Comparative spatio-spectral heterogeneity analysis using multispectral and hyperspectral airborne images

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Knowledge of spatio-spectral heterogeneity within multisensor remote sensing images across visible, near-infrared and short wave infrared spectra is important. Till now, little comparative research on spatio-spectral heterogeneity has been conducted on real multisensor images, especially on both multispectral and hyperspectral airborne images. In this study, four airborne images, Airborne Thematic Mapper, Compact Airborne Spectrographic Imager, Specim AISA Eagle and AISI Hawk hyperspectral airborne images of woodland and heath landscapes at Harwood, UK, were applied to quantify and evaluate the differences in spatial heterogeneity through semivariogram modelling. Results revealed that spatial heterogeneity of multisensor airborne images has a close relationship with spatial and spectral resolution and wavelength. Within the visible, near-infrared spectra and short wave infrared spectra, greater spatial heterogeneity is generally observed from the relatively longer wavelength in short wave infrared spectra. There are dramatic changes across the red and red edge spectra, and the peak value is generally examined in the red middle or red edge wavelength across the visible and near-infrared spectra for vegetation or non-vegetation landscape respectively. In all, for real multisensor airborne images, the change in spatial heterogeneity with spatial resolution will accord with the change of support theory depending on whether dramatic change exists across the corresponding wavelength. Besides, if with close spatial resolution, the spatial heterogeneity of multispectral images might be far from the overall integration of these bands from the hyperspectral images involved. A comparative assessment of spatio-spectral heterogeneity using real hyperspectral and multi-spectral airborne images provides practical guidance for designing the placement and width of a spectral band for different applications and also makes a contribution to the understanding of how to reconcile spatial patterns generated by multisensors.

Keywords: variogram modelling; spatio-spectral heterogeneity; ATM; CASI; Eagle; Hawk airborne imagery; multi-sensors

1. Introduction

Spectral reflectance from the earth’s surface varies with wavelength. Spectral heterogeneity analysis on multispectral images will enrich our knowledge in this field and help us to design optimal sampling schemes across wavelengths (1). A large amount of research has investigated spatial heterogeneity in relation to spectral wavelength and found that the near-infrared (NIR) waveband contains greater within-scene variation than the visible bands, especially in images covering densely vegetated areas (1–4). Most research in this field has been applied to multispectral images such as Landsat TM and SPOT images (5–8). Several studies took this approach further and explore the spatio-spectral heterogeneity using hyperspectral images (1–9). For example, Atkinson and Emery (1999) investigated the spatial variability and spatial structure across visible and near-infrared spectra comprising 252 wavebands through variogram modelling (1). Chen and Henebry (2010) examined and compared spatial heterogeneity of EO-1 Hyperion imagery within visible, near-infrared and short-wave infrared spectra with simulating Landsat TM/ETM bands (9). However, little comparative research has been conducted on hyperspectral airborne images and their corresponding multispectral images regarding the effect of both spatial and spectral resolution on spatial heterogeneity. To fill this gap, we quantify and evaluate the differences in spatial heterogeneity between airborne thematic mapper (ATM), compact airborne spectrographic imager (CASI), Specim AISA Eagle and AISI Hawk hyperspectral airborne images at Harwood, UK.

2. Study area and database

The study area is located in Harwood Forest, Northumberland, NE England (55°10′N, 2°3′W), 30 km inland from the North Sea coast. Average annual rainfall is about 950 mm (10). The dominant vegetation type is Coniferous trees. The ATM, CASI, Eagle and Hawk airborne imagery was acquired with nine 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. To evaluate the effect of spectral resolution on spatial heterogeneity, two multispectral airborne images, one with relatively broad spectral bands and another with relatively narrow spectral bands, ATM and CASI, and other two hyperspectral airborne images, namely Specim AISA Eagle and AISI Hawk hyperspectral airborne images, are utilized.

