Tradeoffs in the Spatial and Spectral Resolution of Airborne Hyperspectral Imaging Systems: A Crop Identification Case Study

Jianxin Jia, Jinsong Chen, Xiaorou Zheng, Yueming Wang, Shanxin Guo, Haibin Sun, Changhui Jiang, Mika Karjalainen, Kirsi Karila, Zhiyong Duan, Tinghuai Wang, Chong Xu, Juha Hyyppä, and Yuwei Chen

Abstract—Airborne hyperspectral images are used for crop identification with a high classification accuracy because of their high spectral resolution, spatial resolution, and signal-to-noise ratio (SNR). However, the tradeoffs between the three core parameters of a hyperspectral imager (SNR, spatial resolution, and spectral resolution) should be considered for designing an efficient imaging system. Only a few reported studies on the analysis of the impact of SNR on identification accuracy are available. Further, the tradeoffs and mutual interactions among these parameters are rarely considered. In this empirical study, our aim was to understand the relationship among the core parameters and their effects on crop identification accuracy by analyzing the tradeoffs and mutual interactions among these parameters. We analyzed the hyperspectral images of a typical plain agricultural area in Xiongan, China, acquired by the newly developed sensor airborne multimodular imaging spectrometer (AMMIS). The fundamental images were transformed to form datasets with different ranges of spectral resolution, spatial resolution, and SNR using data reconstruction methods. We adopted the classification and regression tree (CART), random forest (RF), and k-nearest neighbor (kNN) classifiers, and observed the overall accuracy (OA) across the degraded hyperspectral datasets. The experimental results indicated that the OA decreased with a decreasing SNR. As the spectral resolution became coarser, the OA first increased, plateaued, and then decreased. However, the OA increased with decreasing spatial resolution. This study was performed with the goal of bridging the knowledge gap between the back-end hyperspectral sensor designing and its front-end applications.

Index Terms—Hyperspectral imager, parameter optimization, system design, tradeoff.

Jianxin Jia is with the Department of Photogrammetry and Remote Sensing, Finnish Geospatial Research Institute, 02430 Kirkkonummi, Finland, and also with the Center for Geo-Spatial Information, Shenzhen Institute of Advanced Technology, Chinese Academy of Sciences, Shenzhen 518055, China (e-mail: jianxin.jia@nls.fi).

Jinsong Chen, Xiaorou Zheng, and Shanxin Guo are with the Center for Geo-Spatial Information, Shenzhen Institute of Advanced Technology, Chinese Academy of Sciences, Shenzhen 518055, China (e-mail: xiaorou.zheng@siat.ac.cn).

Yueming Wang is with the Key Laboratory of Space Active Opto-Electronics Technology, Shanghai Institute of Technical Physics, Chinese Academy of Sciences, Shanghai 200083, China (e-mail: wangym@mail.sitp.ac.cn).

Haibin Sun is with the Key Laboratory of Intelligent Infrared Perception, Shanghai Institute of Technical Physics, Chinese Academy of Sciences, Shanghai 200083, China.

Changhui Jiang, Mika Karjalainen, Kirsi Karila, Juha Hyyppä, and Yuwei Chen are with the Department of Photogrammetry and Remote Sensing, Finnish Geospatial Research Institute, 02430 Kirkkonummi, Finland (e-mail: yuwei.chen@nls.fi).

Zhiyong Duan is with the School of Physical and Microelectronics, Zhengzhou University, Zhengzhou 450001, China.

Tinghuai Wang is with Huawei Helsinki Research Center, 00180 Helsinki, Finland.

Chong Xu is with the Jihua Laboratory, Foshan 528200, China.

Digital Object Identifier 10.1109/TGRS.2021.3096999

I. INTRODUCTION

THE accurate identification of vegetation species plays an essential role in forest management, environmental monitoring, ecosystem detection, and agricultural decisions [1], [2]. The identification of forest cover types and the spatial distribution of tree species are the basic requirements for sustainable forest management and contribute to the study of scientific issues related to forest ecosystem function [3]. The accurate classification of mangrove species is a crucial part of mangrove inventories and wetland ecological management [4]. Thematic vegetation classification is usually associated with environmental issues, such as biodiversity, carbon storage, and carbon flux [5]–[7]. Crop identification and classification provide necessary information support for many agricultural decisions and precision management [8], [9]. Hyperspectral image data have been increasingly used in crop identification research, owing to their spatial texture and continuous spectral characteristics [10], [11]. In particular, the demand for airborne hyperspectral imaging systems with high spatial and spectral resolutions is increasing for generating accurate maps [12].

The core parameters, i.e., spatial resolution, spectral resolution, and signal-to-noise ratio (SNR), of the hyperspectral imager are the main factors that affect the crop species identification accuracy [13], [14]. Hyperspectral images with high spatial resolution, spectral resolution, and SNR yield high identification accuracy. However, there are tradeoffs between the three core parameters when designing a hyperspectral imaging system. This implies that an increase in one parameter will decrease the other two parameter values [15]. As evident

from (1) and (2), the SNR of a hyperspectral imaging system is related to many factors, such as the optical aperture (D_0), instantaneous field of view (IFOV; β), sensor integration time (T_{int}), solar altitude (θ), system noise (N_{noise}), wavelength range (λ), solar spectrum irradiance [$E(\lambda)$], optical transmittance [$\tau_o(\lambda)$], atmosphere transmittance [$\tau_a(\lambda)$], ground surface albedo [$\rho(\lambda)$], and quantum efficiency of the detector [$\eta(\lambda)$]. Because the IFOV, detector size (d), focal length (f), ground sample distance (GSD), detection distance (H), and F-number ($F\#$) are all related to each other, the detector size can also affect the SNR.

$$\text{SNR} = \frac{D_0^2 \beta^2 T_{\text{int}} \sin\theta}{4hcN_{\text{noise}}} \int_{\lambda_1}^{\lambda_2} E(\lambda)\tau_o(\lambda)\tau_a(\lambda)\rho(\lambda)\eta(\lambda)\lambda d\lambda$$

$$\beta = \frac{d}{f} = \frac{\text{GSD}}{H}, \quad F\# = \frac{f}{D_0} \tag{1}$$

Then,

$$\text{SNR} = \frac{d^2 T_{\text{int}} \sin\theta}{4(F\#)^2 hcN_{\text{noise}}} \int_{\lambda_1}^{\lambda_2} E(\lambda)\tau_o(\lambda)\tau_a(\lambda)\rho(\lambda)\eta(\lambda)\lambda d\lambda \tag{2}$$

where h is the Planck's constant and c represents the velocity of light. Thus, to improve the SNR, a detector with a large pixel size can be used; however, it will decrease the spatial resolution (GSD). Another approach is to design a system that can accept light from a wider spectral interval to increase light collection; however, in this case, the spectral resolution will be decreased. Balancing these tradeoffs to achieve the best configuration of the three parameters for improving the classification accuracy will impact the instrument design and its actual applications. However, to the best of our knowledge, this scientific issue has not been thoroughly analyzed and studied because of the knowledge gap between the design of hyperspectral imaging systems and the application of hyperspectral data. For example, the airborne multimodular imaging spectrometer (AMMIS) is a recently developed hyperspectral imaging system, which has been applied in many civilian applications in China [16]. Initially, the requirements of various applications, such as in forestry, agriculture, geology, and oceanography, were thoroughly studied to design the instrument parameters. However, using the feedback obtained from recent applications and the joint analysis performed by professionals working in this field, it has been found that the application of AMMIS for crop species identification can be improved further by optimizing the parameter configurations. One of the keys to achieve this goal is to accurately understand the relationship between the tradeoffs of the core parameters and the crop identification accuracy.

The relationship between the hyperspectral sensor parameters and the identification accuracy of crops has been described in several reports. However, these reported studies merely focused on the spatial and spectral resolutions. Roth *et al.* [17] spatially aggregated airborne visible/infrared imaging spectrometer (AVIRIS) datasets to 20, 40, and 60 m resolutions to study the variations in the accuracy of vegetation species classification. They found that the best accuracy was obtained at a spatial resolution of 40 m; however, some finer species information may be lost at coarser resolutions. Ghosh *et al.* [13] mapped tree species of a central European

forest using two airborne and one spaceborne hyperspectral imagers across three spatial scales of 4, 8, and 30 m, respectively. The experimental results showed that the overall classification accuracy of the 8-m resolution image was slightly higher than that of the 4-m resolution image for the study area. From similar studies [18]–[22], it can be concluded that many factors such as target scale, application requirement, and geographical environment affect the spatial resolution requirement of hyperspectral imagery [7], [14], [23], [24]. Dalponte *et al.* [12] conducted an empirical study to understand the impact of spectral resolution and classifier complexity on the classification accuracy of forest areas obtained with an airborne imaging spectrometer for different applications. In this case, the classification accuracy was analyzed with changing spectral resolution. Studies related to the spatial and spectral resolutions have significantly contributed to the identification of crop species. However, the results obtained from these studies are not sufficient to design the most suitable hyperspectral imaging system that can achieve the highest identification accuracy.

The SNR has long been recognized as a critical parameter in hyperspectral imager design; however, only a few scientists have investigated its impact on crop species identification. In some existing studies, it has been speculated that a higher SNR results in higher accuracy; however, it cannot be confirmed owing to the unavailability of convincing quantitative experimental demonstrations [12], [13]. To address this issue, scientists may require professional knowledge about instrument design. For example, the designers of the operational land imager instrument reported the impact of improved SNR on the algorithm implementation in three geoscience applications [25]. The spatial resolution, spectral resolution, and SNR should be considered synchronously owing to their tradeoffs and mutual interactions in the hyperspectral imaging system. Finer spatial resolution may be useful for identification; however, when the spectral resolution or SNR decreases, will the accuracy improve? Does a hyperspectral dataset with a finer spatial resolution provides better classification accuracy than that with a finer spectral resolution in terms of crop identification? How can the hyperspectral imager's core parameters be configured to achieve the best results in crop identification applications? To address these scientific problems, the relationship between the core parameters of the hyperspectral imager and the identification accuracy of crops should be studied, and the tradeoffs among these parameters should be considered.

