Monitoring and assessing of landscape heterogeneity at different scales

Angela Lausch · Marion Pause · Daniel Doktor · Sebastian Preidl · Karsten Schulz

Abstract In numerous studies, spatial and spectral aggregations of pixel information using average values from imaging spectrometer data are suggested to derive spectral indices and the subsequent vegetation parameters that are derived from these. Currently, there are very few empirical studies that use hyperspectral data, to support the hypothesis for deriving land surface variables from different spectral and spatial scales. In the study at hand, for the first time ever, investigations were carried out on fundamental scaling issues using specific experimental test flights with a hyperspectral sensor to investigate how vegetation patterns change as an effect of (1) different spatial resolutions, (2) different spectral resolutions, (3) different spatial and spectral resolutions as well as (4) different spatial and spectral resolutions of originally recorded hyperspectral image data compared to spatial and spectral up- and downscaled image data. For these experiments, the hyperspectral sensor AISA-EAGLE/HAWK (DUAL) was mounted on an aircraft to collect spectral signatures over a very short time sequence of a particular day. In the first experiment, reflectance measurements were collected at three different spatial resolutions ranging from 1 to 3 m over a 2-h period in 1 day. In the second experiment, different spectral image data and different additional spatial data were collected over a 1-h period on a particular day from the same test area. The differently recorded hyperspectral data were then spatially and spectrally rescaled to synthesize different up- and down-rescaled images. The normalised difference vegetation index (NDVI) was determined from all image data. The NDVI heterogeneity of all images was compared based on methods of variography. The results showed that (a) the spatial NDVI patterns of up- and down-scaled data do not correspond with the un-scaled image data, (b) only small differences were found between NDVI patterns determined from data recorded and resampled at different spectral resolutions and (c) the overall conclusion from the tests carried out is that the spatial resolution is more important in determining heterogeneity by means of NDVI than the depth of the spectral data. The implications behind these findings are that we need to exercise caution when interpreting

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and combining spatial structures and spectral indices derived from satellite images with differently recorded geometric resolutions.

Keywords Monitoring · Landscape heterogeneity · Hyperspectral imagery · Semivariogram · Scale effects

Introduction

The monitoring of vegetation and land surface processes on a global scale requires high spatial and temporal frequency observation data. As the availability of optical remote sensing data of different temporal, spectral and geometric resolution (ASTER, IKONOS, RapidEye) is becoming more readily available and less costly, there is an unprecedented opportunity to use high resolution spectral and spatial data products to investigate vegetation, landscape patterns and biochemical vegetation properties and process interactions at different scales. As a result, the pressure has also increased to generate and up- and downscale information more quickly to derive land surface variables such as normalised difference vegetation index (NDVI) or leaf area index (LAI). Spatial and spectral rescaling to derive land surface variables from remote sensing data have thus been established as common practical research methods.

Recent investigations in this field use complex mathematical–statistical methods and models for rescaling to quantify land surface variables (Garrigues et al. 2006, 2008; Tarnavsky et al. 2008). According to Malenovský et al. (2007) and Wu (2009), there are still no truly suitable methods available at present to derive land surface variables from remote sensing data from different spatial and spectral resolutions and therefore from scaling. Wu (2009) states the reasons for this: The research on scale, the effect of different scales, scale transition and methods of scaling in remote sensing are still at the very beginning. There are many reasons why the transfer of information over different scales is so difficult: (1) Different remote sensing instruments have a different field of view (FOV) and types of lenses that correspond to different spatial resolutions. (2) Instruments of a comparable target measurement have different technical designs and acquisition parameters. (3) The earth's surface processes are highly nonlinear and can create quite unexpected patterns. (4) The calibration and validation of models is generally characterized by specific spatial and spectral data characteristics. (5) There is a big discrepancy between the observation scale, the model scale and the land surface process scale. (6) Different factors, such as funding, the time of data recording and available manpower, constrain the choice of scale and the mode and intensity of airborne and even satellite-based observations. Hence, a data product may not be exploited to its full potential. Therefore, many methods and models in the scaling of remote sensing data products are often 'show case'-type studies without the possibility of a true comparison or generalization.

The spectral reflectance from vegetation and surface objects and thus the heterogeneity of the land surface are influenced by a number of factors. In addition to atmospheric influences, the spectral, spatial and temporal resolutions of remote sensing sensors all play a decisive role.

Older studies postulate that the derivation and quantification of biophysical surface variables such as NDVI and LAI scales are invariant and that a rescaling to other geometric resolutions by deriving average values should not really pose a problem (Hall et al 1992; Atkinson and Tate 2000). However, more recent investigations show that by simply deriving average values for spatial and spectral rescaling, this can lead to a considerable misinterpretation and false quantification of land surface variables from remote sensing data. Furthermore, the nonlinearity of the earth's surface processes causes a nonlinearity of the spatial and temporal heterogeneity and patterns of land surface variables.

Over the recent years, research has therefore focused increasingly more on the specific analysis of individual variables affecting the spatial heterogeneity of land surface variables from remote sensing data on different scales. For example Briggs and Nellis (1991) and later Goodin and Henebry (1998) investigated the seasonal effect on the spatial heterogeneity of tall grass prairie based on SPOT and Landsat TM data across a growing season. Garrigues et al. (2008) modelled the influence of temporal vegetation changes on spatial NDVI heterogeneity based on SPOT-HRV data, whereas Goodin et al. (2004) analysed the effect of the solar illumination angle and the sensor view angle on observed patterns and the spatial structure in tall grass prairie. Their results from the geostatistical analysis show that the spatial structure of the reflectance

and the NDVI change with the viewing angle of the sensor used and the solar illumination angle. The change of the spatio-spectral heterogeneity as a function of the spectral wavelength and the spatial resolution based on EO-1 Hyperion imagery and Landsat TM data was investigated by Chen and Henebry (2010). They found that the heterogeneity of surface reflectance is (a) dependent of spatial and spectral sensor characteristics and (b) that it 'would be necessary to distinguish actual changes on surface reflectance from the uncertainties in-duced by the discrepancies among the sensors in their spectral characteristics'.

The effect of different rescaling on the spatial prop-erties and the heterogeneity of vegetation patterns has only rarely been observed based on empirical studies (Levesque and King 1999).

Atkinson (1993) empirically analysed the effect of two spatial resolutions (1.5 and 2 m) of airborne MSS imagery on the heterogeneity of different wavelengths. Furthermore, another empirical study was undertaken by Goodin and Henebry (2002). They analysed the differences of recording and rescaling the spatial res-olution of aircraft sensor data on the heterogeneity of NDVI. For these investigations, simple camera sys-tems (Dycam Agricultural Digital Camera) were mounted on the aircraft that generated different geo-metric images at flight heights between 0.625 and 3.125 m. They found that the spatial heterogeneity of the NDVI from recorded and spatially rescaled images was not identical.

Until now, no investigations have been conducted on the spatial and spectral scaling effect on spectral vegetation indices based on spatial and spectral high resolution hyperspectral remote sensing data. In this paper, we report on experimental studies based on the airborne hyperspectral remote sensor Airborne Imaging Spectrometer for Applications (AISA)-EAGLE/HAWK (DUAL) with following research objectives: (a) How do vegetation patterns change as a result of different spatial and spectral sampling scales? (b) Which scale factor (spatial or spectral) has the strongest influence on the quantification and heterogeneity of the derived spectral vegetation in-dices? (c) How do different spatial and spectral resolutions affect the heterogeneity of NDVI in dif-ferent types of land cover classes? (d) Can the re-sults from the analyses derived in this project be generalised and applied to a wider context?