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, with approximate bands of Landsat TM image (Table 1). The IresCompact airborne spectrographic imager (CASI) contains a two-dimensional CCD array-based pushbroom imaging spectrograph that can acquire up to 288 channels within the 430–870 μm spectral region. The CASI data used in this study comprises 11 channels with nominal spectral bandwidth within 3–7 μm in Harwood (Table 2). 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 μm. The Eagle hyperspectral image was collected in 252 channels with nominal spectral bandwidth of 2.4 μm in Harwood. The AISA Hawk is a 14-bit sensor able to capture short wave infrared wavelengths, 970–2450 μm. This makes the Hawk an ideal tool for data acquisition on spectral signatures characteristic to chemical compounds and man-made targets that cannot be distinguished using the Eagle instrument. The Hawk hyperspectral airborne image was collected in 237 channels with nominal spectral bandwidth of 6 μm in Harwood. The ATM, CASI, Eagle and Hawk data were gathered for the Harwood study area at a spatial resolution of 6, 7.2, 2.5 and 5 m, respectively. Further information about ATM, Eagle and Hawk airborne images can be found at website: http://arsf.nerc.ac.uk/instruments/.

To analyse the effect of spatial and spectral resolution on spatial heterogeneity from different earth surface reflectances, a comparative analysis was conducted on woodland and heath landscapes. Four sampling sites (sub-images) were adopted, representing woodland, heath landscape within our study areas (Figure 1, Table 3). Considering the relative narrow stripes boundary of Hawk hyperspectral airborne images, the sizes of A and C for ATM, CASI and Eagle airborne images are 1200 × 1200 m, and the other two sites for Hawk airborne images are 900 × 900 m. The spectral values recorded by the ATM, CASI and Eagle sensors were radiometrically calibrated to at-sensor radiance. Calibrated data were then multiplied by 1000 to allow subsequent data handling as a 2-byte (16-bit) short integer, without loss of numerical precision. An Azimuth Systems program (AZGCORR, http://arsf.nerc.ac.uk) was used to (I) 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 (DSM). A much greater mean reflectance was generally observed in the near-infrared wavelength than that in visible bands regardless of the landscapes. To eliminate the atmospheric influence and compensate the decrease in solar irradiance at longer wavelengths, the image bands were radiometrically normalized by dividing each pixel’s value by the spectrally uniform mean value for that spectral band.

| Table 1. Spectral range for each spectral band of ATM image in Harwood. |
|----------------|----------------|----------------|----------------|
| Channel | Spectral range (nm) | Channel | Spectral range (nm) | Channel | Spectral range (nm) |
| 1     | 420–450         | 5      | 630–690       | 9      | 1550–1750         |
| 2     | 450–520         | 6      | 695–750       | 10     | 2080–2350         |
| 3     | 520–600         | 7      | 760–900       | 11     | 8500–13000        |
| 4     | 605–625         | 8      | 910–1050      |        |                  |
According to change of support geostatistical theory, increasing size of the spatial support (spatial resolution) of data leads to decrease in the variogram sill. The change of support is referred to the largest area or time intervals for which the property of interest is considered homogeneous, which is the spatial resolution as regards to remote sensing images. In this study, ATM, CASI, Eagle and Hawk airborne images in our study areas are assumed to be isotropic and the experimental variograms are computed by pooling together all directions.

### 3.2. Variogram modelling

Theoretical variogram models are typically fit through empirical semivariograms to quantify the spatial variability components. Variogram modelling is based on a probabilistic approach considering the image as one among all possible realizations of a second-order stationary random function. The variograms under study here generally show more than one range, indicating spatial structuring at multiple scales (Figures 2–5, 7). A linear combination of two or more functions can be used to better represent the multiscale spatial structures (Equation (1)). This extended model of the variogram is a weighted sum of two elementary variogram models.

\[
\gamma(h) = C_0 + C_1 \sum_{k=1}^{L} b_k g_k(r_k, h) \quad (1)
\]

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. It provides both components of spatial heterogeneity: (1) the degree of image spatial variability, which is given by the sill and nugget; (2) the image spatial structures, which are characterized by the parameters corresponding to each elementary model \(g_k\): range \(r_k\) and fraction of the total variance \(b_k\) related to each range \(r_k\). Here we used the linear combination of spherical and exponential models.

