source data, which have rarely been reported for crop parameter prediction using UAV images in existing studies. (3) For different data fusion strategies, the LAI prediction model created with the feature-level data fusion strategy performed better than the model created with the pixel-level data fusion strategy. This may be because LAI prediction models based on the pixel-level fusion strategy have flaws caused by spatial registration errors between images and errors created by the method used for pixel-level fusion. LAI prediction models created with the feature-level fusion strategy directly extract features from different images separately and then combine them using statistical methods, reducing the errors during data preprocessing. In summary, from the above analysis, a feature-level data fusion method is recommended for creating an LAI prediction model when multisource image data are available.

#### 4.3. Limitations and Future Work

The data measured in this study are limited to the topdressing management stage of maize (V4–V9), and the data in the later growth stage were not collected, which limited the ability of the model developed in this study to be applied to other growth stages of maize. Therefore, to apply the best LAI prediction model created in this study in different scenarios, it is necessary to collect a large dataset from different locations, years, and growth stages to further optimize the model in the future. Moreover, the aim of this study is to determine the best strategy for using multisource UAV images to predict LAI, so only SMLR was used because it is simple and can clearly analyze the independent variables used in the model. For the future, it is possible to use more complex methods, such as deep learning methods, to predict LAI based on feature-level fusion strategies.

### 5. Conclusions

In this study, different treatments (different amounts of organic fertilizer, inorganic fertilizer, and straw returned to the field, and different planting densities) were used to obtain maize plants with different growth statuses, and field LAI data and corresponding UAV MS and RGB images were measured at different growth stages. Single-source image-based scenarios, pixel-level multisource data fusion scenarios, and feature-level multisource data scenarios were designed based on these data, and LAI prediction models were created under different scenarios, leading to a recommendation of the optimal LAI prediction strategy. The results showed that (1) combining spectral and texture features to predict LAI performed better than using only spectral or texture information; (2) compared with using a single-source image, using a multisource data fusion strategy can increase the accuracy of the model in predicting LAI; and (3) among different multisource data fusion strategies, the feature-level data fusion strategy performed better than the pixel-level fusion strategy in the LAI prediction model. Among all the LAI prediction models, the prediction model that used SI and textural features of both MS + RGB had the highest accuracy, with calibration  $R^2_{adj}$  of 0.883,  $RMSE_{cal}$  of 0.261, and AIC of  $-236.61$ , and validation  $R^2$  of 0.905 and  $RMSE_{val}$  of 0.263. The feature-level multisource data fusion strategy is recommended as the optimal strategy for creating an LAI prediction model in this study, providing a reference for people to more accurately estimate crop LAI in the field.

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**Data Availability Statement:** The data presented in this study are available upon request from the corresponding author. The data are not publicly available due to their use in subsequent studies.

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**Conflicts of Interest:** The authors declare no conflict of interest.

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