**Relationship between spatial heterogeneity and wavelength in multisensor airborne images**

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Vario gram has been utilized to exploring the spatial heterogeneity of remote sensing images, especially its association with spatial resolution. However, very few attentions have been drawn on evaluating the spatial heterogeneity of multisensor airborne imagery and its relationship with spectral wavelength. Therefore, an investigation was carried out on multisensor airborne images to determine the relation between spatial heterogeneity and spectral wavelength for woodland, grass, and urban landscapes by applying variogram modeling. The airborne thematic mapper (ATM), compact airborne spectrographic imager (CASI), and Specim AISA Eagle airborne images at Harwood Forest, Monks wood, Cambridge, and River Frome areas, UK, were utilized. Results revealed that (1) the red band contained greater spatial variability than near-infrared wavelengths and other visible wavebands; (2) there was a steep gradient at the red edge in reference to its spatial variability of multisensor airborne images; (3) only for natural landscape such as woodland and grass, near-infrared waveband contains greater within-scene variations than the blue and green bands; (4) compared with the discrepancy of spatial resolution introduced by multisensor images (ATM, CASI, and Eagle), the specific landscape and spectral bands were more important in determining heterogeneity by means of original visible, near-infrared bands, and normalized difference vegetation index (NDVI). These findings remained us to be caution when combining and interpreting spatial variability and spatial structures derived from airborne images with different spatial resolution and spectral wavelength. Additionally, the outcomes of this study also have considerable implications in terms of designing and choosing suitable images for different applications.

**Keywords:** variogram modeling; spatial heterogeneity; airborne thematic mapper (ATM) imagery; compact airborne spectrographic imager (CASI) imagery; Eagle airborne imagery; landscape; wavelength

1. Introduction

Both vegetation cover dynamics and urban development played an important role in the development of environmental processes. It is necessary to collect surface measurements to investigate those dynamic processes, which is often accomplished using remote sensing images. Multisensor images have been applied in vegetation and urban observation in the past few decades (1–3). Accurately quantifying the spatial heterogeneity in remote sensing images is an important prerequisite for using such data to investigate subsequent environmental processes. In addition, the increasing availability and accessibility of multisensor images along with their applications in surface observation prompts the need to integrate those multisensor results into a long-term data record.

The spatial heterogeneity is an important property of natural landscapes and it can be defined through the spatial variability and the spatial structures related to objects or patches over the observed scene (4). A large amount of research has investigated spatial heterogeneity in relation to spatial resolution through variogram analysis (5). However, obtaining sufficient samples to characterize the spatial heterogeneity of multisensor remote sensing observations could be challenging, partly due to the lack of data collected from multisensor images synchronously.

A large proportion of multiscale investigation was conducted on single-sensor images that were spatially aggregated to multiple resolutions (6–9). It was revealed that the spatial patterns of up- and down-scaled data do not correspond with the unscaled image data (10, 11). Several studies took this approach further and quantified the decay of spatial variability for real multisensor data with multiple spatial resolutions (10, 12–14). However, numerous studies have applied satellite image data and very few attentions have been drawn on evaluating the spatial heterogeneity of multisensor airborne imagery. In addition, little is known how spatial heterogeneity in one waveband differs to another. Several studies discovered that the near-infrared waveband contains greater within-scene variation than the visible bands, especially in images covering densely vegetated areas (15–18). But the question is “does this conclusion still hold in urban areas and in airborne remote sensing images, especially hyperspectral airborne images?”

To address this need, we quantify and evaluate the differences in spatial heterogeneity of woodland, grass, and urban landscapes between airborne thematic mapper (ATM), compact airborne spectrographic imager (CASI), and Specim AISA Eagle airborne images at Harwood, Monks, Cambridge, and River Frome, UK. First, we...
attempt to obtain and interpret how spatial heterogeneity changes with the spectral bands using ATM and Eagle hyperspectral airborne images of woodland and urban landscapes; second, we evaluate the differences in spatial variability and spatial structure from multisensor airborne images in blue, green, red, and near-infrared bands and normalized difference vegetation index (NDVI) data-sets at landscape scale through variogram modeling.