The overarching aim of conducting this study was to use crop identification as an example to investigate the influence of spatial resolution, spectral resolution, and SNR of hyperspectral imagers on general classification tasks by considering the tradeoffs and mutual interactions among these parameters. In particular, we attempted to answer the following questions.

1) What effect does the instrument's SNR have on crop identification accuracy, and how to determine these effects quantitatively?
2) Among the spatial resolution, spectral resolution, and SNR, which is the most critical factor that affects crop identification?

Fig. 1. (a) AMMIS. (b) Aircraft platforms.

3) How can the current AMMIS configuration be optimized to achieve the best performance for crop identification? How to design an airborne hyperspectral imaging system, especially for identifying crops in the future?

To address these questions, we analyzed hyperspectral imagery acquired by the AMMIS over a plain agricultural area in North China (Xiongan, Hebei Province). The main species of the selected area are economic crops. The original image data had spatial and spectral resolutions of 0.5 and 2.4 nm, respectively. The spatial and spectral resolutions of the images were degraded to varying ranges using different data reconstruction methods to form the datasets. We adopted classification and regression tree (CART), random forest (RF), and k-nearest neighbors (kNNs) classifiers and observed the variation in the overall accuracy (OA) across different hyperspectral datasets. The impact of the SNR was also considered synchronously and quantitatively analyzed. The optimal configuration of AMMIS for identifying the crops in the selected study area was achieved using the relationship between the three core parameters and the classification accuracy. An improved understanding of the tradeoffs of core parameters is necessary to set up an optimized processing chain while designing a hyperspectral instrument for crop classification. The results of this study can be used to bridge the knowledge gap between the back-end hyperspectral sensor design and its front-end applications.

II. INSTRUMENT AND DATASETS

A. AMMIS

The AMMIS, developed by the Shanghai Institute of Technical Physics (SITP), Chinese Academy of Science (CAS), is the latest airborne hyperspectral imaging system used for civilian applications. As shown in Fig. 1, the AMMIS has three modules covering the visible near-infrared (VNIR), shortwave infrared (SWIR), and longwave infrared (LWIR) spectral ranges. Each module is equipped with three spectrometers, and a large FOV of 40° was achieved using the FOV stitching technology. Nine spectrometers were integrated into one imaging system to ensure that the hyperspectral images from VNIR to LWIR could be acquired. The final system was integrated successfully to meet the precision requirement of spectral registration by adapting the mount interface for the PAV80 Gyro-stabilized platform [26]. Compared with other existing airborne hyperspectral imagers, AMMIS is highly competitive in terms of spectral range, spectral resolution, spatial resolution, and FOV, as evident from Table I [15]. Initially, we comprehensively investigated the requirements of various applications, such as forestry, agriculture, geology, and oceanography, to design the instrument. Since 2016, more than ten flight campaigns have been conducted on various aircraft platforms (Fig. 1), and large amounts of hyperspectral image data have been obtained.

B. Study Area and Data Collection

The dataset was collected from 3:40 pm to 4:03 pm on October 3, 2017. The SITP and the Institute of Remote Sensing Applications (IRSA) of CAS jointly completed a flight campaign in Xiongan, Hebei Province, China. Xiongan is another epoch-making national-level area delineated by the State Council of China on April 1, 2017, after the Pudong New Area of Shanghai and Shenzhen Special Economic Zone, and belongs to the Baoding City, Hebei Province. The area is

TABLE I
COMPARISON OF SOME TYPICAL AIRBORNE HYPERSPECTRAL SENSORS

Name	Designer	Wavelength range (μm)	Channels	Spectral resolution (nm)	IFOV (mrad)	FOV (°)
AISA-FENIX 1K	Specim, Finland	0.38–0.97, 0.97–2.5	348, 246	≤4.5, ≤12	0.68	40
APEX	ESA, Switzerland, Belgian	0.372–1.015 0.94–2.54	114, 198	0.45–0.75, 5–10	0.489	28.1
AVIRIS-NG	NASA/JPL, USA	0.38–2.52	430	5	1	34
CASI-1500/ SASI-1000A / TASI-600	Itres, Canada	0.38–1.05, 0.95–2.45, 8–11.5	288, 100, 32	2.3, 15, 110	0.49, 1.22, 1.19	40
AMMIS	China	0.4–0.95, 0.95–2.5, 8–12.5	256, 512, 128	2.34, 3, 32	0.25, 0.5, 1	40
SYSIPHE	France and Norway	0.4–1, 0.95–2.5, 3–5.4, 8.1–11.8	560 (total)	5, 6.1, 11 cm⁻¹, 5 cm⁻¹	0.25	15

mainly composed of plains and located in the mid-latitudes with a warm monsoon continental climate. The aircraft was flown at an altitude of 2000 m, covering an area of 1320 km². The study area is the Matiwan village of the Xiongan New Area in Hebei Province, China, which has 12 types of categories containing nine economic crop species.

In this study, the hyperspectral image data of the VNIR module of AMMIS were used, with a spatial resolution of 0.5 m and spectral resolution of 2.4 nm. We used the POS610 position and orientation system for obtaining high-accuracy attitude angles to correct the distortion caused by the residual error of the PAV80 Gyro-stabilized platform; this also enabled high-precision geometric correction and band registration. To complete the radiometric calibration, field calibration experiments, using some diffuse reflection boards, and calibration in the laboratory, using an integrating sphere, were performed. The residual stripe noise was removed using several state-of-the-art destriping approaches [16]. The one-level hyperspectral image data with 256 bands could be used after performing the radiometric calibration and geometric correction. The data were acquired in cloud-free weather to ensure that the hyperspectral image data were less affected by clouds and the atmosphere. To obtain accurate information about the categories in the study area, the IRSA performed simultaneously ground investigations as well. A total of 57 sample areas were investigated, 39 field photos were taken, and data on 12 types of categories were obtained, as shown in Table II. Fig. 2 shows the RGB image acquired by AMMIS and the manually labeled land cover map of the study area.

III. METHODOLOGY

A. Evaluation and Testing of SNR

The SNR is one of the major factors that influences the performance of remote-sensing instruments and is therefore crucial for remote-sensing data applications [27], [28]. It can be evaluated using the design values of the instrument parameters before developing the instrument and tested through auxiliary equipment after the instrument is developed. As indicated

TABLE II
SAMPLE SIZE OF DIFFERENT LAND REGIONS IN XIONGAN NEW AREA

Label	Common name / Latin name	Sample size
1	Box elder / *Acer negundo*	225,647
2	Willow / *Salix*	180,766
3	Paddy / *Oryza sativa*	452,144
4	Chinese Scholar Tree / *Sophora japonica*	475,591
5	Ash / *Fraxinus chinensis*	169,342
6	Water	165,647
7	Post-harvest field	193,830
8	Corn / *Zea mays*	59,165
9	Pear / *Pyrus*	1,026,513
10	White poplar / *Populus*	91,072
11	Weeds	421,790
12	Peach / *Amygdalus*	65,514
Total samples		3,527,021

by (1) and (2), the performance of the hyperspectral imager can be evaluated using suitable SNR calculation models, before developing the instrument [15], [29], [30]. Laboratory-based [31] and dark current [32] methods are always used to test the SNR after the designers develop the instrument. In these methods, the SNR testing is performed using some unique and uniform devices, such as integrating spheres and diffuse reflection boards. Generally, a hyperspectral imager takes multiframe images of a uniform object (i.e., the integrating sphere or diffuse reflection board). Finally, the ratio of the average value of the response digital numbers (DNs) values for the multiframe images to the standard deviation is used as the SNR. Fig. 3 shows the result of SNR testing of the VNIR sensor (of the AMMIS) tested by the SITP using some diffuse reflection targets (Labsphere Inc., USA). The calibration data were obtained by performing an in-flight calibration experiment. Several image methods, such as the homogeneous area method [33], local means and local standard deviations [34], geo-statistics [35], and decorrelation [36], [37] are used by the hyperspectral data users to evaluate the SNR.

Notably, the SNR calculated from image data can be used as a reference value and is different from the ground truth because

Fig. 2. Aerial hyperspectral remote-sensing image and reference land cover map of Matiwan village. (a) RGB image obtained from the AMMIS (red: 659.9 nm, green: 561.6 nm, blue: 458.5 nm). (b) Reference land cover map of Matiwan Village.

Fig. 3. SNR test result of the VNIR sensor of AMMIS.

the objects in the image are not always uniform. As shown in Fig. 4, we adopted the homogeneous area method to calculate the SNRs of different hyperspectral image datasets. In this method, a portion of the water area in the image [Fig. 4(b)] was selected as the uniform area to calculate the SNR. Specifically, 100 pixels in the same column direction (scanning direction) in the water area were selected, and the ratio between the average and the standard deviation of these

pixel DNs was used as one SNR. The SNR for other four adjacent lines can also be calculated. To reduce the errors, the average of five SNRs was used as the final SNR for the one-band image. This operation was repeated for all the band images, and the SNRs for 256 band images were obtained as shown in Fig. 4(c).

B. Data Generation

To analyze the influence of the instrument SNR on the identification accuracy, datasets with different SNRs must be generated while keeping the spatial and spectral resolutions unchanged. A state-of-the-art model was used to obtain signal-relevant noise, and it was appropriately introduced into the original hyperspectral data [25]. In this model, the radiance, after adding noise (L_d), can be obtained as follows:

$$N(L) = \frac{L}{\text{SNR}(L)} \qquad (3)$$

$$N_d(L) = \sqrt{N_i(L)^2 - N(L)^2} \qquad (4)$$

$$L_d = L + Rnd(0, 1) \cdot N_d(L) \qquad (5)$$

where L is the original radiance, *Rnd (0, 1)* is used to generate a Gaussian random noise with a mean of 0 and a standard

Fig. 4. SNR of the hyperspectral image. (a) Original RGB image. (b) Selected uniform area. (c) SNR of the selected area for all bands.