Methods

Site description

For our heterogeneity analysis, we used two different study areas. The first study area is part of the Terrestrial Environmental Observatories (TERENO) long-term monitoring region (www.tereno.net; Zacharias et al. 2011), situated in the Harz region of Central Germany (Fig. 1). Remote sensing data were recorded using the hyperspectral sensors along a 25-km land cover gradient (N51.36°, E11.00°–N51.45°, E11.26°) with a ground resolution of 1, 2 and 3 m. The second study area—Kreinitz (N51.23°, E13.15°)—is situated to the East of Leipzig. Hyperspectral remote sensing data were recorded using a 2-km land use gradient (Fig. 1).

A number of spectral and spatial scale tests could be carried out (cf. Chapter 2.2). To minimize any differences with illumination, weather conditions, geo-metrically effects of vegetation, as well as phenologi-cal and biophysical differences in the vegetation, the hyperspectral data were taken within a short time frame on the same day. This ensures the greatest comparability of hyperspectral information with dif-ferent ground resolutions of 0.5, 1, 2 and 3 m. The flight lines were always flown in the same direction: the investigation site of the TERENO gradient was flown west to east while the investigation site of the Kreinitz study was flown southeast to northwest. More specifications of the hyperspectral data are provided in Table 1.

Both investigation sites contain agricultural and seminatural land use categories. For the tests, the following land cover types were selected: grassland, rural vegetation, deciduous forest, mixed hardwood forest and bare soil.

Experimental description and airborne imagery

The analysis of spatial–spectral heterogeneity of land-scapes was realised through the 'One Sensor at Different Scales' (OSADIS) approach (Lausch et al. 2012, 2013). The basis of this approach is that all data were collected using the same hyperspectral sensor (AISA-EAGLE/HAWK (DUAL)). The airborne sur-veys flown at different flight altitudes were recording spectral images with ground resolutions of 0.5–3 m. The flight campaigns were done within a very short time frame on the same day and same study area. The

Fig. 1 Study area of the TERENO land cover gradient (25 km long) in Sachsen-Anhalt, Germany and the Kreinitz gradient (2 km long) in Saxony, Germany
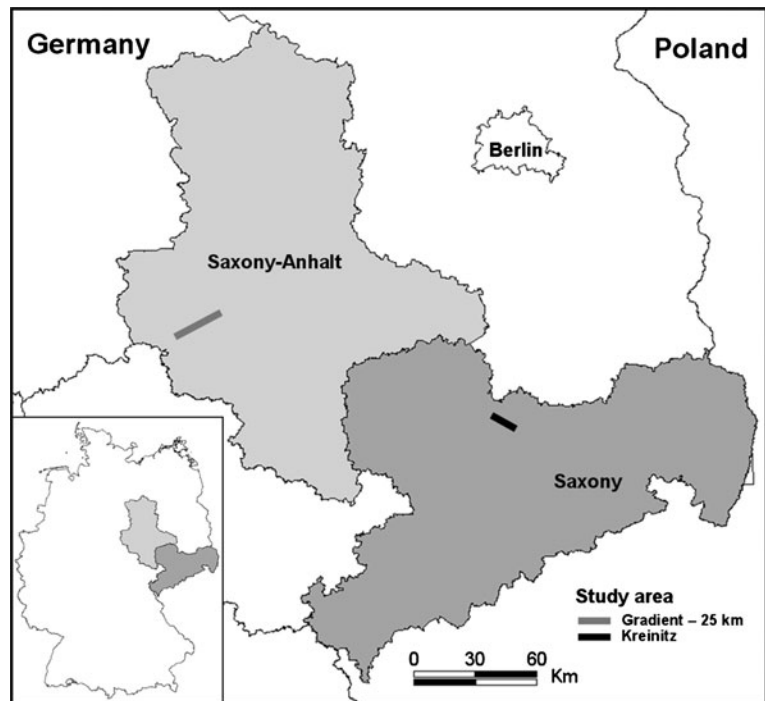
exact specification of the flight campaigns is provided in Table 1.

The following airborne tests were conducted as follows:

1. Three identical surveys transect along the '25-km gradient site' with a constant spectral resolution (491 bands), but with different spatial ground resolutions (1, 2 and 3 m; cf. Chapter 3.1; Figs. 4 and 5)
2. Six identical surveys transect along the '2-km site' with a constant spatial ground resolution (1 m), but with different spectral resolutions (491, 367, 244, 183, 121 and 91 bands; cf. Chapter 3.2; Figs. 6 and 7)
3. Two identical surveys transect along the 2-km site with a constant spectral resolution, but different spatial ground resolutions (0.5 and 1 m; cf. Chapter 3.3; Fig. 8)

Tests (1) and (3) were flown at different altitudes, whereas test (2) used different band files.

Data preprocessing

After recording, the airborne AISA-DUAL raw data were radiometric corrected based on the procedure CaliGeo (Spectral Imaging Ltd; Mäkisara et al. 1993)

run under ENVI (ITT Visual Information Solution, Boulder, CO, USA). After radiometric correction, ocular linear and nonlinear miscalibrations in the hyperspectral data were reduced by implementing an image-driven, radiometric recalibration and rescaling method (reduction of miscalibration effects; Rogaß et al. 2011). The atmospheric correction was performed using the software ATCOR4 (Richter and Schlapfer 2002) and the radiative transfer algorithm MOD TRAN-2. The programme corrects at-sensor radiance images for solar luminance, aerosol and Rayleigh scattering. The ATCOR programme was adapted for the specific band characteristics of the AISA sensors. The atmospheric correction has no effect on spatially accuracy. The orthorectification of the airborne hyperspectral image was carried out using a digital elevation model together with the geocoding procedure CaliGeo. After preprocessing, the hyperspectral data were referred to as ground reflectance data with four different spatial ground resolutions of 0.5, 1, 2 and 3 m.

For all spatially and spectrally corrected hyperspectral data, another geometrical correction was carried out based on ortho-photos with a spatial resolution of 0.2 m. This geometrical corrector was carried out in ENVI for resampling with the correction parameters—'polynomial correction first order' and 'nearest neighbour'. For all test data sets, a root mean

Table 1 Specifications of the hyperspectral data recorded (AISA-EAGLE/HAWK DUAL)