2. Study area and database

Four study areas, Harwood Forest, Monks wood Natural reserve area, Cambridge city, and River Frome areas were selected. (1) Harwood Forest area is located in Northumberland, NE England (55°10′ N, 2°3′ W), 30 km inland from the North Sea coast. Average annual rainfall is about 950 mm (19). The dominant vegetation type is coniferous tree. The ATM, CASI, and Eagle airborne imagery were acquired with nine ATM, CASI, and Eagle stripes on 11 September 2007, taken at an altitude of approximately 11,600–11,700 feet above the ground during cloud-free periods in the daytime. (2) Monks Wood Natural reserve area is located at 52°24′ N, 0°14′ E in Cambridgeshire. The reserve covers 157 ha of mostly temperate deciduous woodland. The ATM and CASI airborne imagery were acquired with seven stripes on 16 July 2003, taken at an altitude of approximately 3381 feet above the ground in the daytime. (3) Cambridge city is located in Cambridgeshire, SE UK. Average annual rainfall is about 550 mm. The ATM and Eagle airborne imagery were acquired with two stripes on 20 June 2007, taken at an altitude of approximately 3616–3705 feet above the ground in the daytime. (4) The River Frome is located in state of Dorset, South United Kingdom. For the period 1965–2005, the mean annual rainfall at East Stoke was 1020 mm. The ATM and Eagle airborne imagery were acquired with seven stripes on 24 August 2008, taken at an altitude of approximately 4420–4560 feet above the ground in the daytime.

Three airborne images, ATM, CASI, and Specim AISA Eagle airborne images were utilized. The main characteristics of the ATM, CASI, and Eagle sensors are summarized in Table 1. As shown in Figure 1, the ATM sensor acquired data in 11 bands of fixed wavelength positioned in the visible, near, short-wave, and thermal infrared parts of the electromagnetic spectrum, approximate bands of Landsat TM image. The CASI sensor is a pushbroom imaging spectrometer which can acquire up to 288 channels in the 430–870 nm spectral region. The CASI data used in this study comprises 11 channels in Harwood, 15 channels in Cambridge and Monks area. The AISA Eagle is a 12 bit, pushbroom, hyperspectral sensor with a 1000 pixel swath width, covering the visible and near-infrared spectrum 400–970 nm. The Eagle hyperspectral image was collected in 252 and 126 channels with nominal spectral bandwidth of 2.4 and 4.7 nm in Harwood and River Frome area, correspondently. Further information about ATM, CASI, and Eagle airborne images can be found at website: http://arsf.nerc.ac.uk/instruments/.

Considering the spatial resolution of ATM data in the study of Qiu et al. (20, 21) in Harwood forest area, we adopted 9 m of ATM data in this area indicated from the pixel calculator (http://arsf.nerc.ac.uk/pixelsize/pixel size.html). But actually, the ground pixel size is affected by a number of factors and cannot be accurately computed directly from the level 1 file. To obtain a “best” pixel size, we need to run AZGCORR program and pick a pixel size that is close to the “across line centre” value. Here, we utilized this method to get a proper pixel size for ATM, CASI, and Eagle airborne images. To evaluate the influences of different landscapes, three typical landscapes including woodland (dominant by coniferous tree), grassland, and urban landscapes were considered. For this study, 12 sample sites (sub-images) were adopted, representing these three landscapes within our study areas (Table 2). Considering the stripes boundary, the size of sites A, B, and C was 1200 m × 1200 m, and other sites were 700 m × 700 m. There are totally 27 images in our study areas (Figure 2).

