Scaling up and scaling down: The relevance of the support effect on remote sensing of vegetation

Jennifer L. Dungan

1 Introduction

Remotely sensed images of the Earth's surface are an extremely useful source of information about the spatial distribution of vegetation. Research and applications to map the location of vegetation, its quality and quantity, are numerous and continually expanding. There are several multifaceted scaling issues in these investigations and applications, such as, how can data collected at a small number of plots be extrapolated to answer questions about a large region? What spatial resolution is required to accurately map vegetation? How can estimates made from coarse-resolution remote sensing be validated? To make progress on these issues, we will need to understand a number of different facets of scaling, specify their characteristics precisely, and create new experiments to test them and models to explain them.

The purpose of this chapter is to identify one specific aspect of the scaling process and show how it pertains to remote sensing of vegetation and related remote sensing estimation problems.

Modelling Scale in Geographic Information Science. Edited by Nicholas J. Tate and Peter M. Atkinson. 2001 John Wiley & Sons, Ltd. Pages 221- 235.

It will show how this issue, the *support effect*, is part of a larger framework of scaling issues previously identified in geography. An example using data from optical sensors is used to illustrate some support effects in red and near-infrared reflectance and their relationships with forest canopy cover.

2 Scale: a multifaceted issue

Literature on scaling issues has proliferated in the last decade (Foody and Curran, 1994; Marceau *et al*., 1994; Wickham and Riiters, 1995; Moran *et al*., 1997; Quattrochi and Goodchild, 1997; Bian and Butler, 1999; Kustas and Jackson, 1999). Though this literature shares use of the term 'scale,' it contains myriad contexts for the word. The classical, cartographical meaning of the term is the ratio between distance portrayed on a map and the corresponding real-world distance represented by the map. This cartographic ratio implies that 'large scale' goes hand in hand with small extent, and 'small scale' usually implies a large extent. Common usage in landscape ecology and other Earth sciences takes the opposite perspective (Turner *et al*., 1989), defining scale as 'the spatial or temporal dimension of an object or process, characterized by both grain and extent.' This implies that 'large scale' refers to large areas; 'small scale' refers to small areas. The terms resolution, grain and extent are also used individually as synonyms for 'scale.'

The above-mentioned conflicting definitions of the word scale are further confused by at least two other definitions without reference to space. Scale can mean the magnitudes of numbers used to represent a phenomenon (i.e., the Fahrenheit temperature scale ranges from 32° to 212° between the freezing and boiling points of water; the normalized difference vegetation index scale ranges from -1 to 1). The rescaling of digital images in this sense can affect analysis

(Teillet *et al*., 1997). In statistics, it is used to describe the width of a distribution (i.e., the scale parameter of a normal distribution is its variance). With the latter definition, it is possible to make the amazingly ambiguous statement, 'we are studying the change of scale (the statistical parameter) with increasing scale (the resolution, grain and/or extent).' It is no wonder more precise language is needed!

Because of the multiple, sometimes opposing, definitions for the word 'scale,' it is becoming increasingly difficult to navigate interdisciplinary literature. Quattrochi (1993) made a plea for a standardized lexicon. He suggested using 'scale' in the sense of 'the integral of space and time over which a measurement is made'. This meaning is very close to that of the term, 'support,' a word in use in geostatistics since the 1960s. The definition, as stated in the geostatistical dictionary (Olea, 1990) is:

> **SUPPORT.** (a) An *n*-dimensional volume within which linear average values of a regionalized variable may be computed. The complete specification of the support includes the geometrical shape, size, and orientation of the volume. The support can be as small as a point or as large as the entire field. A change in any characteristic of the support defines a new regionalized variable. Changes in the regionalized variable resulting from alterations in the support can sometimes be related analytically.

Any variable distributed in space is a 'regionalized variable.' Therefore, all variables investigated using remote sensing methods are regionalized. The concept of temporal support is analogous to spatial support but is beyond the scope of this chapter. Spatial support is specific to the length, area or volume that a measurement value represents. It is narrow in meaning, and can be used to isolate the spatial aspect of the measurement unit from its spectral and radiometric aspects and the extent of the study region. The adoption of the term support in reference to remote sensing and GIS clarifies one type of scaling, that is the change of the size of a measurement unit.

The area of each plot that is being characterized determines the support of ground measurements. The support of optical remotely sensed data is determined by the instantaneous field of view of the sensor, its sampling rate, platform altitude and, in some cases, the atmosphere. The concept of support is closely related to the definition of effective resolution element (ERE), the size of targets for which the spectral properties can be recorded by the sensor to a given accuracy. It is often difficult to obtain a precise value of the ERE (Wilson, 1988) and, depending on the sensor, it may vary throughout an image. Quantitative investigations of relationships between variables linked by a physical process, such as the radiation flux measured by the sensor and the amount of vegetation reflecting that radiation from the ground, make the most sense when the supports of the image and ground data are equivalent. With the practical difficulties of both ground and remote observation, this ideal can only be approximated in the real world.