Recording date	Recording time [UTC]	Recording ground resolution [m]	Focal length	FOV [deg]	Swath [m]	Flight altitude [m]	Frame per second [fps]	Mean ground speed [m/s]	Spatial/ spectral binning	Exposure time [ms]	Spectral range [nm]	Spatial pixel	Spectral resolution [nm]	Direction of flight lines	Spectral bands	sensor	Platform	Test site
11 September 2010	11:17	1	18.5/22.5	36.7	300	768	50	50	2/2 (EAGLE)	10	400–2,400	300	2.12–6.26	West to east	491	AISA-EAGLE/ HAWK (DUAL)	Aircraft, Cessna 206	Gradient – 25 km Saxony-Anhalt
	9:50	2			600	1,537	25		1/1 (HAWK)	10								
	9:26	3			900	2,300	17			10								
26 April 2011	10:08	0.5	18.5/22.5	36.7	150	384	54	50	2/2 (EAGLE) 1/1 (HAWK)	10	400–2,400	300	2.12–6.26	Southeast to northwest	491	AISA-EAGLE/ HAWK (DUAL)	Aircraft, Cessna 206	Kreinitz- 2 km Saxony
26 April 2011	9:33	1	18.5/22.5	36.7	300	768	50	50	2/2 (EAGLE)	10	400–2,400	300	2.12–6.26	Southeast to northwest	491	AISA-EAGLE/ HAWK (DUAL)	Aircraft, Cessna 206	Kreinitz- 2 km Saxony
	9:59	1											4.24–6.29		367			
	9:39	1											4.24–12.58		244			
	9:55	1							1/1 (HAWK)				8.48–12.58		183			
	9:44	1											8.48–25.16		121			
	9:50	1											16.96–25.16		91			

square error of ca. 1 pixel/spatial cell size was ascertained. Finally, to ensure absolute spatial compliance of the data, a geometrical image to image correction was carried out. Here, the image with the smallest spatial resolution was defined as the master image, to which all subsequent spectral data with the next highest geometrical resolution (slave images) were then geometrically aligned.

Analysis of heterogeneity

To assess landscape heterogeneity, the land surface variable NDVI was calculated for all image data. The NDVI is a vegetation index that expresses reflectance between red and near-infrared regions of a surface spectrum (Rouse et al. 1974). Based on Sellers (1985), the NDVI is related to greenness, vegetation abundance, biomass and structure of the vegetation. There are many NDVI variations depending on how the index is used. In the following study, we used the reflectance values at a wavelength of 680 nm as red and 800 nm as NIR. This index range between −1 and 1 is expressed as:

$$\text{NDVI} = (R800 - R670)/(R800 + R670) \tag{1}$$

NDVI was calculated for all recorded and resampled hyperspectral image data and subsequently compared with one another based on the semivariance analysis and the heterogeneity of the landscape.

One index for detecting and quantifying the spatial heterogeneity of landscape vegetation patterns (NDVI as a proxy of landscape vegetation patterns) is defined by the correlation length (Isaak and Srivastava 1989; Blöschl 1999; Ettema and Wardle 2002; Hornschuch and Riek 2009). Correlation length is based on the variogram $\gamma(h)$, which is usually estimated from the experimental variogram.

The semivariance is the average squared difference between the value pairs of the sample of a so-called regionalised variable (NDVI), separated by the vector of distance h (distance vector or lag). The calculation of the semivariance $\gamma(h)$ is described by Webster and Oliver (2001) and is calculated using the following equation:

$$y(h) = \left(1/2n(h)\text{sum}[z(xi + h) - z(xi)]\right)^2. \tag{2}$$

Here, $y(h)$ is the semivariance for the distance h, $z(xi)$ is the data or measurement points at locations x

and $x+h$, where h is the distance or lag between two data or measurement points, and $z(xi)$ are the number of pairs of measurement points with distance h.

To reveal spatial structures, the average semivariances of points with similar lags are consolidated. The semivariances averaged from lags are referred to as bins. For example, with a lag of 100 m, all semivariances of point pairs that are 0 to 100 m apart from each other are consolidated to the first bin. The second bin encompasses the interval class 100 to 200 m. In the variogram, semivariances calculated with respect to h for different distance vectors are graphically portrayed. The variogram represented by the bins is referred to as an experimental semivariogram and is described by the variables sill, range, nugget and total variance. As a result of these variogram variables, the spatial structure of all NDVI image data can be described quantitatively and compared (Fig. 2).

Spatial and spectral rescaling

The hyperspectral data recorded at the different spatial resolutions of 0.5, 1, 2 and 3 m were spatially rescaled using the frequently used methods nearest neighbour

(standard) and additional techniques of cubic convolution, bilinear resampling and pixel aggregate resampling (ENVI, v.4.7) algorithm to spatially synthesize down- and upscaled images. The spectral resampling was carried out by the definition of spectral filter functions or the use of pre-defined filter functions for common satellite sensors such as the ASTER satellite.

Results

Spatial scale effect on heterogeneity

For land uses of different heterogeneity and structure (grassland, rural vegetation, deciduous forest, mixed hardwood forest as well as bare soil), the NDVI was calculated using hyperspectral data recorded at spatial resolutions of 1, 2 and 3 m. In Fig. 3a–c, one can clearly see how the spatial pattern of NDVI of grassland changes depending on the spatial resolution of the data.

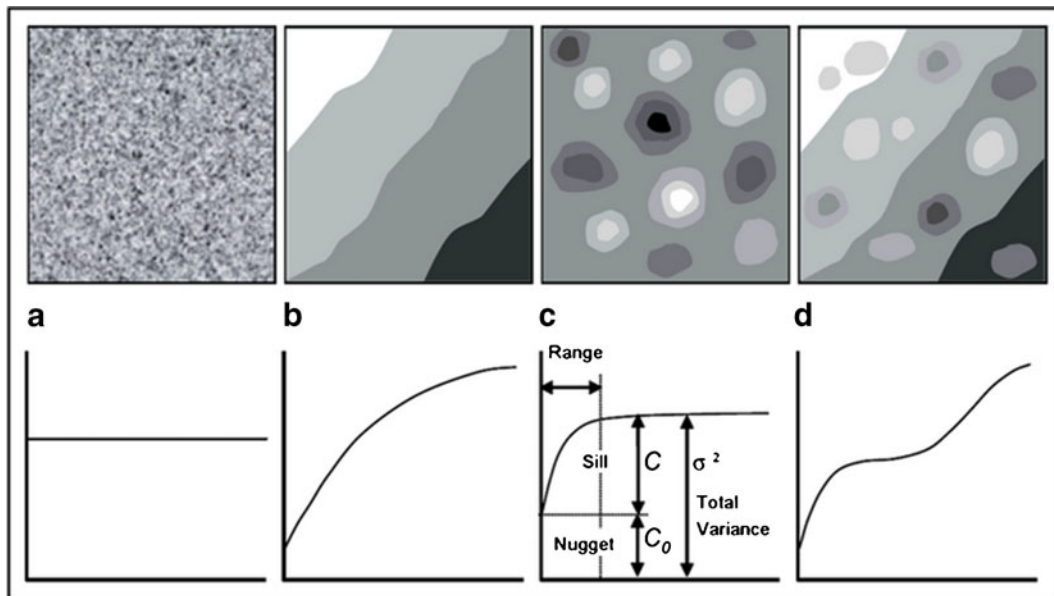To compare heterogeneities, the median, minimum and maximum values as well as the semivariances