An Azimuth Systems program (AZGCORR, ftp://ftp. nerc-arsf.ac.uk/software/azgcors/) was used to (1) apply the aircraft navigation data to each scan line of the normalized image files and (2) project those data onto a geoid-based projection to determine the exact intersection of each pixel’s view angle with a digital surface model. The NDVI value was computed by taking the difference between near-infrared (NIR) and red channel reflectance values, and then normalizing by the sum of these two channels: \[ \text{NDVI} = \frac{(\text{NIR} - \text{RED})}{(\text{NIR} + \text{RED})}. \] The band 2 (450–520 nm), band 3 (520–600 nm), band 5 (630–690 nm), and band 7 (760–900 nm) of ATM airborne images corresponded to the blue, green, red band, and near-infrared bands of Landsat TM image, respectively.

### Table 1. Characteristics of ATM, CASI, and Eagle images of the four study areas.

| Image | Cambridge | River Frome | Monks wood | Harwood |
|-------|-----------|-------------|------------|---------|
| ATM   | 2         | 4.5         | 2          | 6       |
| CASI  | 2.4       | 2.4         | 7.2        |         |
| Eagle | 1.3       | 2.5         |            |         |

Figure 1. Wavelength of ATM and CASI image in Harwood, Monks, and Cambridge.
Variogram modeling is based on a theoretical variogram model. Empirical variograms have several key properties that can be derived through empirical variograms to quantify spatial heterogeneity. Multisensor airborne images in our study were band 11, band 13, and band 13 for Harwood, Monks, and Cambridge, respectively. To eliminate the difference of multisensor airborne images caused by sunlight, data normalization was conducted by dividing the mean value of the whole image at each spectral band, respectively. The normalized value was used when calculating the variogram. To obtain an approximate spectral response of the corresponding wavelength, we choose to use the average operator for the reduction of spectral resolution.

### 3. Methodology: geostatistical analysis of spatial variability

The empirical variogram measures the average of the squared differences between pairs of regionalized variable \( z \) values at locations \((x, x+h)\), separated by a vector \( h \) \((22)\). Multisensor airborne images in our study areas are assumed to be isotropic and the experimental variograms are computed by pooling together all directions. Empirical variograms have several key properties \((22)\). The sill is the maximum value that can be attained by the variogram. The range is the distance from the origin of the variogram to the sill. Nugget effect, a discontinuity of the variogram at the origin, can be related to either uncorrelated noise (measurement error) or to spatial structures at a length scale smaller than the pixel size. These three key properties could be derived through theoretical variogram modeling.

Theoretical variogram models are typically fit through empirical variograms to quantify spatial heterogeneity \((23, 24)\). Variogram modeling is based on a probabilistic approach considering the image as one among all possible realizations of a second-order stationary random function \((22)\). The variograms under study here generally show more than one range, indicating spatial structuring at multiple scales. A linear combination of two or more functions can be used to represent multi-scale spatial structures \((22)\) (see Equation \((1)\)). This extended model of the variogram is a weighted sum of two elementary variogram models \((25)\).

\[
\begin{align*}
\gamma(h) &= C_0 + \sigma^2 \sum_{k=1}^{k=2} b_k g_k(r_k, h) \\
&= C_0 + \sigma^2 \left( b_1 C_1 + b_2 C_2 \right)
\end{align*}
\]

where \( C_0 \) is the nugget, \( \sigma^2 \) plus \( C_0 \) is the variogram sill, \( r_k \) is the variogram range associated with function \( g_k(r_k, h) \), and \( b_k \) is the fraction of the total variance related to each
range $r_b$. Here, these two elementary functions are spherical and exponential models. The parameters of the variogram including the sill and the variance weights ($b_1$ and $b_2$) are automatically estimated by an iterative weighted least square optimization (21, 26). The two ranges ($r_1$ and $r_2$) can be used to identify the two characteristic scales of image variation. The structural information of the variogram provided by the ranges and the fraction of total variance can also be summarized into a single characteristic area-based metric $A$ (the integral range): 