Fig. 5. Comparison of the SNR obtained while imaging the water area to verify whether the required level of SNR was achieved. The SNR shown in Fig. 4(c) was used as the 100% SNR. "10 % designed" means the results of Fig. 4(c) multiplied by 10%. "Achieved" shows the results obtained (3)–(5).

deviation of 1, $N(L)$ can be calculated from the SNR results for L, $N_d(L)$ is the noise that is added to the original image data to decrease the SNR, and $N_i(L)$ is the resulting data noise obtained after adding noise L_d.

The SNR curves for each band are shown in Fig. 4(c), and the noise level is calculated using (3). Then, (4) is used for each band image, and the required image datasets with different SNRs can be obtained using (5). In our study, the procedure for calculating SNR(L) was different from the method described in [25], in which the SNR(L) was directly obtained from the instrument developer. First, it is difficult for data users to obtain the SNR results of the sensor. Second, a difference exists between the noise level tested by the instrument and the actual image noise. Therefore, the SNR shown in Fig. 4(c) was used as the 100% SNR in our method. Notably, the SNR obtained from the image was slightly different from that of the instrument. However, this did not affect our study because our aim was to obtain various datasets with different SNRs and not the precise sensor SNR. Fig. 5 shows the results obtained when the required noise was added correctly. The actual SNR of each band was very close to the desired SNR, and the

randomness of the added noise and difference in the response DNs of the objects (the water area is not entirely uniform) together generated a minor difference in the results shown in Fig. 5. Visual inspections also revealed the SNR variation in the uniform water area images, as depicted in Fig. 6, which shows an intuitive visual representation of the SNR level from 100% to 10%. Datasets with different SNR levels were generated using this method while keeping the spatial and spectral resolutions unchanged.

1) Generation of Datasets With Different Spatial Resolutions: To investigate the impact of spatial resolution on the identification accuracy, we adopted two spatial resampling methods to generate a range of hyperspectral datasets with different spatial resolutions and identical spectral resolutions. In the nearest neighbor interpolation sampling (NNIS) method, the target pixel value was replaced by the value of the nearest neighbor pixel [38]. Using this method allowed the original gray value of the image to be retained, and the SNR of the image remained almost unaltered. The other spatial resampling method used was the neighbor average sampling (NAS) method. In this method, the target pixel value was obtained

Fig. 6. Simulated color images of the water area to represent various SNR levels.

Fig. 7. Average SNRs of all the band images for the two spatial resampling methods.

from the average value of the neighboring pixels. This method could remove the noise due to the average value, thus improving the SNR of the image and smoothing the scene. Using these two resampling methods, the original image data with a spatial resolution of 0.5 m were degraded to obtain a spatial resolution of 5 m. To verify the influence of the two spatial resampling methods on the SNR, the average SNRs of all the band images were calculated, as shown in Fig. 7. Evidently, the NNIS method had almost no effect on the SNR; however, application of the NAS method led to an increase in the SNR. Although the spectral resolution of the image dataset obtained using the two resampling methods was the same, the identification results differed owing to the difference in the SNRs. To obtain consistent results with the degraded datasets, corresponding reference maps with different spatial resolutions were obtained. The original reference map was degraded using the NNIS methods to generate reference labels for the datasets

generated by the NNIS method. For datasets generated by the NAS method, the label with the largest proportion in the neighboring pixels was used as the new reference label.

2) Generation of Datasets With Different Spectral Resolutions: To evaluate the influence of spectral resolution on the identification accuracy, a spectral resampling method, called the average spectral resampling (ASR), was used to generate a range of hyperspectral datasets with various spectral resolutions and identical spatial resolutions. We simulated the hyperspectral image datasets with a series of spectral resolutions that averaged the adjacent spectral channels. Specifically, we degraded the spectral resolution from 2.4 to 153.6 nm, implying that the number of spectral channels were reduced from 256 to 4. In this process, the pixel gray value of the target image was obtained by averaging the pixel gray value of the contiguous band images. The SNR of the target image increased owing to the decrease in the noise. These results were compared with those of another band extraction method called the interval spectral resampling (ISR) method, which does not affect the SNR [12]. In the ISR method, the spectral channels were degraded from 256 to 4 by extracting the hyperspectral image data from the original 256 bands at the same intervals. For example, we can select the odd number of spectral channels to compose the new dataset with 128 bands, and select the bands of 1, 65, 129, and 196 to compose a new four band dataset. Therefore, the pixel values and SNR of each extracted band image were retained, and the average SNR of all the extracted band images remained almost unchanged. Notably, the ISR method used in this study is also known as the method of selection of channels at the highest spectral resolution [12]. The ISR method is mainly used to verify the impact of SNR and compare the corresponding results with those of the ASR method. Some hyperspectral image band selection studies [39]–[41] were not considered in

Fig. 8.   Average SNRs of all the band images for the two spectral resampling methods.

this study. The hyperspectral image datasets, obtained using the ISR method set, had spectral channels same as those of the datasets obtained using the ASR method; however, the influence on the SNR varied. To verify the impacts of the two spectral resampling methods on the SNR, the SNRs of the produced uniform water area datasets were calculated. The results shown in Fig. 8 demonstrate the veracity of our analysis. Notably, we needed to consider only the finer than 30-nm spectral resolutions because the spectral resolutions of most of the currently used hyperspectral imagers are finer than 30 nm.

C. Classifiers and Accuracy Assessment

To verify the consistency and universality of our results, a lazy learner and an eager learner classification technique were selected as the representatives for performing multiclassification in our study. The kNN classifier with excellent classification performance was selected as the representative lazy learner classifier [42]. Unlike the lazy learners, the eager learner classifiers (e.g., support vector machine (SVM), RF, CART, etc.) often build models explicitly for classification. Many studies have verified that the SVM and the RF classifiers are advantageous for classification accuracy, as compared to the other eager learner classifiers. However, the SVM classifier has a O $(n^2 – n^3)$ time complexity; despite that it uses a kernel function to avoid "dimension disaster."

In contrast, the time complexity of the RF and CART classifiers are both only O $(n \times lg(n))$ [43], [44]. The computational time problem becomes significant when the number of bands increases dramatically in the hyperspectral image classification [44]. In addition, SVM is specifically considered for binary classification, and a performance deviation is often encountered when SVM is used for multiclassification. Hence, we selected RF and CART as the representative eager learner classifiers in this study.

The three classifiers were programed using Python 3.6 with scikit-learn [43]. All the computations were performed on Ubuntu 14.0 platform using a CPU with Intel Xeon e5-2620 processor and four TITAN XP graphics cards.

1) CART Eager Classifier: The CART eager classifier, commonly used in data mining [42], [45], finds the split nodes of the binary tree by constructing an IF impurity function [46]. The decision trees can be easily visualized, understood, and interpreted.

The CART algorithm in "DecisionTreeClassifier" is based on the "sklearn.tree" package [43], which requires optional parameters. Selecting the optimal parameters is challenging because the applied conditions, such as the environment and data types, vary considerably [47]. The default parameters of the classifiers in Sklearn are continuously updated according to the recommendations of algorithm developers and requirements of various experiments [43]. Thus, it is generally safe to adopt the default parameters to achieve a better performance and have common applicability. Consequently, we used the default parameters of the CART classifier in this study. Notably, the GINI index was selected as the fixed default parameter to construct the IF impurity function in our study.

2) RF Eager Classifier: The ensemble method aims to integrate some weak learners to enhance the classifier's performance [48]. RF is a type of ensemble learning [46] that has been widely used to classify various types of remotely sensed data, especially hyperspectral data with high dimensionality [49].

The RF algorithm is based on the "sklearn.ensemble" package, which also requires specific parameters [43]. Same as in CART, we used the default parameters of the RF classifier for most of the optional parameters in this study. Generally, CART [46] is regularly applied as a weak learner classifier in the RF ensemble method. It has been observed that the classification performance can be influenced by n_{tree}, which is the most crucial hyperparameter in RF. When n_{tree} increases to a certain extent, the accuracy improvement is far less than the time cost. In our study, n_{tree} was fixed at the default value of 100 [43]. Boosting, bagging, and bootstrapping are the main ensemble methods used in RF. In our study, the bootstrap

Fig. 9. Flowchart of the experimental design.

method was used owing to the complex and strong characteristics of the model. In this method, the sample size subsets were randomly extracted from the training set with replacement, without special requirements. The RF classifier builds a tree for each subset of forests [50].

3) kNN Lazy Classifier: The kNN classifier is one of the top ten algorithms used in data mining [42]. It memorizes all the training samples and performs classification when the test sample is provided [51]. It has been extensively utilized for hyperspectral image classification in recent years [52], [53].

The kNN algorithm in "KNeighborsClassifier" is based on the "sklearn.neighbors" package [43]. To classify a test sample, the distance of this test sample to the training samples is computed according to the similarity metric, its kNNs in the training samples are recognized, and the labels of the nearest neighbors are used to determine the test sample label [42]. Tuning of the kNN method includes finding the optimum value for the nearest neighbors' number (k) and a suitable similarity metric. It has been observed that the effects of k on OA are more sensitive to the variations in the datasets. Therefore, k was fixed at a default value of 11, which is the optimal value obtained in our repeated experiments. In our study, we commonly used the Euclidean distance as the similarity metric to calculate the distance [54]. Any other parameter that is not explicitly mentioned in this article were set to their default values during the study.

IV. EXPERIMENTS AND RESULTS

We designed three experiments: 1) analysis of the impact of SNR on the crop identification performance with unchanged spatial and spectral resolutions; 2) study on the influence of spatial resolution on the crop identification performance using two spatial resampling methods; and 3) study on the effect of spectral resolution on the crop identification performance using two spectral resampling methods. A flowchart of the experimental design is shown in Fig. 9.