Table 2. Central wavelength (CW) and bandwidth (BW) for each spectral band of CASI image in Harwood.

| Channel | Centre (nm) | Width | Channel | Centre (nm) | Width | Channel | Centre (nm) | Width |
|---------|-------------|-------|---------|-------------|-------|---------|-------------|-------|
| 1       | 448         | 11    | 5       | 567         | 3     | 9       | 760         | 4     |
| 2       | 487         | 11    | 6       | 668         | 7     | 10      | 777         | 7     |
| 3       | 529         | 4     | 7       | 706         | 5     | 11      | 817         | 7     |
| 4       | 550         | 7     | 8       | 746         | 5     |         |             |       |

Table 3. Characteristics of sample sites.

| Landscape | Site name | Site | Latitude           | Longitude          |
|-----------|-----------|------|--------------------|--------------------|
| Woodland  | Wood01    | A    | -2°01’68.56” to -1°99’79.02”W | 55°20’66.39”–55°21’74.76”N |
|           | Wood02    | B    | -2°00’97.26” to -1°99’54.86”W | 55°20’88.68”–55°21’80.09”N |
| Heath     | Heath01   | C    | -1°95’49.33” to -1°93’60.41”W | 55°24’81.7”–55°25’89.61”N |
|           | Heath02   | D    | -1°94’60.4” to -1°95’49.33”W  | 55°24’81.5”–55°25’809.62”N |

Figure 1. Study sites A (a, Eagle image), B (b, Hawk image), C (c, Eagle image) and D (d, Hawk image) (band centre of Eagle image: 473,556,661, band centre of Hawk image: 1138, 1688, 2167).
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 (16). 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): $A = \frac{1}{2} \int_{0}^{r_1} (C_0 + C_1 - \gamma(h))dh$. The integral range of the linear

$$g_1(h) = \begin{cases} C_0 + C_1 \left[ \frac{1}{2} \left( \frac{h}{r} \right) - \frac{1}{2} \left( \frac{h}{r} \right)^2 \right] & h \leq r \smallskip \\ C_0 + C_1 & h > r \end{cases} \quad (2)$$

$$g_2(h) = C_0 + C_1 \left[ 1 - \exp \left( -\frac{3h}{r} \right) \right] \quad (3)$$

Figure 2. Omnidirectional semivariograms for ATM airborne images of (a) woodland and (b) heath landscape.

Figure 3. Omnidirectional semivariograms for CASI airborne images of (a) woodland and (b) heath landscape.

Figure 4. Omnidirectional semivariograms for Eagle airborne images invisible and near-infrared bands for woodland.

Figure 5. Omnidirectional semivariograms for Eagle airborne images invisible and near-infrared bands of Heath landscape.
A model of regionalization is computed as $A = \sum_{k=1}^{l} b_k A_k$. Where $A_1 = \frac{2\pi z}{\Gamma}$ for the exponential and $A_2 = \frac{\pi z}{3}$ for the spherical functions. Garrigues et al. (2006) used the square root of the integral range $A$, denoted as $D_c$, to quantify the mean length scale of spatially aggregated images. It has been shown to be suitable for comparing mean length scales of multiresolution datasets (6, 15) and is thus adopted here.

4. Results and discussion

4.2. Comparative result within visible and near-infrared spectra

Empirical semivariograms were computed on ATM, CASI, Eagle airborne images for woodland (site A), heath (site C) up to a half of sub-image size for some representative wavebands within visible and near-infrared spectra (Figures 2–5). Noise images are observed in band 1 from ATM airborne images and thus not considered here. The empirical semi-variograms of ATM, CASI, Eagle airborne images are modelled using the linear model of regionalization (Figure 6). Results demonstrate that landscape character, different airborne images and its corresponding wavelength all play their roles in explaining within-image spatial variability and spatial structures (Figures 3 and 4).

Considering a woodland landscape, the spatial variability indicated by the sill first increases gradually along with the wavelength and then it rises sharply in the red edge, obtaining its peak values in the middle red band, after that it decreases dramatically and finally almost levels off in near-infrared bands. Thus, across the visible and near-infrared spectra, the greatest spatial variability is generally obtained in the middle red wavelength. Spatial variability in the near-infrared bands is generally stronger than that found in other visible bands excluding the red spectral bands, as observed from the ATM, CASI and Eagle airborne images of a woodland landscape.

Similar to woodlands, there are also dramatic changes of spatial variability across the red edge, as observed from ATM, CASI and Eagle hyperspectral images of heath landscape across the visible and near-infrared spectra. Specially, there are three local maximums: the first local maximum at middle green band, the second local maximum at middle red band, the third maximum (peak value) in the red edge (from visible to near-infrared wavelength). Numerous studies have revealed that the near-infrared (NIR) waveband contains greater within-scene variation than the visible bands, especially in images covering densely vegetated areas (1–4, 9). From this study, the variogram analysis on barely non-vegetated areas, heath landscape, generally confirmed that great within-scene variations were observed in the near-infrared (NIR) waveband than in visible bands. Nevertheless, it was generally not examined on vegetation areas (woodland), as disclosed in comparative research on ATM, CASI and Eagle airborne images in this study.