$$ A = \frac{1}{(C_0 + C_1)} \int_{[r_1,r_2]} (C_0 + C_1 - \gamma(h)) \, dh. $$

The integral range of the linear model of regionalization is computed as $A = \sum_{k=1}^l b_k A_k$, where $A_1 = \frac{2r_1^2}{\pi}$ for the exponential and $A_2 = \frac{8r_2^2}{\pi}$ for the spherical functions. Garrigues et al. (7) used the square root of the integral range $A$, denoted as $D_n$, to quantify the mean length scale of spatially aggregated images. The spatial heterogeneity of multisensor images can be quantified by geostatistical components: overall image spatial variance (sill) and the mean characteristic length scale. This model has been well established and proved to be particularly appropriate to describe independent sets of spatial structures, related to different length scales and spatial variability (7, 14). It has been shown to be suitable for comparing mean length scales of multiresolution data-sets and is thus adopted here (7, 14).

4. Results

4.1. Spatial heterogeneity as a function of wavelength

To obtain an overview of the effect of wavelength on variogram of ATM, CASI, and Eagle airborne images, empirical variograms were computed for woodland, grass, and urban landscapes up to a half of sub-image size for each waveband within spectral wavelength 433–988 nm, respectively. The empirical variograms of these multisensor airborne images were modeled using the linear model of regionalization (Figures 3 and 4). Spatial variability indicated by the sill increased with wavelength and reaches its peak (677 nm for site A and 671 nm for site K) in red band, but then it decreased dramatically and almost leveled off in near-infrared bands (Figure 3, results from site A and site G were similar, thus was omitted). It revealed that much greater spatial variability were observed in red bands and relatively little spatial variability were obtained in shorter spectral bands such as blue and green bands. For natural landscapes, greater spatial variability was observed in near-infrared bands than blue and green band (Figure 3(a)). However, for urban landscape, near-infrared bands showed no greater heterogeneity over the visible wavebands (Figure 3(b)).

Similar to Eagle hyperspectral airborne images, spatial variability of ATM airborne images indicated by the sill generally increased with wavelength and reached the peak at band 5 (red band: 630–690 nm), then it dropped and almost leveled off from band 6 to band 8 (near-infrared bands) (Figure 4(a)). Additionally, the effect of wavelength on spatial variability from CASI images was similar to those from Eagle and ATM airborne images (Figure 4(b)). Obvious peak in the red middle and sharp discontinuity at the red edge were observed. Only for vegetation landscape such as woodland and grass, greater spatial variability was observed in near-infrared bands than blue and green band. To get an approximate spectral response of the corresponding wavelength, we used approximately the medium band corresponding to the wavelength of ATM airborne images as the representation of blue, green, red, and near-infrared bands of Eagle and CASI airborne images, respectively. In this paper, their central wavelength of the representative blue, green, red, and near-infrared bands of Eagle airborne images was 485, 561, 651, and 829 nm, correspondingly. Thus, the utilized blue, green, red, and near-infrared bands of Eagle airborne images in Harwood was about 484–486, 560–562, 660–662, and 828–830 nm, correspondingly. We utilized band 2 as the representation of blue band for CASI airborne images in Harwood, Monks, and Cambridge area. Band 4 in Harwood and band 3 in Monks and Cambridge were applied as the green band for CASI airborne images. For ATM airborne images, band 2 and band 3 corresponded to the blue and green bands of Landsat TM images, which were utilized here.