In these three experiments, training data and test data were obtained from each dataset to reduce the spatial autocorrelation and redundancy. The training data and testing data were sampled using the "hold-out" sampling method, without reinserting the selected samples. Meanwhile, the number of selected testing data was fixed to half of the training data size to maintain the ratio between the testing and training data. Approximately 2 116 000 samples were selected as the training data, and 1 058 000 samples were selected as the testing data for experiments (i) and (iii), whereas approximately 21 160 samples were used as the training data, and 10 580 samples were selected as the testing data for experiment (ii). The sample size in experiment (ii) was smaller than that in the other experiments. In experiment (ii), as the spatial resolution decreased (from 0.5 to 5 m), the number of training samples also decreased (from 2 116 000 to 21 160). The same training and testing sample sizes should be used to fairly compare the datasets with different spatial resolutions. To eliminate any uncertainty, the results were obtained by averaging the values of the three independent tests. For assessing the accuracy of the classification performed using hyperspectral imagery, two parameters are commonly measured: 1) OA and 2) Kappa coefficient [55]. OA has the advantage of being directly interpretable as the ratio of the number of samples classified correctly to the total number of samples and was used as our evaluation metric in this study [56], [57]. Notably, we did not intend to obtain a high accuracy, as the main objective of our study was to evaluate the variations in the classification results with different spatial resolutions, spectral resolutions, and SNRs.

A. Analysis of the Effects of SNR on the Classification Results

In this experiment, we mainly focused on analyzing the effects of SNR on the classification accuracy obtained using the CART, RF, and kNN classifiers. To perform the analysis, we simulated datasets with different SNRs by adding Gaussian random noise to the original hyperspectral images. Particularly, we degraded the SNR of the datasets from 100% to 10% in steps of 10%. The spatial resolution and spectral resolution were maintained as constants in this process, as shown in Figs. 5 and 6. Fig. 10 shows the OA obtained using the three classifiers for a range of SNRs. Based on these results, we can infer that changing the SNR affects the accuracy of the classification.

As discussed before, the classification accuracy is notably affected by the SNR. The OA of the CART, RF, and kNN classifiers reduced by 28.05%, 28.65%, and 24.86%, respectively, as the SNR degraded from 100% to 10%. Notably, the spatial and spectral resolutions of the dataset did not change with the SNR variations. Hence, it was concluded that SNR is the main factor that affects the classification accuracy. It is worth analyzing the behaviors of the three classifiers, in terms of OA, with decreasing SNR. The kNN classifier yielded a higher OA than the CART and RF classifiers did for all the SNR values. This was observed possibly because most classes have a large number of samples, even for performing

Fig. 10. Variation of OA with SNR for the three classifiers.

Fig. 11. Variation of OA with spatial resolution for the two spatial resampling methods.

classifications in a small area. In this case, kNN will show excellent classification accuracy, because the unknown testing data will likely be very similar to the training data as both come from the same fields. That is, kNN will easily identify its highly similar kNNs with the correct label from the training data. In our case, the OA produced by the kNN classifier reduced by only 3.23% when the SNR varied from 100% to 50%. In contrast, the OA produced by the RF and CART classifiers reduced by 8.53% and 8.95%, respectively, when the SNR varied from 100% to 50%. However, the OA achieved by applying the kNN classifier reduced by 21.63% when the SNR varied from 50% to 10% and that shown by the RF and CART classifiers reduced by 20.11% and 19.1%, respectively, under the same conditions. The results indicate that the three classifiers showed slightly different performance with respect to SNR variation.

B. Evaluating the Influence of Spatial Resolution on the Classification Result

In this experiment, we analyzed the effect of spatial resolution on the classification accuracy using the NNIS and NAS spatial resampling methods while keeping the original spectral resolution unchanged. We particularly wanted to determine whether: 1) the selection of hyperspectral images with a finer spatial resolution is more effective than selecting one with a coarser spatial resolution and 2) differences exist in the classification results when using the datasets prepared by the two spatial resampling methods and the reasons for the differences. Notably, the sample size was also reduced with the degradation of the spatial resolution. Hence, the same training and testing sample sizes should be used for all the image datasets to remove the impact of sample size on the results.

Fig. 11 shows the classification accuracy versus different spatial resolutions obtained by the three classifiers. From the experimental results, it was noted that the hyperspectral image with finer spatial resolution showed a lower OA than that shown by the hyperspectral image with coarser spatial resolution. While using the NAS method, the OA increased with the degradation of spatial resolution. In contrast, the OA

obtained using the NNIS method was almost constant with changes in the spatial resolution. Comparing with the results shown in Fig. 7, it can be deduced that the improvement in OA using the NAS method was mainly due to the increase in SNR and the smoothing of the image, and the differences between the classification results of the two resampling methods were consistent with the variation of SNR in the image. The OA obtained using the CART, RF, and kNN classifiers increased by 17.13%, 14.47%, and 10.12%, respectively, when the spatial resolution was degraded from 0.5 to 5 m using the NNIS method. This implies that the OA produced by the RF and CART classifiers showed a more remarkable change than that produced by the kNN classifier, owing to the SNR variations. This result is consistent with those of experiment (i).

Additionally, the image OA obtained from the kNN classifier was marginally lower than that obtained from the RF classifier for all the spatial resolutions. This observation is different from the results of the first experiment. When the sample size is insufficient (the minimum sample size for some classes is less than 355), finding the kNNs with the same classes as those used in the test samples is often difficult. Thus, the classification ability of kNN is dramatically reduced. In RF, some rules can still be found from a small number of samples to build a model.

C. Investigating the Effects of Spectral Resolution on the Classification Result

We analyzed the effect of spectral resolution on the classification accuracy obtained from the three classifiers while keeping the spatial resolution unchanged. We mainly sought to verify whether: 1) the selection of hyperspectral images with a finer spectral resolution is more effective than selecting a hyperspectral image with a coarser spectral resolution (fewer spectral channels) and 2) differences exist in the classification results when using the datasets prepared by the two spectral resampling methods and the reasons for the difference.

Fig. 12 shows the classification results of the three classifiers at different spectral resolutions. The OA obtained using the ASR method first increased, then plateaued, and finally

Fig. 12.   Variation of OA with spectral resolution for the two spectral resampling methods.

decreased, as shown in Fig. 12. However, the OA obtained using the ISR method showed a continuous decrease with the degradation of the spectral resolution. As an overall pattern, the experimental results showed that the selection of hyperspectral images with a finer spectral resolution is more effective than selecting a hyperspectral image with a coarser spectral resolution. The OA produced by the CART, RF, and kNN classifiers decreased by 12.91%, 17.6%, and 17.87%, respectively, when the ASR method was used to degrade the spectral resolution from 2.4 to 153.6 nm. Remarkably, the OA produced by the CART, RF, and kNN classifiers decreased by 19.19%, 23.69%, and 23.81%, respectively, when the ISR method was used in the same case. This indicates that the spectral resolution has an almost similar effect on the three classifiers, and the OA decreases with the degradation of the spectral resolution. Further, the results obtained using the ASR method were different from those of the ISR method.

As shown in Fig. 12(a), the OA obtained using the ASR method first increased and then decreased with decreasing spectral resolution. The highest OA produced by the RF and CART classifiers was 86.02% and 79.21%, respectively, at a spectral resolution of 19.2 nm (32 spectral bands). Conversely, the highest OA produced by the kNN classifier was 86.06% at a spectral resolution of 9.6 nm (64 spectral bands). Combined with the results shown in Fig. 8, it can be concluded that the improvement in OA obtained using the ASR method was mainly due to the increase in SNR and the smoothing effect. The effect of increasing SNR was more significant than that of the spectral resolution degradation when an image with a finer spectral resolution was used. This resulted in an increase in the OA. However, the OA began to decrease when the spectral resolution was notably decreased for two reasons. First, the effect of increasing the SNR was smaller than that of the degradation of the spectral resolution. Second, the amplitude of the SNR was observed to improve slowly with increasing spectral resolution. Additionally, using the ISR method, the image OA obtained from the kNN classifier

was slightly higher than that obtained from the RF classifier for all the spectral resolutions. This was observed because of the same reasons as those used to explain the results of experiment (i). Fig. 13 shows the spectral curves with different spectral resolutions, processed by the ASR method. These spectral curves were similar and smoother when the spectral resolution varied within the range of 2.4–19.2 nm. The results processed by the ISR methods were similar to those shown in Fig. 13.

V. DISCUSSION

A. Analysis of the Main Factors That Affect the OA and Tradeoffs in the Hyperspectral Imaging System

As explained before, the SNR, spatial resolution, and spectral resolution are the three essential parameters of the hyperspectral imaging system, and there are tradeoffs and mutual interactions among them. In this Section, the primary and secondary factors affecting the OA are determined by analyzing and comparing the results based on the same original hyperspectral dataset. In addition, the relationships between these three parameters and other system components have been analyzed in detail based on the experimental results and our experience in developing hyperspectral imagers over the past 30 years.

The experimental results presented in Fig. 10 clearly show the impact of SNR on the OA. A larger SNR results in a higher OA. Similarly, the experimental results presented in Figs. 11 and 12 also show that a hyperspectral image data with a higher SNR can yield better identification results. In this study, the SNR decreased owing to the increase in the image noise, as shown in Fig. 6. A class with large variance and image noise usually has blurred boundaries with others. That is, the features of many samples with blurred boundaries used in this class are easily confused with those used in the other classes. As we all know, the goal of most machine learning classifiers is to learn and create simple

Fig. 13. Spectral curves with different spectral resolutions, processed by the ASR method. The spectral resolutions are (a) 2.4 nm, (b) 4.8 nm, (c) 9.6 nm, and (d) 19.2 nm.

and balanced decision rules from the data features. A large number of confused features have a serious impact on the classification performance of classifiers, and this is how the SNR affects the classification accuracy. Thus, the SNR of a hyperspectral imaging system has an evident influence on the OA, and it should be increased to improve the application of the instrument in crop identification processes. However, (1) implies that a finer spatial or spectral resolution lead to a decrease in the SNR. Hence, other methods should be considered if the spatial and spectral resolutions remain constant; for example, improving the spectral transmittance of an optical system, increasing the detector quantum efficiency, and decreasing the noise of the detector and electronic subsystem can improve the system SNR while maintaining constant spatial and spectral resolutions. A larger optical aperture can increase the collection of light photons, thereby improving the SNR. However, this will lead to an increase in the cost. Image motion compensation technology and the use of time delay integration-enabled detectors are other methods that can improve the SNR. Therefore, the SNR should be increased with the development of the optical subsystem, detector subsystem, and electronic subsystem. For example, the SNR of a typical airborne hyperspectral imager AVIRIS

has been increased from 150 to 2000 (AVIRIS-NG), which is also crucial for improving the instrument performance [35], [58]. The improvement in the SNR allowed the AVIRIS-NG to detect methane [59].