Fig. 2 Semivariograms for different surface structures and patterns. **a** Pure nugget effect. The variance is not spatially structured, random or with non-dissolvable variance. **b** Large-scale heterogeneity. Patches are few, large, continuous and large scale. **c** Small-scale heterogeneity. Many small patches, sharply discontinuous, 'salt and pepper' effect. **d** Nested heterogeneity. Different scales of patchiness exist because different factors influence heterogeneity at different scales (according to Ettema and Wardle 2002)
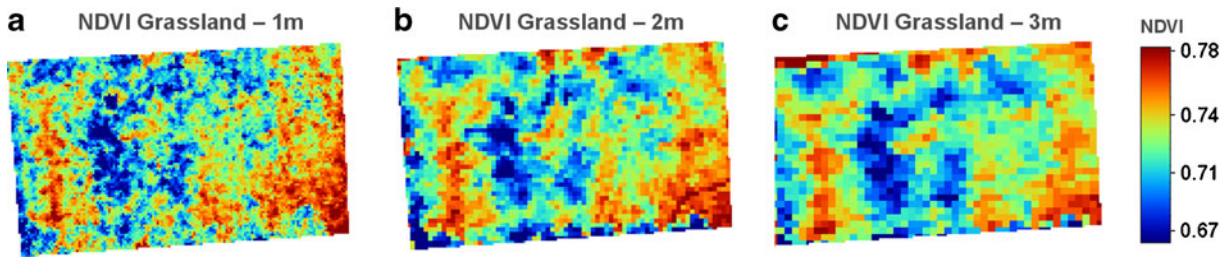
Fig. 3 Calculation of NDVI from the AISA-EAGLE/HAWK (DUAL) hyperspectral data recorded with different ground resolutions of 1 m (**a**), 2 m (**b**) and 3 m (**c**)

with a lag distance of 50 m were calculated (Fig. 4a–j). The median of the NDVI values is shown in Fig. 4a–j. Resolutions of the individual land use classes (Fig. 4a–j) only slightly differ between the individual land use classes. For grassland, deciduous forest as well as mixed hardwood forest, the NDVI is ca. 0.8. Likewise, the NDVI for the hyperspectral data at 1, 2 and 3 m resolution for the individually investigated land use structures grassland (Fig. 4b), ruderal vegetation (Fig. 4d), deciduous forest (Fig. 4f), mixed hardwood forest (Fig. 4h) and bare soil (Fig. 4j) only differs very slightly from one another. Furthermore, the NDVI that was ascertained for grassland, ruderal vegetation, mixed hardwood forest as well as bare soil displayed a high NDVI range, respectively (min–max values). Only the NDVI for the relatively homogeneous deciduous forest shows a low range of minimum and maximum values (Fig. 4e).

Using the semivariance analysis, spatial comparisons can be made between the heterogeneity of NDVI for the differently recorded spatial resolutions of 1, 2 and 3 m. The semivariance for grassland with a spatial resolution of 1 m obtains a higher variance compared to the image data of grassland with a recorded spatial resolution of 2 and 3 m. Up to a lag distance of 10 m, the sill increases strongly, becoming flatter and smoother up to a lag distance of 50 m (Fig. 4b). For grassland, no stable sill is reached (maximum semivariance). In spite of only slight average differences in NDVI between 1 and 3 m (Fig. 4a), considerable differences result in the spatial distribution and the heterogeneity of NDVI between the three spatial scales investigated. For the land uses deciduous forest, mixed hardwood forest and bare soil, the semivariance analyses of NDVI show a trend at 1, 2 and 3 m (Fig. 4f–j) comparable to that of the grassland (Fig. 4b). After an initial sharp increase (range) in the variances (1, 2 and 3 m) up to a lag distance of ca. 10 m, a sill is

then reached. This is maintained up to a lag distance of 50 m. The semivariance analyses of rural vegetation (Fig. 4d) show a completely different course compared to the other land cover classes investigated. Here, the variability increases systematically up to a lag distance of 50 m and no sill is reached.

Spatial scale effect on heterogeneity—up- and downscaling The hyperspectral data originally recorded at 1–3 m were transformed into other geometric resolutions using the spatial resizing methods nearest neighbour, cubic convolution and bilinear method (Fig. 5). In this way, an upscaling of the ground resolution was carried out from 1 to 2 and 3 m respectively as well as a downscaling from 3 to 2 and 1 m spatial ground resolution (Fig. 5).

In the box plot as well as in the semivariance analysis, it can be seen that after implementing the upscaling or downscaling methods with for example the spatial resolution from 3 to 1 m, although the geometrical characteristics of the new data set are altered, the spectral characteristics of the respective originally recorded image remain the same. Hence, a resampling of 1 to 2 m or 1 to 3 m results in the same median, minimum and maximum value as the output data set of 1 m. The same also applies to the semivariance of the NDVI for resampled hyperspectral data sets. The semivariance curves of the up- and downscaling resampled data still resemble their output data set in terms of the trend of their curves (Fig. 5).

Spectral scale effect on heterogeneity

In the study area of Kreinitz, hyperspectral data were recorded with different spectral characteristics (Table 1) within a short time frame of 20 min. Therefore, the data sets can be compared with one another with respect to their spatial heterogeneity as a function of the spectral

Fig. 4 NDVI derived from hyperspectral data (AISA-EAGLE/HAWK) recorded at spatial resolutions of 1, 2 and 3 m. Box plot for NDVI median and min–max values of grassland (**a**), ruderal vegetation (**c**), deciduous forest (**e**), mixed hardwood forest (**g**) and bare soil (**i**) and the semivariances with a lag distance of 50 m—grassland (**b**), ruderal vegetation (**d**), deciduous forest (**f**), mixed hardwood forest (**h**), bare soil (**j**)—at the investigation site with the land cover gradient of 25 km
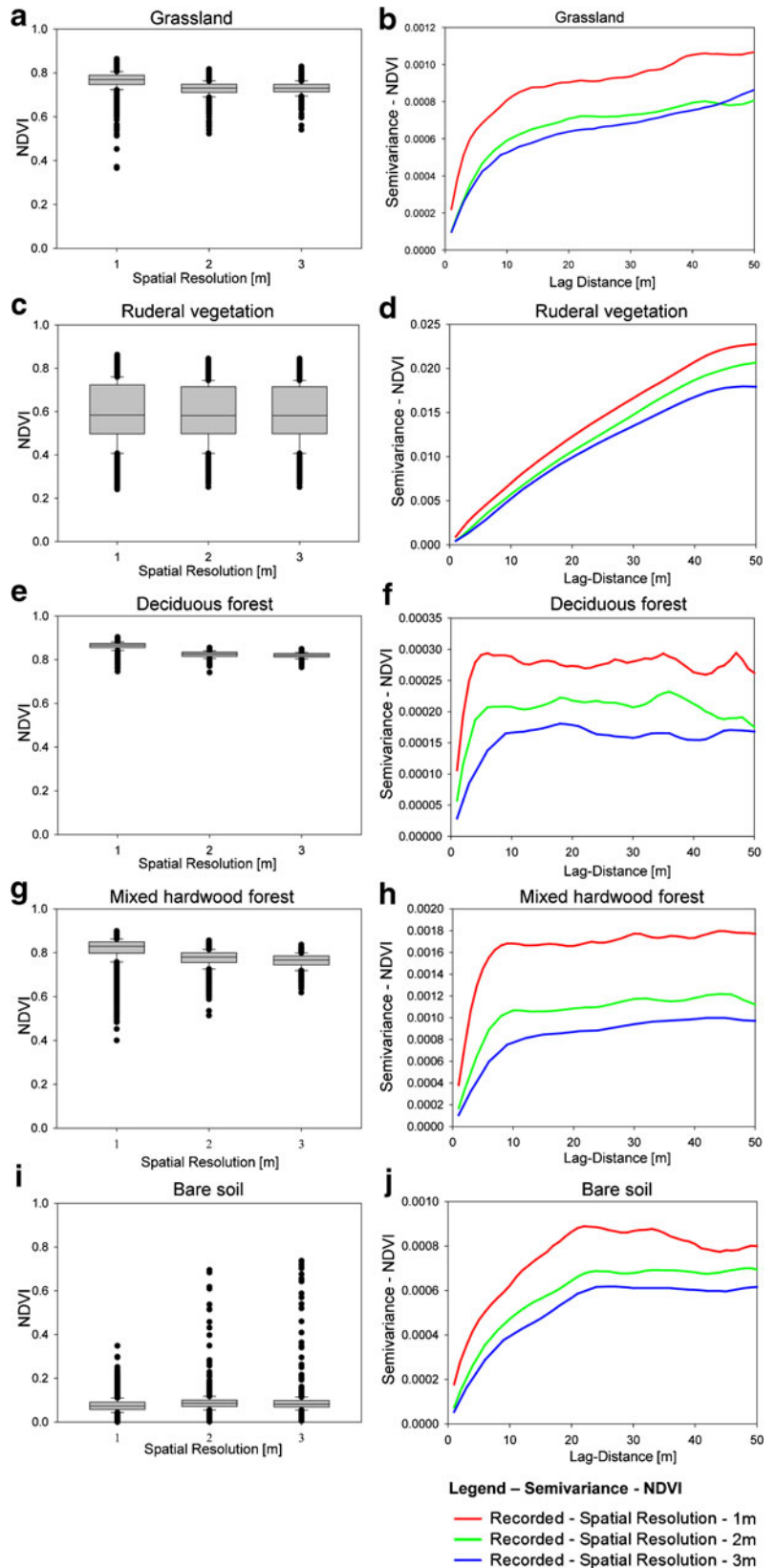
resolution (91, 121,183, 244, 367 and 491 spectral bands ranging from 400 to 2,500 nm). The effects of the different spectral sampling resolution on the median, minimum and maximum values as well as the semivariances of the NDVI for the five land use classes are presented in Fig. 6. The median, minimum and maximum NDVI values for all six land use classes show similar values. Hence, there are no statistically significant differences to calculate NDVI as a function of the spectral resolution depth of the hyperspectral sensor. This not only concerns the median, but also the variability of NDVI values for every land use structure investigated.