On the whole, semi-variogram analysis from ATM, CASI and Eagle airborne images present consistent results. But the finer spectral resolution of Eagle hyperspectral airborne images reveals significant details about the local maximums and significant details in red edge transition. Comparing the spatial variability of ATM, CASI and Eagle airborne images, it seems that the Eagle hyperspectral airborne images with relatively higher spatial and spectral resolution always occupy great within-scene spatial heterogeneity than ATM and CASI airborne images. Relatively larger spatial variability is generally observed from ATM airborne images than CASI airborne images excluding in the red spectral bands. Therefore, the spatial variability of ATM, CASI and Eagle airborne images is highly dependent on the spatial, spectral resolution and the wavelength. Conform to the change of support theory, airborne images with smaller pixel size generally present greater spatial variability. Comparing airborne images with close pixel size but different spectral bands, much greater spatial variability might be observed from airborne images with narrow spectral bands within the wavelength composing the local maximum or peak value, even though it has a relatively coarse spatial resolution, as observed from the ATM and CASI airborne images. The reasons might be that multi-spectral airborne images with relatively broader spectral

Figure 6. Effect of wavelength on variogram of ATM, CASI and Eagle airborne images from (a) woodland and (b) heath landscape.
bands such as ATM images are involved across all these related spectral bands and its peak values could be averaged. Thus, a conclusion can be reached that the spatial variability in airborne images with close wavelengths might accord with the change of support theory, otherwise, it might not when there are dramatic changes across the corresponding wavelength.

4.3. Comparative result within short-wave infrared spectra

Empirical semivariograms were computed on ATM, Hawk airborne images for woodland (site B), heath (site D) up to a half of sub-image size for some selected wavebands in short wave infrared spectra (Figure 7). The empirical semivariograms of ATM, Hawk airborne images are also modelled using the linear model of regionalization (Figure 8 and 9). Noise images are observed in Hawk hyperspectral images within the wavelength of 962–987 μm, 1359–1485 μm, 1807–2028 μm and 2305–2451 μm and thus not considered here. Results also illustrate that spatial variability of airborne images is highly dependent on different landscapes, airborne images from multisensors and its corresponding wavelength.

For woodland and heath landscapes, the hawk hyperspectral images exhibit stronger spectral heterogeneity. There is an overall tendency of increase across short wave infrared wavelength. For woodland, the dramatic increases occur in three spectral ranges, namely 1350–1500 μm, 1800–2050 μm, and 2200–2300 μm. For heath landscape, two sharp increases of spatial variability are also obtained within the first two ranges. However, compared with the woodland landscape, some tremble values are observed within 993–1150 μm from heath landscape and no obvious increases are examined in 2200–2300 μm. For those two landscapes, each dramatic enhancement of the total spatial variability is followed by relatively slightly decrease, which makes the figure shaping like a leaning ladder.

Regarding the question of evaluating the spatial heterogeneity observed from multispectral and hyperspectral images, it was revealed that the output of simulated sensors were actually the overall integration of these bands involved through rescaling the Hyperion bands to get simulated Landsat TM images (17). However, our research on two real airborne images, one multispectral image with relatively broad spectral band, one hyperspectral images with relatively narrow spectral band, provide a different answer to this question. With a similar spatial resolution to the Hawk airborne images, the spatial variability of ATM airborne images of woodland and heath landscapes are consistently stronger than that of Hawk hyperspectral airborne images in the two short wave infrared bands (1150–1750 μm and 2080–2350 μm). Spatial heterogeneity of multi sensor images does not definitely in accord with each other in some specific spectral domain such as the short wave infrared spectra. In this study, the spatial variability observed from multispectral

Figure 7. Omnidirectional semivariograms for Hawk airborne images of (a) woodland and (b) heath landscape.

Figure 8. Effect of wavelength on variogram of ATM, Hawk images in short-wave wavelength from (a) woodland and (b) heath landscape.
airborne images of woodland is consistently greater than those from hyperspectral airborne images at the corresponding wavelength, which is impossible if examined from simulated images through rescaling.