The experimental results shown in Fig. 11 indicate that the OA increased when the spectral resolution and SNR remained constant. This indicates that the change in spatial resolution from 0.5 to 5 m had obvious effect on the OA. By comparing the curves shown in Fig. 7, it can be concluded that the OA increases proportionally with SNR; additionally, smoothening the image data also improves the OA. Notably, the original OA produced by the CART, RF, and kNN classifiers, as shown in Fig. 11, was only 59.69%, 69.26%, and 67.59%, respectively, whereas that shown in Fig. 12 was 72.94%, 82.67%, and 84.72%, respectively. This was mainly because of the differences in the sample size [60], [61]. The number of pixels in the image decreased as the spatial resolution decreased. To avoid the influence of sample size differences in our experiments, we used training data and test data with the same sample sizes for all the datasets. The sample size was reduced to 1% of its original size when the spatial resolution was degraded from 0.5 to 5 m. We performed an additional comparative experiment to verify

Fig. 14.   Impact of sampling size on the classification accuracy.

the impact of the sample size on the classification accuracy, as shown in Fig. 14. It was observed that the sample size had a noticeable impact on the OA produced by the three classifiers. This is why the original OA shown in Fig. 11 is different from that shown in Fig. 12. Compared to the results shown in Fig. 7, those in Fig. 11 also indicate that the SNR had a severe impact on the identification accuracy for datasets with a small sample size. The OA obtained from the CART, RF, and kNN classifiers increased by 17.13%, 14.47%, and 10.12%, respectively, as the SNR increased by approximately 2.5 times. The experimental results depicted in Fig. 11 are similar to those of some reported studies related to the characteristics of the observation area and target size [13], [17]. Different regions and applications have different spatial resolution requirements. A 30-m resolution may be sufficient to map tundra peatland environments [14], [18]. However, to develop accurate maps, a spatial resolution of less than 5 m is required [22], [24]. Centimeter-level spatial resolution is required to map peatland plants [20]. In this study, our research area was mainly plains, where the species distribution is relatively even. Although the OA changed when the spatial resolution varied from 0.5 to 5 m, some species with variations and classes in small patches may not be observed and mapped if an instrument with a coarser spatial resolution is used [17]. We aimed to investigate the tradeoffs between the spatial resolution and the other two parameters to achieve the best crop identification accuracy. The selection of spatial resolution for different observation areas was not considered in this study.

As a coarser spatial resolution yields a better classification result, the spatial resolution can be reduced to improve the other parameters and thus obtain a better classification accuracy. Further, the imaging swath can be enlarged and the instrument's operation efficiency can be improved as the requirement of spatial resolution is decreased [14], [19]. It can be observed from (1) and (2) that a reduction in the spatial resolution can improve the SNR of the system, thereby improving the image quality. If the spatial resolution is decreased while the SNR remains unchanged, then the spectral resolution can be increased for some special applications in with higher spectral resolutions are required.

The experimental results shown in Fig. 12 indicate that the OA changed with the degradation of the spectral resolution. The OA obtained using the ASR method first increased, plateaued, and then decreased. However, the OA obtained using ISR method showed a decreasing trend; however, this decrease was not very high. When using the ISR method, the OA produced by the CART, RF, and kNN classifiers reduced by 0.19%, 1.26%, and 0.83%, respectively, when the spectral resolution was degraded from 2.4 to 9.6 nm. As explained before, two comparative spectral resampling methods were used to demonstrate the influence of the SNR. In the ASR method, when the spectral resolution used by the RF and CART classifier was finer than 19.2 nm and that used by the kNN classifier was finer than 9.6 nm, the SNR had a more significant effect on the OA than spectral resolution had, and the OA increase. When the spectral resolution used by the RF and CART classifier was coarser than 19.2 nm and that used by the kNN classifier was coarser than 9.6 nm, the reverse was observed, i.e., the spectral resolution had a greater effect on the OA than the SNR had, and the OA decreased in this case. These experimental results agree well with the theoretical expectations. According to the experimental results, the best tradeoff between the spectral resolution and SNR is achieved when the spectral resolution is 19.2 nm for the RF and CART classifiers and 9.6 nm for the kNN classifier. The highest OA produced by the CART, RF, and kNN classifiers was 79.21%, 86.02%, and 86.06%, respectively. Notably, we selected equal number of spectral channels for the two spectral resampling methods. Our aim was to analyze the behavior of the classification accuracy with variations in the spectral resolution or the number of spectral channels, and compare these results with those obtained from other experiments. Fig. 13 shows the spectral curves with different spectral resolutions, obtained using the ASR method. Evidently, similar spectral features and the smoother curves are obtained when the spectral resolution varies in the range of 2.4–19.2 nm. This is consistent with the results in shown in Fig. 12.

If the spectral resolution negligibly affects the classification accuracy within a specific range, then the spectral resolution can be appropriately decreased to improve the other parameters for improving the imaging performance of the instrument. The spectral channels will reduce as the spectral resolution decreases, the data volume will decrease, and the difficulty in data processing will also decrease. It can be observed from (1) and (2) that a reduction in the spectral resolution can improve the system SNR, which will improve the image quality. If the spectral resolution is reduced while the SNR remains unchanged, then the spatial resolution can be increased. This is especially important for applications where higher spatial resolutions are required.

In summary, the SNR, spatial resolution, and spectral resolution have significant effect on crop identification. The tradeoffs between the spectral resolution and the SNR should be considered while designing a hyperspectral imaging system. The experimental results shown in Fig. 12 indicate that the highest identification accuracies can be achieved with 19.2-nm spectral resolution for the RF and CART classifiers and 9.6-nm spectral resolution for the kNN classifier. Therefore, AMMIS

may not require 256 spectral bands to identify the crops. Furthermore, 32–64 spectral channels should be used to obtain higher accuracy owing to the increase in the SNR.

B. Suggestions for Improving the Hyperspectral Imager for Crop Identification

According to the experimental results, appropriate optimization operations can be performed for the AMMIS to improve its crop identification performance. First, the design requirement for the spatial resolution can be reduced for crop identification of similar sites. The instrument's swath can be increased to improve the operational efficiency, and the system SNR can be increased to improve the hyperspectral image quality. A spatial resolution of better than 5 m can meet the requirements based on the experimental results. Second, the spectral resolution or number of spectral channels can be reduced. This will reduce the difficulties in data processing and improve the system SNR. The band numbers from 32 to 64 can meet the performance requirements, as evident from the experimental results. Third, multioperational modes that can adjust the spatial and spectral resolutions should be designed to meet different application requirements. In fact, two working modes were designed in the AMMIS as the detector used in AMMIS performs binning of the pixel. These two modes are: 1) 0.125-mrad IFOV and 64 spectral bands and 2) 0.25-mrad IFOV and 256 spectral bands. Some commercial hyperspectral imagers, such as Specim AFX10, already have multiple operation modes with spatial and spectral binning options [62]. The frame frequency can also be increased when the band number decreases. The observation distance can then be adjusted to meet the requirements of the application. Therefore, when selecting hyperspectral image data, the spatial and spectral resolutions should be considered along with the instrument SNR because it has a significant influence on the instrument application. In addition, the results of the hyperspectral data preprocessing should be noted. The accuracy of radiometric calibration, geometric correction, and atmospheric correction significantly impacts the applications, especially the quantitative applications.

C. Extension of the Study to a Different Site With Various Crop Classes

Based on the objective of this study, unique hyperspectral datasets with high spatial resolution, spectral resolution, and SNR were required. To analyze the impact of spectral resolution on the identification accuracy, the original spectral bands should be retained. Hence, dimensionality reduction processing cannot be used. Therefore, large FOV and corresponding ground investigations are also needed to obtain a sufficient sample size to avoid the Hughes phenomenon [63]. These factors make it difficult to compare the results with those of the other study sites or the publicly available hyperspectral datasets. However, we can discuss how similar the results would be over a different study site with various crop classes. Our experimental results showed that the SNR has an evident impact on the identification accuracy. This result should be applicable to most study sites with different crop classes. This

has been proposed in some published literature as well [13]; however, they were verified in our study. We found that the spectral resolution affects the identification accuracy but the identification accuracy shows less variations when the spectral resolution changes slightly. This result is also similar to those of some of the published reports [12]. However, in our study, the influence of SNR was also considered in addition to that of the spectral resolution.

There are some limitations that should be considered while analyzing the role of spatial resolution. Reference data limitations, target characteristics, and within-class spectral variability are the three main factors that affect the spatial resolution when its influence on the accuracy is analyzed [17]. In this study, the reference map used for evaluating the classification results was typical of many such benchmark datasets (e.g., the Purdue Indian Pines, Pavia data, etc.). These hyperspectral datasets are suitable for the classification of crops. In the case of uniform distribution of crop types, the same species are clustered together, and there is not much crossover between the species. However, some areas such as roads and borders of fields are left blank, and the effect of spatial resolution on the classification of these areas may be different. In addition, the experiments are designed around aspatial (i.e., per-pixel) classification. With an aspatial classifier, reducing the spatial resolution of an input image will improve the classification accuracy because of the reduced variance in the image itself. As shown in Fig. 11 and described previously, the accuracy improved because of the smoothing of the image and increase in the SNR. Spatial classifiers based on deep learning [64]–[66] may also be used, and a different result related to the role of spatial resolution may be found.