A comparison of the NDVI values of the six land use class investigated shows an expected high NDVI value for grassland of 8.5–9, of 6.5–7 for ruderal vegetation, an NDVI value of 8.5–9 for deciduous forest, an NDVI value of 7.5–8 for mixed hardwood forest as well as an NDVI value of 6.5–7 for bare soil, respectively.

The investigations on the heterogeneity of the NDVI plotted against the spectral resolution can be seen more clearly in Fig. 6b–j. The semivariances–NDVI for the six different spectral resolutions within the spectrum of 400–2,500 nm for all land use structures are only slightly different from one another. Moreover, there is no recognisable effect in the value of the total variance for data with a low number of spectral bands (91 spectral bands) compared to hyperspectral information with a high number of bands (491 spectral bands) and thus a narrow spatial range.

Spectral scale effect on heterogeneity—up- and downscaling The AISA hyperspectral data recorded at different spectral bands were transformed to the corresponding other recorded AISA-specific spectral band widths. This enables the investigation of the effect of spectral up- and downscaling using spectral resampling methods. The statistical parameters as well as the semivariances–NDVI after an up- and downscaling of the output data are provided in Fig. 7. The average values of the NDVI of grassland for the spectral bands 91, 121, 183, 244, 367 and 491 only change slightly (Fig. 7a, legends 1–4). After carrying out a spectral downscaling with a spectral resampling of originally 491 spectral bands to 367, 244, 183 as well as 91 spectral bands, respectively (Fig. 7a, legends 8–11), the spectral information of the output data set

(spectrally resampled hyperspectral data with 491 spectral bands) remains constant. Comparable results are obtained after a spectral upscaling from 91 to 183 bands, 183 to 491 bands, 91 to 491 bands and 244 to 491 spectral bands (Fig. 7a, legends 12–15)
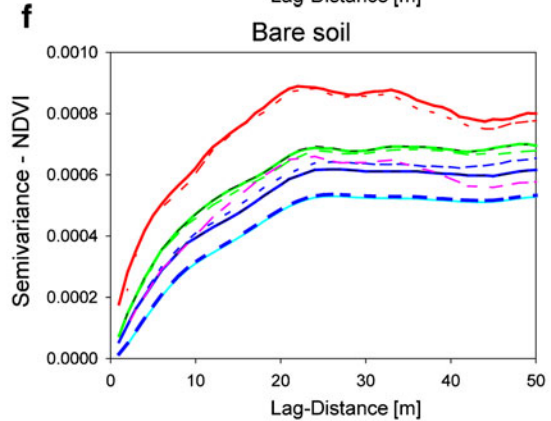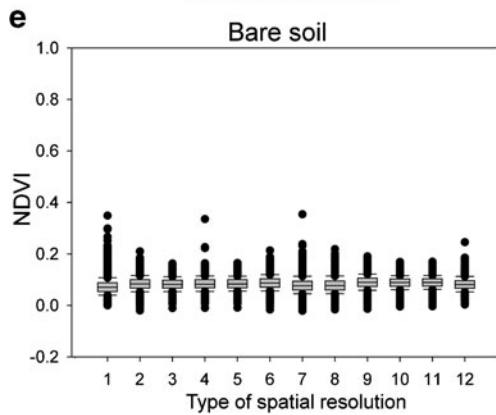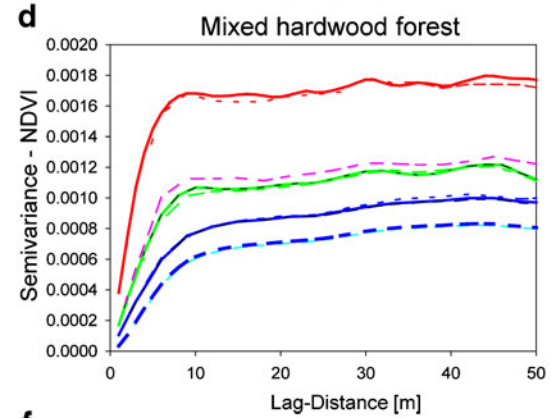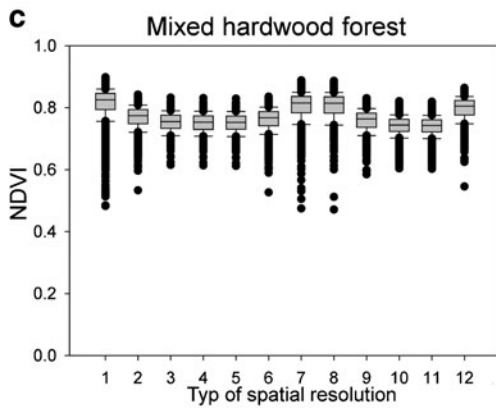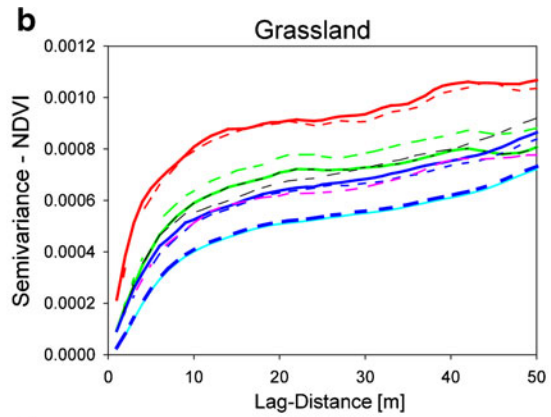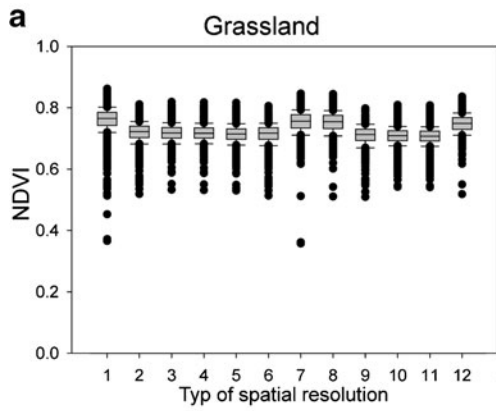
The effects on the NDVI patterns resulting from spectral up- or downscaling of the original data are illustrated in Fig. 7. In this way, the spectral band widths of the data set change after a spectral upscaling from 91 to 183, whereas the semivariance characteristics are still very similar to the output data set, hence the hyperspectral data set with 91 spectral bands. The same results were found for the data set transformations from 91 to 491 spectral bands as well as 183 to 491 spectral bands. The same effect also occurred with the downscaling of the spectral bands and a spectral resampling (Fig. 7c). This becomes most noticeable with the downscaling from 491 to 183 or 91 spectral bands.