4.2. Description of spatial heterogeneity

4.2.1. Overall spatial variability

Apparent divergence of spatial variability was examined in different spectral bands (Figure 5). For natural landscapes such as woodland and grass, ATM, CASI, and

![Figure 3](image-url)  
**Figure 3.** Effect of wavelength on variogram of Eagle airborne images on (a) site A and (b) site K.
Eagle airborne images in red bands were generally the most heterogeneous. However, for urban landscapes, ATM and CASI airborne images in the red band did not always enclose greater within-scene variation than the near-infrared bands and other visible bands. The spatial variability of ATM, CASI, and Eagle airborne images generally decreased with pixel size, which conformed to the change of support theory. According to change of support geostatistical theory, increasing size of the spatial support (spatial resolution) of data leads to decrease of the variogram sill and respective loss of short-scale variations smaller than two times the pixel size which is reflected in increasing mean characteristic length scale values. The Eagle hyperspectral airborne image was generally most heterogeneous. Specifically, only for woodland landscapes in blue and green bands, slightly weak spatial heterogeneity was examined in Eagle airborne images than ATM airborne images. Besides, the CASI airborne image was commonly the least heterogeneous in blue, green, near-infrared bands, and NDVI data-set. Only for grass and urban landscapes in blue and green bands, the total spatial variability of CASI airborne images was slightly stronger than that of ATM airborne images. Compared with Qiu et al.’s study, it seems that the spatial variability of ATM airborne images almost keep unchanged when the spatial resolution varies from 9 to 6 m.

The diversity of spatial variability could also be explained by the type of landscapes (Figure 5). Urban sites were most heterogeneous, which could be described by the mosaic of buildings with different roofs and vegetation such as trees and grass. Woodland and grass sites are more homogeneous than urban sites. Nonetheless, type of landscape was not always sufficient to explain the total spatial variability. The heterogeneity of land use within the observed area might increase the spatial variability. For example, the mosaic bare soil field with coniferous tree increased the spatial variability of woodland on site A. Conversely, on site D, the presence of a homogeneous forest area explained the relatively low sill value from woodland sites.

Compared to Qiu et al.’s study, the nugget effect (nugget:sill ratio) was fairly small. Very small nugget effect was obtained in Eagle airborne images. Considerably, larger nugget effect can be found in ATM airborne images at site B, C in blue band, site K in red band, and NDVI data-set. The nugget effect represents intraspatial variance, including uncertainty in local value or measurement error. It was revealed that larger nugget effect could be found on remote sensing images with relatively coarse spatial resolution, which was also confirmed in our study.

For NDVI data-set, the size sequence of total spatial variability characterized by the sill was generally similar to those from visible and near-infrared wavebands. The mean NDVI values obtained from ATM, CASI, and Eagle airborne images were comparable. Slightly greater mean values of NDVI data-set were always observed.
from CASI airborne images of woodland and grass landscapes. The smallest mean value of NDVI data-sets was consistently obtained from the ATM airborne images of woodland and grass landscapes. However, distinguishable differences could be found on the total spatial variability between NDVI data-sets from those three airborne images. Greater spatial variability was generally observed from NDVI data-set of Eagle airborne images than ATM and CASI airborne images. In addition, for grass landscape in Cambridge and River Frome, even with very close spatial resolution, NDVI data-set from ATM airborne images were usually a little more heterogeneous than that from CASI airborne images.

4.2.2. Characteristic length scales
Similar to the spatial variability, the mean characteristic length scale also varied with multisensor airborne images (as shown in Figure 6), the spectral bands and wavelength. The mean characteristic length scale of ATM, CASI, and Eagle airborne images generally decreased with the nominal spatial resolution. For example, the mean characteristic length scale of Eagle airborne images was usually the smallest.

The mean characteristic length scale of multisensor airborne images ranged between 100 and 600 m in visible and near-infrared bands for different landscapes. Specifically, for woodland landscape, the mean characteristic length scale of ATM, CASI, and Eagle airborne images in visible and near-infrared band fluctuated between 100 to 600 m, 100 to 510 m, and 100 to 380 m, respectively. For grass landscape, the mean characteristic length scale varied between 100 and 310 m. Compared with woodland and grass landscape, generally smaller mean characteristic length scales were observed in urban landscape. For NDVI data-set, considerably larger spatial structure was observed for woodland landscape on site A, C, and D.