VI. CONCLUSION

The configuration of the hyperspectral imaging system parameters influence the instrument applications. In this article, we report an experimental study on the relationship among the three core parameters (i.e., SNR, spectral resolution, and spatial resolution) of an airborne hyperspectral imager and the identification accuracy of crops. This analysis focused on the Xiongan New Area in China, which is endowed with different classes of crops. The study was conducted using CART, RF, and kNN classifiers. The experiments were designed to analyze the following issues: 1) the effect of SNR on the identification accuracy using hyperspectral datasets with different SNRs; 2) the influence of spatial resolution on the identification accuracy using datasets with the spatial resolution degraded from 0.5 to 5 m; and 3) the impact of spectral resolution on the identification accuracy using datasets with the spectral resolution degraded from 2.4 to 153.6 nm. The experimental analysis resulted in exciting conclusions related to the relationship among the three parameters as well as the identification accuracy. In particular, we proposed that the tradeoffs among these three core parameters should be considered to achieve the best results for any applications.

The major conclusions from this study are as follows.

1) The instrument SNR has a noticeable impact on the crop identification accuracy. The higher the SNR, the better is the identification accuracy. A high SNR is an essential

requirement for the development of a hyperspectral imaging system.

2) Based on the hyperspectral image datasets of the AMMIS, it was found that the SNR, spatial resolution, and spectral resolution have significant impact on crop identification. The tradeoffs between the spectral resolution and the SNR should be noted while designing a hyperspectral imaging system.

3) To achieve better accuracy in crop identification, the AMMIS can be optimized as follows: the spatial resolution can be decreased (better than 5 m), the number of spectral bands can be reduced (more than 32), and efforts should be made to improve the SNR. In the future, the SNR should be noted in addition to the spatial and spectral resolutions while developing improved hyperspectral imagers and selecting hyperspectral data.

In summary, the results provide significant insights into the design of hyperspectral sensors and data selection methods used to identify crops. These results aid in framing important recommendations on the tradeoffs among the spatial resolution, spectral resolution, and SNR in such applications. It is worth noting that the results of our study can also be used in other areas, where hyperspectral image data are used. The inferences drawn from the reported results will aid in bridging the gap between the back-end hyperspectral sensor designing and front-end applications.

REFERENCES

[1] E. Adam, O. Mutanga, and D. Rugege, "Multispectral and hyperspectral remote sensing for identification and mapping of wetland vegetation: A review," *Wetlands Ecol. Manage.*, vol. 18, no. 3, pp. 281–296, Jun. 2010, doi: 10.1007/s11273-009-9169-z.

[2] J. Zhang, B. Rivard, A. Sánchez-Azofeifa, and K. Castro-Esau, "Intra- and inter-class spectral variability of tropical tree species at La Selva, Costa Rica: Implications for species identification using HYDICE imagery," *Remote Sens. Environ.*, vol. 105, no. 2, pp. 129–141, Nov. 2006, doi: 10.1016/j.rse.2006.06.010.

[3] M. Dalponte, L. Bruzzone, and D. Gianelle, "Fusion of hyperspectral and LiDAR remote sensing data for classification of complex forest areas," *IEEE Trans. Geosci. Remote Sens.*, vol. 46, no. 5, pp. 1416–1427, May 2008, doi: 10.1109/TGRS.2008.916480.

[4] J. Cao, W. Leng, K. Liu, L. Liu, Z. He, and Y. Zhu, "Object-based mangrove species classification using unmanned aerial vehicle hyperspectral images and digital surface models," *Remote Sens.*, vol. 10, no. 2, p. 89, Jan. 2018, doi: 10.3390/rs10010089.

[5] P. Gong *et al.*, "Finer resolution observation and monitoring of global land cover: First mapping results with Landsat TM and ETM+ data," *Int. J. Remote Sens.*, vol. 34, no. 7, pp. 2607–2654, Apr. 2013, doi: 10.1080/01431161.2012.748992.

[6] N. Pettorelli *et al.*, "Framing the concept of satellite remote sensing essential biodiversity variables: Challenges and future directions," *Remote Sens. Ecol. Conservation*, vol. 2, no. 3, pp. 122–131, Sep. 2016, doi: 10.1002/rse2.15.

[7] A. Räsänen and T. Virtanen, "Data and resolution requirements in mapping vegetation in spatially heterogeneous landscapes," *Remote Sens. Environ.*, vol. 230, Sep. 2019, Art. no. 111207, doi: 10.1016/j.rse.2019.05.026.

[8] F. Löw, U. Michel, S. Dech, and C. Conrad, "Impact of feature selection on the accuracy and spatial uncertainty of per-field crop classification using support vector machines," *ISPRS J. Photogramm. Remote Sens.*, vol. 85, pp. 102–119, Nov. 2013, doi: 10.1016/j.isprsjprs.2013.08.007.

[9] S. Murmu and S. Biswas, "Application of fuzzy logic and neural network in crop classification: A review," *Aquatic Procedia*, vol. 4, pp. 1203–1210, Jan. 2015, doi: 10.1016/j.aqpro.2015.02.153.

[10] N. R. Rao, "Development of a crop-specific spectral library and discrimination of various agricultural crop varieties using hyperspectral imagery," *Int. J. Remote Sens.*, vol. 29, no. 1, pp. 131–144, Jan. 2008, doi: 10.1080/01431160701241779.

[11] J. Wilson, C. Zhang, and J. Kovacs, "Separating crop species in Northeastern Ontario using hyperspectral data," *Remote Sens.*, vol. 6, no. 2, pp. 925–945, Jan. 2014, doi: 10.3390/rs6020925.

[12] M. Dalponte, L. Bruzzone, L. Vescovo, and D. Gianelle, "The role of spectral resolution and classifier complexity in the analysis of hyperspectral images of forest areas," *Remote Sens. Environ.*, vol. 113, no. 11, pp. 2345–2355, Nov. 2009, doi: 10.1016/j.rse.2009.06.013.

[13] A. Ghosh, F. E. Fassnacht, P. K. Joshi, and B. Koch, "A framework for mapping tree species combining hyperspectral and LiDAR data: Role of selected classifiers and sensor across three spatial scales," *Int. J. Appl. Earth Observ. Geoinf.*, vol. 26, pp. 49–63, Feb. 2014, doi: 10.1016/j.jag.2013.05.017.

[14] C. C. Treat *et al.*, "Tundra landscape heterogeneity, not interannual variability, controls the decadal regional carbon balance in the Western Russian Arctic," *Global Change Biol.*, vol. 24, no. 11, pp. 5188–5204, Nov. 2018, doi: 10.1111/gcb.14421.

[15] J. Jia, Y. Wang, J. Chen, R. Guo, R. Shu, and J. Wang, "Status and application of advanced airborne hyperspectral imaging technology: A review," *Infr. Phys. Technol.*, vol. 104, Jan. 2020, Art. no. 103115, doi: 10.1016/j.infrared.2019.103115.

[16] J. Jia *et al.*, "Destriping algorithms based on statistics and spatial filtering for visible-to-thermal infrared pushbroom hyperspectral imagery," *IEEE Trans. Geosci. Remote Sens.*, vol. 57, no. 6, pp. 4077–4091, Jun. 2019, doi: 10.1109/TGRS.2018.2889731.

[17] K. L. Roth, D. A. Roberts, P. E. Dennison, S. H. Peterson, and M. Alonzo, "The impact of spatial resolution on the classification of plant species and functional types within imaging spectrometer data," *Remote Sens. Environ.*, vol. 171, pp. 45–57, Dec. 2015, doi: 10.1016/j.rse.2015.10.004.

[18] A. Bartsch, A. Höfler, C. Kroisleitner, and A. Trofaier, "Land cover mapping in northern high latitude permafrost regions with satellite data: Achievements and remaining challenges," *Remote Sens.*, vol. 8, no. 12, p. 979, Nov. 2016, doi: 10.3390/rs8120979.

[19] G. J. Laidler and P. Treitz, "Biophysical remote sensing of Arctic environments," *Prog. Phys. Geogr., Earth Environ.*, vol. 27, no. 1, pp. 44–68, Mar. 2003, doi: 10.1191/0309133303pp358ra.

[20] M. Palace *et al.*, "Determining subarctic peatland vegetation using an unmanned aerial system (UAS)," *Remote Sens.*, vol. 10, no. 9, p. 1498, Sep. 2018, doi: 10.3390/rs10091498.

[21] A. Räsänen, S. Juutinen, M. Aurela, and T. Virtanen, "Predicting aboveground biomass in Arctic landscapes using very high spatial resolution satellite imagery and field sampling," *Int. J. Remote Sens.*, vol. 40, no. 3, pp. 1175–1199, Feb. 2019, doi: 10.1080/01431161.2018.1524176.

[22] J. Schneider, G. Grosse, and D. Wagner, "Land cover classification of tundra environments in the Arctic Lena Delta based on Landsat 7 ETM+ data and its application for upscaling of methane emissions," *Remote Sens. Environ.*, vol. 113, no. 2, pp. 380–391, Feb. 2009, doi: 10.1016/j.rse.2008.10.013.

[23] M. B. Siewert, N. Hanisch, N. Weiss, P. Kuhry, T. C. Maximov, and G. Hugelius, "Comparing carbon storage of Siberian tundra and taiga permafrost ecosystems at very high spatial resolution," *J. Geophys. Res., Biogeosci.*, vol. 120, no. 10, pp. 1973–1994, Oct. 2015, doi: 10.1002/2015JG002999.