Combined spatial–spectral scale effect on heterogeneity

For investigations on the effect of the spatial and spectral resolution on the heterogeneity of NDVI, hyperspectral data sets were implemented with a spatial resolution of 0.5 and 1 m with a spectral resolution of 91, 183 and 491 spectral bands. Furthermore, spectral downscaling was carried out for the spatial resolution of 0.5 and 1 m (491 spectral bands at 0.5 and 1 m, respectively, with 14 spectral bands of ASTER image data) (Fig. 8a). The results of the spatial–spectral scale effects on NDVI heterogeneity for grassland, mixed hardwood forest as well as bare soil can be seen in Fig. 8.

Therefore, the geometric resolution of a hyperspectral scene with 491 band widths (geometric resolution recorded at 0.5 m) has a higher NDVI semivariance compared to the reference data set with 491 band widths recorded at 1 m. The geometric resolution of a hyperspectral scene thus has a stronger influence on the semivariance or the heterogeneity of NDVI than the spectral resolution with 14, 91, 183 or 491 hyperspectral bands with a 1-m geometric soil resolution.

The spectral downscaling of the hyperspectral data set from 491 spectral bands to the spectral band width of the ASTER satellite data with 14 spectral bands does indeed reduce the respective heterogeneity of

a Grassland

b Grassland

c Mixed hardwood forest

d Mixed hardwood forest

e Bare soil

f Bare soil

Legend – Type of spatial resolution

1 - Recorded - 1m
2 - Recorded - 2m
3 - Recorded - 3m
4 - Recorded 3m - Resampling to 2m
5 - Recorded 3m - Resampling to 1m
6 - Recorded 2m - Resampling to 1m
7 - Recorded 1m - Resampling to 2m
8 - Recorded 1m - Resampling to 3m
9 - Recorded 2m - Resampling to 3m
10 - Recorded 3m - Resampling to 1m   Bilinear
11 - Recorded 3m - Resampling to 1m   Cubic convolution
12 - Recorded 1m - Resampling to 3m   Pixelaggregation

Legend – Semivaricanc - NDVI

- Recorded - 1m
- Recorded - 2m
- Recorded - 3m
- Recorded 3m - Resampling to 2m
- Recorded 3m - Resampling to 1m
- Recorded 2m - Resampling to 1m
- Recorded 1m - Resampling to 2m
- Recorded 1m - Resampling to 3m
- Recorded 2m - Resampling to 3m
- Recorded 3m - Resampling to 1m   Bilinear
- Recorded 3m - Resampling to 1m   Cubic convolution
- Recorded 1m - Resampling to 3m   Pixelaggregation

Fig. 5 NDVI derived from hyperspectral data (AISA-EAGLE/ HAWK) recorded at spatial resolutions of 1, 2 and 3 m and spatially up- and downscaled data. Box plot for NDVI median and min–max values of grassland (**a**), mixed hardwood forest (**c**) and bare soil (**e**) and the semivariances with a lag distance of 50 m—grassland (**b**), mixed hardwood forest (**d**) and bare soil (**f**)—at the investigation site with the land cover gradient of 25 km

NDVI, although this remains within the value range of the spectral output data set of 491 spectral bands.

Discussion

Using a set of hyperspectral data specifically sampled on spatially and spectrally different scales, as well as subsequently up- and down-sampled data, we were able to investigate (a) the effect of the spatial resolution–spatial rescaling, (b) the effect of spectral resolution–spectral rescaling and (c) the interacting effect of spatial and spectral scaling on the land surface NDVI heterogeneity for various land cover classes.

The effect of spatial resolution on NDVI heterogeneity
According to the results of this research on the spectral analysis of NDVI heterogeneity, we were able to determine the following: The spatial NDVI pattern of the data that was recorded was not in agreement with the spatial pattern of the data that was spatially rescaled. The results from the variogram analysis of NDVI heterogeneity for all land cover structures reveal differences in the spatial structure between the recorded and the rescaled hyperspectral images. The trend of a change in NDVI variance between the data recorded at 1 to 3 m resolution is similar, but the magnitude of change is difficult. Not every data set that is recorded changes systematically and significantly with a change in resolution. This contradicts the research by De Cola (1994), whose investigations showed a systematic and monotonic reduction in the variance the more coarse-grained the spatial resolution. The NDVI heterogeneity for the investigated land use structures grassland, ruderal vegetation, deciduous forest, mixed hardwood forest as well as bare soil diminishes as the spatial resolution changes from 1 to 3 m. Here, the total variance between the recorded image data of 1 and 2 m is higher than it is between 2 and 3 m. This also confirms the research conducted by Atkinson (1993)

and Goodin and Henebry (2002). Goodin and Henebry (2002) showed in their analyses that the standard deviation and the coefficient of variation of measured NDVI variance data do not exhibit monotonic trends as spatial resolution changes. Moreover, Goodin and Henebry (2002) point to the fact that the variances for recorded images are around three times higher than for the rescaled data sets. This could not be confirmed with our research. According to our investigations, the spatial characteristics did indeed change after spatial rescaling; however, the heterogeneity characteristics and features in the semivariance are inherited by the rescaling master. The magnitude and the course of the heterogeneity are similar to the rescaling master. A spatial rescaling between 1 and 3 m does not change the pattern of the characteristics according to our research. Goodin and Henebry (2002) assume that the differences in the variance in the heterogeneity between spatially recorded and rescaled data sets are generated by intrinsic variation across the scene. They are not executed further, however, through which these intrinsic variations are caused.