Two spatial structures examined in ATM, CASI, and Eagle airborne images were distinguished: the first spatial structure less than 100 m, and the second spatial structure greater than 100 m. For the ATM and CASI airborne images of woodland and grass landscapes, the second spatial structure usually occupied the greater proportion of the total spatial variability. For Eagle airborne images, the first spatial structure (less than 20 m) generally occupied a greater proportion of total spatial variability in red and near-infrared band. For NDVI data-set, the second spatial structures generally exhibited greater proportion of the total spatial variability.

5. Discussion and conclusions
We provided detailed investigation on spatial heterogeneity of woodland, grass, and urban landscapes in UK from ATM, CASI, and Eagle airborne imagery in this study. Regarding the first question we proposed in the introduction section, conclusions could be drawn that great heterogeneity was observed in both red bands and near-infrared bands but with a steep gradient at the red edge for both vegetation and urban landscapes. The difference of spatial heterogeneity across spectral wavelength between vegetation and urban landscape was that the near-infrared waveband contains greater within-scene variation than the blue and green bands especially for vegetation landscape but not for urban landscape.

In visible bands, it is commonly known that red band is the best bands due to its great information contained. This study on the Eagle hyperspectral airborne image, ATM, and CASI airborne images confirmed this knowledge from analysis of woodland, grass and urban landscapes. In addition, our study further revealed that marvelous discrepancy was observed in the whole range of red waveband in reference to its spatial variability and there was a steep gradient at the red edge, which was also observed in some other remote sensing images (18, 21, 27).

For the range of both visible and near-infrared bands, numerous studies have illustrated that the near-infrared (NIR) waveband contains greater within-scene variation than the visible bands, especially in images covering densely vegetated areas (15, 18, 28). Nevertheless, our
study revealed that the near-infrared band contained relatively large spatial variability, but did not always enclose greater heterogeneity over red band. One possible explanation for Chavez’s study (15), therefore, was that the two SPOT bands he utilized, XS1 and XS3, corresponded roughly to the green and near-infrared portions of the spectrum 0.50 to 0.59 and 0.79–0.89 µm, respectively. And two Landsat TM bands, TM2 and TM4, also corresponded roughly to the green and near-infrared portions of the spectrum 0.52 to 0.62 and 0.76–0.90 µm, respectively. Supposing, we also utilized the blue and green bands to represent the visible bands, Chavez’s conclusion still held in this study. Nevertheless, Atkinson and Emery (18) computed and estimated variograms in 235 different visible and near-infrared wavebands using Spectron SE-590 spectroradiometer, and also drew a conclusion that there was generally an increase in variance with wavelength, which was obviously different from our findings. Another possible explanation was that this difference examined in other research (15–18) was attributable principally to the larger mean reflectance observed in the near-infrared wavebands.

The study of Qiu et al. (20) in Harwood forest area, UK, also indicated that that spatial variability of airborne images was extremely strong in the near-infrared band and relatively low in visible bands. Nevertheless, this phenomena does not appear any more, since we reutilized the band 6 (694–750 nm) and band 5 (694–704 nm) instead of band 7 (690–750 nm) and band 6 (694–704 nm) as the representation of red band for ATM and CASI airborne images, respectively, in this paper (more reasonable). Therefore, we obtained completely different results in reference to the size sequence of spatial variability in NIR and red band, by employing different wavebands in range of red bands. This further confirmed that fundamental discrepancy of spatial variability was illustrated across the whole range of red waveband regardless of the landscape type.