[24] T. Virtanen and M. Ek, "The fragmented nature of tundra landscape," *Int. J. Appl. Earth Observ. Geoinf.*, vol. 27, pp. 4–12, Apr. 2014, doi: 10.1016/j.jag.2013.05.010.

[25] J. R. Schott *et al.*, "The impact of improved signal-to-noise ratios on algorithm performance: Case studies for Landsat class instruments," *Remote Sens. Environ.*, vol. 185, pp. 37–45, Nov. 2016, doi: 10.1016/j.rse.2016.04.015.

[26] Y. Wang *et al.*, "New generation VNIR/SWIR/TIR airborne imaging spectrometer," in *Proc. SPIE, Hyperspectral Remote Sens. Appl. Environ. Monitor. Saf. Test. Technol.*, Beijing, China, Oct. 2016, Art. no. 101560Q, doi: 10.1117/12.2245541.

[27] I. Levin, E. Levina, G. Gilbert, and S. Stewart, "Role of sensor noise in hyperspectral remote sensing of natural waters: Application to retrieval of phytoplankton pigments," *Remote Sens. Environ.*, vol. 95, no. 2, pp. 264–271, Mar. 2005, doi: 10.1016/j.rse.2005.01.001.

[28] F. van der Meer, "The effectiveness of spectral similarity measures for the analysis of hyperspectral imagery," *Int. J. Appl. Earth Observat. Geoinf.*, vol. 8, no. 1, pp. 3–17, Jan. 2006, doi: 10.1016/j.jag.2005.06.001.

[29] J. Jia *et al.*, "High spatial resolution shortwave infrared imaging technology based on time delay and digital accumulation method," *Infr. Phys. Technol.*, vol. 81, pp. 305–312, Mar. 2017, doi: 10.1016/j.infrared.2017.01.017.

[30] L. Junwei *et al.*, "Study on shortwave infrared long-distance imaging performance based on multiband imaging experiments," *Opt. Eng.*, vol. 52, no. 4, Apr. 2013, Art. no. 045008, doi: 10.1117/1.OE.52.4.045008.

[31] G. Vane, W. M. Porter, J. H. Reimer, T. G. Chrien, and R. O. Green, "AVIRIS performance during the 1987 flight season: An AVIRIS project assessment and summary of the NASA-sponsored performance evaluation," in *Proc. Airborne Visible/Infr. Imag. Spectrometer (AVIRIS) Perform. Eval. Workshop*, G. Vane, Ed. Pasadena, CA, USA: NASA/JPL, Sep. 1988, pp. 1–20.

[32] V. Carrere and M. J. Abrams, "An assessment of AVIRIS data for hydrothermal alteration mapping in the Goldfield mining district, Nevada," in *Proc. Airborne Visible/Infr. Imag. Spectro*, Pasadena, CA, USA, 1988, pp. 134–154.

[33] N. Fujimotor *et al.*, "Evaluation of SPORT HRV image data received in Japan," in *Proc. 12th Can. Symp. Remote Sens. Geosci. Remote Sens. Symp.*, Vancouver, BC, Canada, vol. 2, 1989, pp. 463–466, doi: 10.1109/IGARSS.1989.578740.

[34] B.-C. Gao, "An operational method for estimating signal to noise ratios from data acquired with imaging spectrometers," *Remote Sens. Environ.*, vol. 43, no. 1, pp. 23–33, Jan. 1993, doi: 10.1016/0034-4257(93)90061-2.

[35] P. J. Curran and J. L. Dungan, "Estimation of signal-to-noise: A new procedure applied to AVIRIS data," *IEEE Trans. Geosci. Remote Sens.*, vol. 27, no. 5, pp. 620–628, Sep. 1989, doi: 10.1109/TGRS.1989.35945.

[36] L.-R. Gao, B. Zhang, X. Zhang, W.-J. Zhang, and Q.-X. Tong, "A new operational method for estimating noise in hyperspectral images," *IEEE Geosci. Remote Sens. Lett.*, vol. 5, no. 1, pp. 83–87, Jan. 2008, doi: 10.1109/LGRS.2007.909927.

[37] R. E. Roger and J. F. Arnold, "Reliably estimating the noise in AVIRIS hyperspectral images," *Int. J. Remote Sens.*, vol. 17, no. 10, pp. 1951–1962, Apr. 1996, doi: 10.1080/01431169608948750.

[38] M. Dalponte, L. Bruzzone, and D. Gianelle, "Tree species classification in the Southern Alps based on the fusion of very high geometrical resolution multispectral/hyperspectral images and LiDAR data," *Remote Sens. Environ.*, vol. 123, pp. 258–270, Aug. 2012, doi: 10.1016/j.rse.2012.03.013.

[39] B. L. Becker, D. P. Lusch, and J. Qi, "A classification-based assessment of the optimal spectral and spatial resolutions for great lakes coastal wetland imagery," *Remote Sens. Environ.*, vol. 108, no. 1, pp. 111–120, May 2007, doi: 10.1016/j.rse.2006.11.005.

[40] K. S. Schmidt and A. K. Skidmore, "Spectral discrimination of vegetation types in a coastal wetland," *Remote Sens. Environ.*, vol. 85, no. 1, pp. 92–108, Apr. 2003, doi: 10.1016/S0034-4257(02)00196-7.

[41] S. B. Serpico and L. Bruzzone, "A new search algorithm for feature selection in hyperspectral remote sensing images," *IEEE Trans. Geosci. Remote Sens.*, vol. 39, no. 7, pp. 1360–1367, Jul. 2001, doi: 10.1109/36.934069.

[42] X. Wu *et al.*, "Top 10 algorithms in data mining," *Knowl. Inf. Syst.*, vol. 14, no. 1, pp. 1–37, Jan. 2008, doi: 10.1007/s10115-007-0114-2.

[43] F. Pedregosa *et al.*, "Scikit-learn: Machine learning in Python," *J. Mach. Learn. Res.*, vol. 12, pp. 2825–2830, Oct. 2011.

[44] X. Zheng *et al.*, "Full parameter time complexity (FPTC): A method to evaluate the running time of machine learning classifiers for land use/land cover classification," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 14, pp. 2222–2235, Jan. 2021, doi: 10.1109/JSTARS.2021.3050166.

[45] L. Breiman, J. Friedman, C. J. Stone, and R. A. Olshen, *Classification and Regression Trees*. Boca Raton, FL, USA: CRC Press, 1984.

[46] L. Breiman, "Random forests," *Mach. Learn.*, vol. 45, no. 1, pp. 5–32, Oct. 2001, doi: 10.1023/A:1010933404324.

[47] C. Li, J. Wang, L. Wang, L. Hu, and P. Gong, "Comparison of classification algorithms and training sample sizes in urban land classification with Landsat thematic mapper imagery," *Remote Sens.*, vol. 6, no. 2, pp. 964–983, Jan. 2014, doi: 10.3390/rs6020964.

[48] T. G. Dietterich, "Machine-learning research," *AI Mag.*, vol. 18, no. 4, Dec. 1997, Art. no. 4, doi: 10.1609/aimag.v18i4.1324.

[49] J. Ham, Y. Chen, M. M. Crawford, and J. Ghosh, "Investigation of the random forest framework for classification of hyperspectral data," *IEEE Trans. Geosci. Remote Sens.*, vol. 43, no. 3, pp. 492–501, Mar. 2005, doi: 10.1109/TGRS.2004.842481.

[50] G. Louppe and P. Geurts, "Ensembles on random patches," in *Machine Learning and Knowledge Discovery in Databases*. Berlin, Germany: Springer, 2012, pp. 346–361, doi: 10.1007/978-3-642-33460-3_28.

[51] T. Cover and P. Hart, "Nearest neighbor pattern classification," *IEEE Trans. Inf. Theory*, vol. IT-13, no. 1, pp. 21–27, Jan. 1967, doi: 10.1109/TIT.1967.1053964.

[52] E. Blanzieri and F. Melgani, "Nearest neighbor classification of remote sensing images with the maximal margin principle," *IEEE Trans. Geosci. Remote Sens.*, vol. 46, no. 6, pp. 1804–1811, Jun. 2008, doi: 10.1109/TGRS.2008.916090.

[53] L. Ma, M. M. Crawford, and J. Tian, "Local manifold learning-based k-nearest-neighbor for hyperspectral image classification," *IEEE Trans. Geosci. Remote Sens.*, vol. 48, no. 11, pp. 4099–4109, Nov. 2010, doi: 10.1109/TGRS.2010.2055876.

[54] B. G. Batchelor, *Pattern Recognition: Ideas in Practice*. New York, NY, USA: Plenum, 1978.

[55] R. G. Congalton, "A review of assessing the accuracy of classifications of remotely sensed data," *Remote Sens. Environ.*, vol. 37, no. 1, pp. 35–46, Jul. 1991, doi: 10.1016/0034-4257(91)90048-B.

[56] S. V. Stehman, "Selecting and interpreting measures of thematic classification accuracy," *Remote Sens. Environ.*, vol. 62, no. 1, pp. 77–89, Oct. 1997, doi: 10.1016/S0034-4257(97)00083-7.

[57] G. M. Foody, "Explaining the unsuitability of the kappa coefficient in the assessment and comparison of the accuracy of thematic maps obtained by image classification," *Remote Sens. Environ.*, vol. 239, Mar. 2020, Art. no. 111630, doi: 10.1016/j.rse.2019.111630.

[58] D. R. Thompson, V. Natraj, M. C. Helmlinger, B.-C. Gao, M. L. Eastwood, and R. O. Green, "Optimal estimation for imaging spectrometer atmospheric correction," *Remote Sens. Environ.*, vol. 216, pp. 355–373, Oct. 2018, doi: 10.1016/j.rse.2018.07.003.

[59] R. M. Duren *et al.*, "California's methane super-emitters," *Nature*, vol. 575, no. 7781, pp. 180–184, Nov. 2019, doi: 10.1038/s41586-019-1720-3.