Different from spatial variability, the mean characteristic length scales have a tendency of decrease along with the wavelength as observed from Hawk airborne images of woodland and heath landscapes (Figure 9). They vary within the range of 50–350 m, 150–300 m for woodland and heath landscape respectively. Specially, for woodland, the mean length scale firstly drops dramatically within the wavelength of 990–1500 μm, and then, almost levels off along with the wavelength within short-wave infrared spectra. Two spatial structures were distinguished from Hawk airborne images: the first spatial structure less than 100 m and the second spatial structure between 100 and 550 m. It is interesting that the first spatial structure almost remains unchanged across the short wave infrared spectra and the second spatial structure demonstrates similar dynamic pattern as the mean length scale. It is easy to understand since the second spatial structure generally occupied greater proportion of the total spatial variability and the first spatial structure almost remains stable. Thus, two spatial structures, one smaller spatial structure always around 50 m, another larger spatial structure, generally decreasing with spectral wavelength, could be distinguished from the Hawk images of woodland and heath landscapes.

5. Conclusion
The relationship between spatial heterogeneity and spectral wavelength was evaluated with ATM, CASI, Eagle and Hawk hyperspectral airborne imagery using semivariogram analysis. Results demonstrate that spatial heterogeneity of multisensor airborne images is closely related to their spatial, spectral resolution and the wavelength. Airborne images at finer spatial resolution generally contain superior spatial heterogeneity within its corresponding wavelength, conforming to change of support theory. However, it is very complicated to compare two airborne images with different wavelength and band centres, e.g. one multispectral airborne image and another narrowband airborne image. It was revealed that the change of spatial heterogeneity along with spatial resolution might accord with the change of support theory on condition that no dramatic change, especially the spine, exists across the corresponding wavelength, which can be examined from the hyperspectral airborne images. Otherwise, stronger spatial variability might be examined from the airborne images with coarse spatial resolution but relatively narrowband in those wavelengths containing spine values. This study also illustrates that there is significant spatio-spectral heterogeneity across the visible, near-infrared and short wave infrared spectra as observed from those four airborne images. Greater spatial heterogeneity is generally observed from short wave infrared spectra across the visible, near-infrared and short wave infrared spectra, and the peak value within the visible and near-infrared spectra is generally examined from the red middle or red edge wavelength.

Knowledge of spatio-spectral heterogeneity within multisensor remote sensing images is significant for its various applications in earth surface observations. Our research on four real airborne images, two multispectral images with one broad and one narrow spectral band, and another two hyperspectral airborne images, provides some practical insights to this question. These findings have some practical implications. Firstly, this study affords some practical insights into selecting suitable existing airborne images for various applications such as the proper design and selection of spectral bands and pixel size. As revealed in this study, vegetation-related applications could both take advantage of the red middle and considerably longer wavelength in short wave spectra. For barely or non-vegetated area, the red transition edge from red to near-infrared wavelength and also the considerably longer wavelength in short wave spectra are more prior to be utilized. However, for both vegetation- and non-vegetation-related applications, one should be aware of the sharp transitions at red edge and short-wave infrared spectra. For these four airborne images evaluated, ATM airborne images could generally be applied in various applications for its moderate spatial heterogeneity across the visible and near-infrared spectra and relatively high values in the short wave spectra, despite its rela-
tively coarse spatial resolution. Secondly, the change in spatial heterogeneity with wavelengths also provides some guidance for designing the placement and width of a spectral band for different applications. Researchers could take advantage of some specific spectra that could minimize the loss of spatial information. Also indicated in this study, remote sensor designers could also properly exploit the red band and the short-wave infrared spectra to maximum the spectral discrimination. In this study, the spectral range of 2000–2300 μm in the short wave infrared spectra is highly recommended. Thirdly, it could enrich our understanding of how to reconcile spatial patterns generated by multisensors through exploring the difference of spatial heterogeneity between different spectra using real multispectral and hyperspectral images. This study revealed that the spatial variability of airborne images with close wavelength generally in accord with the change of support theory on the condition that there is no dramatic changes across the corresponding wavelength. Besides, if with close spatial resolution, the spatial heterogeneity of multispectral images might be far from the overall integration of these bands from the hyperspectral images involved. It could be much stronger as observed from multispectral airborne images than from its corresponding hyperspectral images in any corresponding wavelengths. Further investigations are needed to explore the reasons behind them.

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