The mean characteristic length scale appears greater for multisensor images in near-infrared wavebands (around 550–620 m) than those in the visible wavebands (about 260–340 m) with a sharp increase at the red edge. The range of the variogram for near-infrared wavebands was almost double that for visible wavebands, similar results were obtained by Atkinson and Emery (18). In general, the mean characteristic length scale of ATM, CASI, and Eagle airborne images decreased with the nominal spatial resolution. Considerably, larger spatial structures were discriminated within airborne images with relatively coarse pixel size such as CASI. For woodland and grass landscape, spatial variability associated with the first spatial structure in ATM, CASI, and Eagle images generally derived from the within-species spectral variation in images, which might include illumination and view angle differences, natural variability in canopy structure and openness, shadowing effects, and crown health.

Regarding the second question we put forward in the introduction section, it seemed that the spatial variability generally decreased and the mean scale increased with pixel size through detailed study on ATM. CASI and Eagle images of woodland, grass, and urban landscapes. The total spatial heterogeneity discrepancy between ATM, CASI, and Eagle airborne images highlighted the different features detected by these three sensors. Greater spatial variability and smaller spatial structure were commonly observed in Eagle airborne images. Additionally, minor spatial variability and larger spatial structure were generally revealed in CASI airborne images. Taking into account NDVI data-set, Eagle airborne images were consistently most heterogeneous and CASI airborne images were generally the least heterogeneous. Compared with the different spatial resolution introduced by different sensors (ATM, CASI, and Eagle), the specific landscape and spectral bands were more important in determining heterogeneity by means of original visible, near-infrared bands, and NDVI. Compared with woodland and grass landscapes, greater spatial variability was obtained images of urban landscapes. Additionally, the functions of spatial heterogeneity with wavelength and landscape observed from those three airborne images were similar.

Some scholars investigated how vegetation patterns (NDVI) changed with spatial and spectral resolutions using hyperspectral AISA-Eagle and Hawk airborne images (10). They drew a conclusion that spatial resolution was more important in determining heterogeneity by means of NDVI than the depth of the spectral bands, which was inconsistent with our study. The possible explanation was that the effects of spectral bands were not fully exploited in their study, which principally focused on NDVI data-sets (10).

These findings have some theory and practical implications. First, it enriched our understanding of how to reconcile spatial patterns observed from multisensors (21). The difference of spatial heterogeneity caused by spectral bands outperformed that introduced by spatial resolution. The spatial heterogeneity observed from multisensor images generally conformed to the change of support theory in its corresponding spectral bands. However, related application of multisensors with different spectral wavelength (e.g. the multispectral and hyperspectral images) keep in mind with the dramatic change in red band. Considering the spectral wavelength, although it is true that all these three airborne images demonstrate greater spatial heterogeneity in red bands, its ratio of red band with peak value to near-infrared bands from Eagle hyperspectral airborne images is much larger than that from ATM and CASI airborne images. It seems that a distinguished peak value of spatial heterogeneity in the red band is obtained from hyperspectral airborne images with relatively small bandwidth.

Second, it provided some guidance for designing suitable sensors for specific applications with reference to ground spatial resolution, wavelength, and width.
As indicated in this study, for both natural and urban-related applications, sensor designers could take advantage of red wavebands instead of the blue and green bands in visible bands. For vegetation-related applications, near-infrared red bands were also highly recommended. But designers and researchers should be very cautious before deciding to choose which specific wavelength as a representation of red band and keep in mind that it really matter, especially for the hyperspectral airborne images.

Additionally, this study also afforded practical implications on selecting suitable airborne images in terms of the spectral band and pixel size. Here are some suggestions for vegetation and urban applications. For vegetation applications, observation of particular species development observations could take advantage of the Eagle images in red bands and near-infrared band in order to gain within-species information on the spatial structure and its variability. Other applications such as mapping vegetation species might exploit the ATM images to obtain more information about the spatial structure and its variability between different vegetation species. CASI airborne images with default vegetation channels were not prior to ATM and Eagle airborne images in vegetation application, considering its relatively homogeneous NDVI value observed. For urban applications, observation for urban planning and management could also take advantage of the Eagle images in visible and near-infrared bands for its higher spatial heterogeneity with considerably smaller spatial structure.

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