[60] E. Tu, J. Yang, J. Fang, Z. Jia, and N. K. Kasabov, "An experimental comparison of semi-supervised learning algorithms for multispectral image classification," *Photogram. Eng. Remote Sens.*, vol. 79, no. 4, pp. 347–357, Apr. 2013, doi: 10.14358/PERS.79.4.347.

[61] Y. Shao and R. S. Lunetta, "Comparison of support vector machine, neural network, and CART algorithms for the land-cover classification using limited training data points," *ISPRS J. Photogramm. Remote Sens.*, vol. 70, pp. 78–87, Jun. 2012, doi: 10.1016/j.isprsjprs.2012.04.001.

[62] D. Schläpfer, C. Popp, and R. Richter, "Drone data atmospheric correction concept for- and hyperspectral imagery—The droacor model," *ISPRS-Int. Arch. Photogramm., Remote Sens. Spatial Inf. Sci.*, vol. 43, pp. 473–478, Aug. 2020, doi: 10.5194/isprs-archives-XLIII-B3-2020-473-2020.

[63] G. Hughes, "On the mean accuracy of statistical pattern recognizers," *IEEE Trans. Inf. Theory*, vol. IT-14, no. 1, pp. 55–63, Jan. 1968, doi: 10.1109/TIT.1968.1054102.

[64] S. Liu, Q. Shi, and L. Zhang, "Few-shot hyperspectral image classification with unknown classes using multitask deep learning," *IEEE Trans. Geosci. Remote Sens.*, vol. 59, no. 6, pp. 5085–5102, Jun. 2021, doi: 10.1109/TGRS.2020.3018879.

[65] H. Guo, Q. Shi, B. Du, L. Zhang, D. Wang, and H. Ding, "Scene-driven multitask parallel attention network for building extraction in high-resolution remote sensing images," *IEEE Trans. Geosci. Remote Sens.*, vol. 59, no. 5, pp. 4287–4306, May 2021, doi: 10.1109/TGRS.2020.3014312.

[66] Q. Shi *et al.*, "Domain adaption for fine-grained urban village extraction from satellite images," *IEEE Geosci. Remote Sens. Lett.*, vol. 17, no. 8, pp. 1430–1434, Aug. 2020, doi: 10.1109/LGRS.2019.2947473.

Jianxin Jia received the B.E. degree in electronic information engineering from Henan Normal University, Xinxiang, China, in 2012, and the Ph.D. degree in electronic science and technology from the University of Chinese Academy of Sciences, Beijing, China, in 2018.

He is a Research Scientist with the Finnish Geospatial Research Institute, Kirkkonummi, Finland. His major research interests include imaging system design, remote-sensing instrument, and hyperspectral image processing, hyperspectral sensor design, hyperspectral image processing and application, and hyperspectral LiDAR.

Jinsong Chen received the Ph.D. degree from the Chinese Academy of Sciences, Shenzhen, China, in 2004.

From 2004 to 2011, he was a Post-Doctoral Researcher and a Professor with The Chinese University of Hong Kong, Hong Kong. He is a Research Professor with the Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences. His research interests include spatial and environmental big data processing methods and multisource spatial and environmental data assimilation and information fusion methods.

Changhui Jiang received the B.S. degree from Soochow University, Suzhou, China, in 2014, and the Ph.D. degree from the Nanjing University of Science and Technology, Nanjing, China, in 2019.

He worked as a Post-Doctoral Fellow with The Hong Kong Polytechnic University from September 2019 to August 2020. He works as a Research Scientist with the Finnish Geospatial Research Institute, Kirkkonummi, Finland. His research interests include hyperspectral LiDAR, GNSS signal processing, cooperative navigation, and multisensor integration.

Xiaorou Zheng is pursuing the joint Ph.D. degree in computer application technology with the Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences, Shenzhen, China, and the Shenzhen College of Advanced Technology, University of Chinese Academy of Sciences, Shenzhen.

Her research interests include land use and land cover classification, semi-supervised learning, weakly supervised learning, fully convolutional networks, and generative adversarial networks.

Mika Karjalainen received the M.Sc., Lic.Sc., and D.Sc. (Tech) degrees from the School of Science and Technology, Aalto University (former Helsinki University of Technology), Espoo, Finland, in 1997, 2008, and 2010, respectively.

He is a Research Manager with the Department of Remote Sensing and Photogrammetry, Finnish Geospatial Research Institute, Kirkkonummi, Finland. His research interests include the applications of synthetic aperture radar (SAR) data, SAR interferometry, radargrammetry, and digital photogrammetry.

Yueming Wang received the B.E. degree in mechanical engineering from Tsinghua University, Beijing, China, in 2000, and the Ph.D. degree in electronic science and technology from the University of Chinese Academy of Sciences, Beijing, in 2005.

He is a Research Professor with the Shanghai Institute of Technical Physics, Chinese Academy of Sciences, Shenzhen, China. He has responsibility for research and development of high-performance imaging spectrometers. His major research interests include the system design and simulation of infrared and hyperspectral imaging system.

Kirsi Karila received the M.Sc. and Lic.Tech. degrees from the Helsinki University of Technology, Espoo, Finland, in 2004 and 2008, respectively.

She is a Specialist Research Scientist with the Department of Remote Sensing and Photogrammetry, Finnish Geospatial Research Institute, Kirkkonummi, Finland. Her major research interests include mapping and monitoring applications (land use, urban areas, and forestry) using radar, LiDAR and optical remote-sensing datasets, and the use of machine learning and artificial intelligence in mapping.

Shanxin Guo received the Ph.D. degree in photogrammetry and remote sensing from Wuhan University, Hubei, China, in 2015.

He joined a Visiting Ph.D. Program with the Department of Geography, University of Wisconsin-Madison, Madison, WI, USA. His research interests include digital soil mapping with remote-sensing data and deep learning for land cover and land use mapping.

Haibin Sun received the M.E. degree in physics from the Harbin Institute of Technology, Harbin, China, in 2012, and the Ph.D. degree in physics from Fudan University, Shanghai, China, in 2016.

He is an Assistant Research Fellow with the Shanghai Institute of Technology Physics, Chinese Academy of Sciences, Shanghai. His research interests include new optical forming technology and infrared weak target detection technology.

Zhiyong Duan received the B.S. degree in applied physical and the M.E. degree in materials physics and chemistry from the Harbin University of Science and Technology, Harbin, China, in 1998 and 2002, respectively, and the Ph.D. degree in microelectronics and solid-state electronics from Shanghai Jiao Tong University, Shanghai, China, in 2005.

Since 2018, he has been a Professor with the School of Physical and Microelectronics, Zhenzhou University, Zhengzhou, China. His research interests include nanoimprint lithography, metal interconnect, and MEMS/NEMS of fluid-transfer pipes.

Tinghuai Wang received the joint M.Sc. degree from the KTH Royal Institute of Technology, Stockholm, Sweden, and RWTH Aachen University, Aachen, Germany, in 2007, and the Ph.D. degree from the University of Surrey, Guildford, U.K., in 2012.

Prior to his current position, he was a Researcher at HP Labs, Bristol, U.K., from 2009 to 2012, and a Senior Scientist and a Principal Scientist at Nokia Corporation, Espoo, Finland, from 2013 to 2019. He has also worked for brief periods at the Chinese Academy of Sciences and Sony Laboratories. He is a Principal Scientist with Huawei Helsinki Research Center. His research interests include machine learning and computer vision. He has more than 70 publications in journals articles, conference proceedings, patents, and standard contributions in these areas.

Dr. Wang has received two IEEE best paper awards and was selected as a Distinguished PC Member of IJCAI 2018.

Juha Hyyppä received the M.Sc., Dr.Ing., and Dr.Sc. degrees (Hons.) from the Helsinki University of Technology, Espoo, Finland, in 1987, 1990, and 1994, respectively.

He is a Professor of remote sensing and photogrammetry and the Director of the Center of Excellence in Laser Scanning Research, Finnish Geospatial Research Institute, Kirkkonummi, Finland, and also a Distinguished Professor with Shinshu University, Matsumoto, Japan. He has 30 years of experience in research team leadership and in the coordination of over ten international science projects. He has authored over 300 ISI Web of Science listed papers with over 20 000 Google Scholar citations. His research interests include laser scanning systems, their performance and new applications, especially related to mobile, personal, and ubiquitous laser scanning, and their point cloud processing especially to forest information extraction.

Chong Xu was born in Baotou, Inner Mongolia, China, in 1958. He received the B.S. degree in solid mechanics from the University of Science and Technology of China, Hefei, China, in 1982, and the M.S. and Ph.D. degrees in optoelectronic technology from the Shanghai Institute of Technical Physics, Chinese Academy of Sciences, Shanghai, China, in 1985 and 1988, respectively.

From 1988 to 1990, he held a post-doctoral position with the Shanghai Institute of Optics and Fine Mechanics (SIOFM), Chinese Academy of Sciences, to research digital image processing techniques. After that, he worked in enterprises as CTO to manage research and development with mechanical, electrical, optical, and software products. In 2019, he joined Jihua Laboratory, as the Project Leader of unified space-time spectrum metrics remote-sensing system and intelligent application. He is interested in researching and developing mechanics, electronics, optics, and software all-in on the system, and is holding several invention patents.

Yuwei Chen received the B.E. and M.Sc. degrees from the Department of Information Science and Electronics Engineering, Zhejiang University, Hangzhou, China, in 1999 and 2002, respectively, and the Ph.D. degree from the Shanghai Institute of Technical Physics, Chinese Academy of Sciences, Shanghai, China, in 2005.

He is working with the Finnish Geospatial Research Institute, Kirkkonummi, Finland, as the Research Manager, where he leads the research group "Remote Sensing Electronics," which focuses on developing new remote sensing systems. He is also a Guest Professor at the Academy of Opto-Electronics, Chinese Academy of Sciences, Beijing, China. He holds 13 patents and has authored and coauthored more than 200 scientific articles and book chapters. His research interests include LiDAR, hyperspectral LiDAR, radar, and navigation and positioning.