Effect of spectral resolution on NDVI heterogeneity In our experiments, the effect of spectral scaling on the heterogeneity of NDVI was investigated using airborne hyperspectral data. Our results show that the spectral scaling effect (and thus the number of bands that is available for all land use structures investigated) only has a slight influence on the change in the NDVI heterogeneity of hyperspectral data. These very slight changes to NDVI heterogeneity due to spectral scaling from 14 to 491 bands can be attributed to changes in the signal-to-noise ratio, which is reduced with a decrease in the number of spectral bands and thus an increase in the spectral resolution of the spectral bands. Since the differences in variance of NDVI are only low between the recorded bands of 91 and 491, the spatial scaling investigations showed no new insights. The NDVI mosaic only changes very slightly due to the resampling scaling effect and is therefore negligible. According to Chen and Henebry (2010), an increase in the band width results in a blurring of spatial structures also leading to a loss in spatial variation. This could not be confirmed by our experiments when comparing the number of bands from 91 to 491. No relationship could be established between the number of bands and the extent and course of the NDVI variability.

Fig. 6 NDVI derived from hyperspectral AISA-EAGLE/HAWK data with a spectral recording resolution of 91 to 491 spectral bands and spectrally up- and downscaled data. Box plot for NDVI median and min–max values for grassland (**a**), ruderal vegetation (**c**), deciduous forest, (**e**) mixed hardwood forest (**g**) and bare soil (**i**) and semivariances with a lag distance of 50 m for grassland (**b**), ruderal vegetation (**d**), deciduous forest (**f**), mixed hardwood forest (**h**) and bare soil (**j**), at the study site of Kreinitz
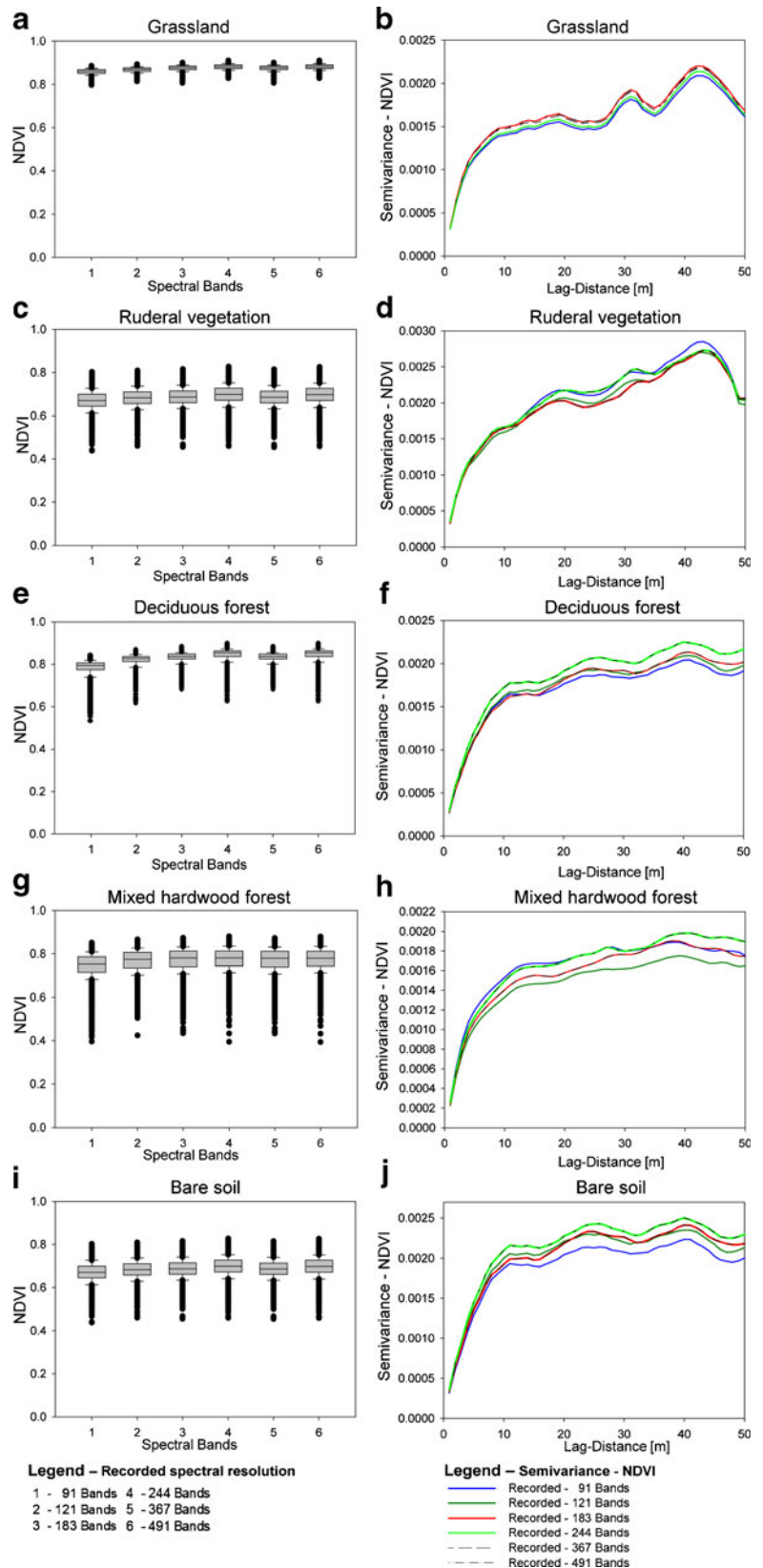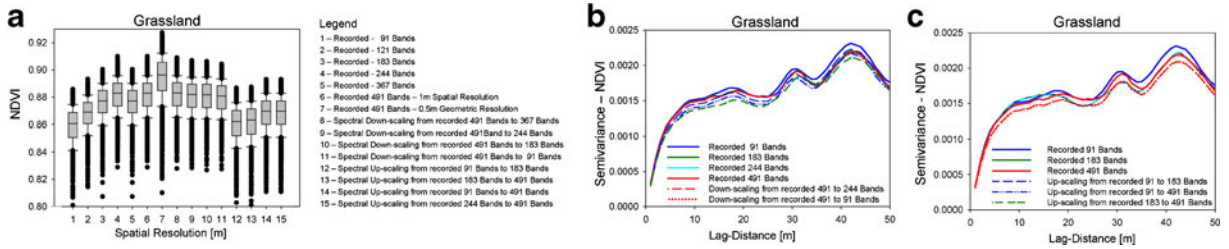
Fig. 7 NDVI derived from hyperspectral AISA-EAGLE/HAWK data with a spectral recording resolution of 91 to 491 spectral bands and spectrally up- and downscaled data. Box plot for NDVI median and min–max values for grassland (**a**) and semivariances with a lag distance of 50 m for grassland with spectral upscaling (**b**) and for grassland with spectral downscaling (**c**), at the study site of Kreinitz

Effect of spatio-spectral resolution on NDVI heterogeneity

In our investigations, the collective scale effect from the spatial and spectral resolution on land surface heterogeneity could be investigated and presented for the first time using NDVI as an example. The results showed that the effect of spatial scaling compared to spectral scaling is of far greater significance for the variance and the heterogeneity of NDVI. The variance with recorded hyperspectral data at 0.5 m spatial resolution increases by almost two times compared to the NDVI variance at 1 m. Therefore, the pattern of land surface structures can be captured twice as well by selecting a high geometric resolution compared to a high spectral data resolution. Furthermore, a spectral down-rescaling from 491 to 14 ASTER space-borne data with a high spatial resolution of 0.5 m still maps a very high variance and NDVI heterogeneity. The positive spatial effect compared to the spectral effect that only had a very low effect on heterogeneity could be proven for all land use structures that were investigated. Siegmann (2011) also presented this effect comparing HyMap and AISA-EAGLE data. Higher classification accuracy could be achieved for the high spatial resolution AISA-EAGLE data (spatial resolution recorded 2×2 m, spectral range 400–970 nm)

compared to the HyMap Data (spatial resolution recorded 4×4 m, spectral range 400–2,500 nm).

Conclusion and outlook

In the study at hand, for the first time ever, investigations were carried out on fundamental scaling issues using specific experimental test flights with a hyperspectral sensor to investigate how vegetation patterns change as an effect of (1) different spatial resolutions, (2) different spectral resolutions, (3) different spatial and spectral resolutions as well as (4) different spatial and spectral resolutions of originally recorded hyperspectral image data compared to spatial and spectral up- and downscaled image data.

Spatial and spectral resolution

- The results of our hyperspectral imagery recorded at different geometric resolutions from 0.5 to 3 m show that the heterogeneity of NDVI changes with a spatial resolution from 1 to 3 m. In addition to spatial resolution, the type of land use land cover also has an influence on the intensity of the spatial
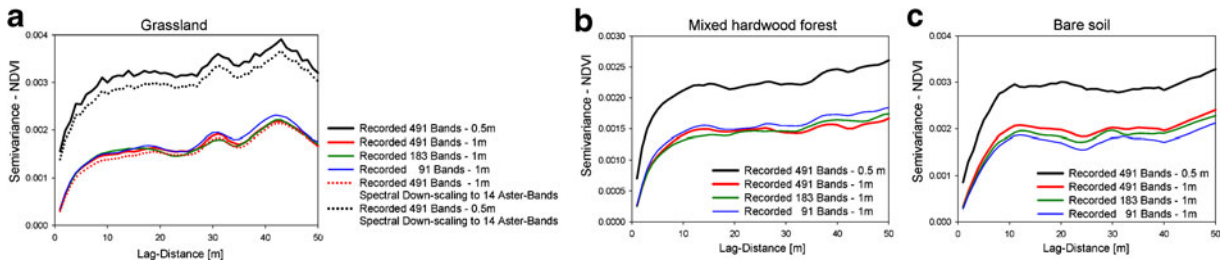

Fig. 8 NDVI derived from hyperspectral AISA-EAGLE/HAWK data with a different spectral resolution (0.5 and 1 m) and spectral recording resolution (17–491 bands) and spectrally up- and downscaled data Semivariances with a lag distance of 50 m for grassland (**a**), mixed hardwood forest (**b**) and bare soil (**c**) at the study site of Kreinitz

heterogeneity of the vegetation or the landscape pattern. For the classes grassland, ruderal vegetation and bare soil, low landscape heterogeneity was found when compared with deciduous forest and mixed hardwood forest.

- The investigations on the effect of spectral resolution demonstrated that the spectral range only has a negligent effect on the spatial heterogeneity of vegetation patterns.

- When comparing spatial and spectral resolutions on vegetation heterogeneity at the same time, the spatial resolution was found to have a much greater influence on the heterogeneity of the vegetation compared to the spectral resolution of the image data. In spite of a very low spectral band width, heterogeneity is mapped better by the geometric resolution of the hyperspectral image data.

Spatial up- and downscaling

- When originally recorded image data are spatially up- or downscaled, then their characteristics for quantifying heterogeneity are transferred from the output data to the up- and downscaled data or 'inherited'. Although slightly changed, the down- or upscaled data set still inherits the heterogeneity characteristics. Spatial data sets maintain their memories or source with the up- and downscaling process. This can also be referred to as the 'spatial genotype' of remote sensing data.

- From the investigations on the effect of spatial up- and downscaling on the heterogeneity of image data, it was demonstrated that spatial upscaling procedures quantify the originally existing heterogeneity of the vegetation better than spatially downscaled data. Spatial downscaling leads to a greater change in heterogeneity compared to the real or original heterogeneity of the heterogeneity of the vegetation. Spatially upscaled data do not obscure the heterogeneity data as much compared to the originally recorded image data.

- Spatially downscaled data may misleadingly indicate a lower spatial heterogeneity compared to the true heterogeneity of the vegetation. With upscaling on the other hand, higher spatial heterogeneities can be misleadingly indicated than the true heterogeneity. This effect is stronger for heterogenous structures such as deciduous forest and mixed hardwoods compared to homogenous classes such as meadows and bare soil.

Spectral up- and downscaling

- Up- and downscaling of the spectral resolution of image data shows only a slight to no effects on the change in heterogeneity compared to the originally ascertained heterogeneity.

Resampling procedures for spatial downscaling

- A comparison of four different frequently used resampling methods (nearest neighbour, cubic convolution, bilinear and pixel aggregate resampling algorithm) for the spatial downscaling of image data resulted in the following: all of the above procedures generated image data in the spatial downscaling process that showed a lower heterogeneity compared to the original true heterogeneity. The resampling procedures can be differentiated however by their degree of change in heterogeneity.

- The worst results, i.e. the procedures that were found to be the most misleading for heterogeneity were the cubic convolution and bilinear resampling methods, both of which generated similar results. The nearest neighbour method demonstrated slightly better results for imaging heterogeneity. The pixel aggregate resampling algorithm came up with the best results for quantifying real heterogeneity in spatial downscaling. For this reason, the pixel aggregate resampling algorithm should be applied as the preferred method for scaling processes with up- and downscaling.

Outlook

- Existing scale investigations with remote sensing methods frequently use very complex methods and models to investigate spatial and spectral scale effects. Empirical investigations are still lacking that reveal the spatial and spectral scale effects of land surface variables while considering the interaction between different scale factors.

- It will therefore be the goal of further research to investigate the factors and the transfer functions between different spatial and spectral scales. Here, it is important not only to take into consideration the spectral characteristics of the vegetation at a given point in time, but also the structure and dynamics of the soil as well as to integrate hydrological properties.

- The multi-dimensional factor of our landscapes and processes requires a focused process analysis

related to spectral signatures at various spatial scales. The use of an even larger number of multi-sensoral and multi-temporal sensor combinations is not the main goal here when the basic problems of the spectral response of land surface variables at different scales for one sensor alone have so far only been answered unsatisfactorily. With this study, we would therefore like to encourage other 'simple enlightening research'; the results of which would however provide a basic understanding of land surface pattern and process interactions in the landscape, as complex interactions are not always revealed through even more complex formulas. A use of the same hyperspectral sensor on different temporal and spatial scales (OSADIS approach; Lausch et al. 2012, 2013) will provide the unique advantage of truly being able to compare hyperspectral remote sensing data on different spatial and spectral scales.

- These results are the start of a new phase in the scale discussion. However, further investigations must follow in order to be able to provide information for land use management in using different remote sensing products with different spatial and spectral resolutions.

- The goal of future research should therefore be to conduct other experiments of this nature, to incorporate other spatial and spectral scaling effects in order to investigate the quantification and transferability by determining the transfer functions and models between remote sensing products with different recording characteristics. A multisensor use of different remote sensing data products must enable comparisons in the quantification of spatial heterogeneity of land surfaces.

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