Currently, the term 'resolution' seems to be the most popular word to summarize the pixel size of remotely sensed images. The term resolution in remote sensing originated with the photographic process, and technically is the size of the smallest object that can be detected in an image. Resolution therefore depends partly on the radiometric sensitivity of the sensor as well as the other factors. During the early development of remote sensing technologies, when surveillance purposes were paramount, stating limits on the size of detectable objects was of primary concern. The detection problem is somewhat different than the quantification problems being addressed today. Therefore, the concept of support is useful to refer only to the spatial component of resolution, rather than the spectral or radiometric component. A distinction between support and resolution is also useful because ground measurements do not have a resolution but they do have a support. To analyze ground measurements in relation to image measurements, it is imperative to explicitly know and compare the supports of both.

3 How support affects data

Knowledge that the characteristics of a regionalized variable depend on the area over which they are calculated is certainly not new (Gehlke and Biehl, 1934; Smith, 1938). In geostatistics, the need for models explaining this dependence arose with the requirements of predicting the tonnage of ore realizable by the truckload based on data from the much smaller core or blasthole samples (Journel and Huijbregts, 1978; Rendu 1981). These were generally called ‘change of support’ or ‘regularization’ models, explaining the effect of support on statistics. Olea (1990) contains the following definition for the support effect:

> **SUPPORT EFFECT.** The influence that the size of the support has on average values of the regionalized variable. Although globally the mean remains unchanged, in general, a larger support will have [...] a smaller a priori variance and more symmetric distribution. The increase in symmetry is a manifestation of the central limit theorem...

This definition translates to a simple prediction of what happens to the univariate statistics of a variable when the support on which it is measured gets larger or smaller. Predictions of what happens to multivariate statistics are not mentioned here, but are guaranteed to be more complicated. A reference to predictions is contained in Olea’s definition of support, that ‘Changes in the regionalized variable resulting from alterations in the support can sometimes be related analytically.’ In order to make progress toward analytical solutions, the full extent of support effects on remote sensing problems must be understood. The alternative is well put by Strahler *et al*. (1986), ‘The spatial domain containing the transition from H- to L-resolution models may require the formulation of models specific to the actual sizes of elements and resolution cells.'

3.1 Implications of support effects in remote sensing of vegetation

Since the 1970s, numerous studies have been done whereby ground measurements of some variable, such as water temperature (Lathrop and Lillesand, 1987), water sediment load (McCluney, 1976; Curran and Novo, 1988), plant canopy foliar biochemical content (Wessman *et al*., 1989) or mineral quantities in surface deposits (White *et al*., 1997) are related to a set of spectral variables, measured at coincident locations, from image data. More than 50 studies in the peer-reviewed literature alone relate labor-intensive ground measurements of vegetation amount within plots to digital numbers, radiance, reflectance or some transform thereof obtained from airborne or satellite sensors (i.e., Pollack and Kanemasu, 1979; Curran *et al*., 1992; Nemani *et al*., 1993, Fassnacht, 1997 and Turner *et al*., 1999). The general approach of these studies is that a small number of vegetation and spectral variables are selected, a number of measurements are collected on the ground and from an image, and relationships between the measurements are compared with null hypotheses. Several alternative variables may be chosen, and the strongest relationships are emphasized as the main results. These relationships are usually expressed as regression models.

Well-known physical mechanisms, such as absorption of red light by chlorophyll in green vegetation and light scattering by leaves in the near infrared, are usually mentioned as assumptions for the selection of specific wavebands in these models. Data that do not fit the models are sometimes explained as erroneous or as influenced by other mechanisms. In some cases, the available data are reduced to a single model that is then applied to image data to generate a map of vegetation amount. Alternative forms of models for the same data are not considered, unless it is to consider multivariate models in comparison to univariate models. Regression diagnostics are rarely presented. The temporal and spatial limits of the regression model are not usually mentioned, except by inference that the available data fit within those limits. Models are evaluated by standard errors of the regression, and occasionally by validation using a test set. The precise set of variables emerging from these studies is never identical. Though these (aspatial) regression models are often reported, but they are rarely applied or quantitatively compared to similar studies.

There are many challenges in these kinds of studies. An important limitation is the difficulty in obtaining a large enough number of measurements to test for statistical significance (Curran and Williamson, 1989). A second one is the spatial registration of ground and image coordinates, since there are several sources of error in precisely co-locating plots and pixels. The accuracy of ground positions is rarely characterized (a situation now presumably improving with the use of Global Positioning Systems tools), and the accuracy of georectification of images varies depending on how satellite and terrain effects are handled and the quality and type of ground control used. Along with misregistration in space comes misregistration in time, because it is often difficult to obtain coincident data, whether from the constraints of weather, the satellite repeat cycle or the logistics of getting out to the field.

Finally, and most importantly for the purpose of this chapter, there are differences between the size of plots and the size of pixels. Discrepancies between them range from slight (i.e., Jensen and Hodgson (1985) compared biomass values from individual trees to spectral data from 2 m^2 pixels from an airborne scanner) to vast (i.e., Box *et al*. (1989) compared productivity values from small plots to integrated spectral index values from 225 km^2 pixels). Investigators have frequently attempted to compensate for the errors of misregistration by averaging over a

3×3 pixel window at each sample location to insure that each ground sample falls somewhere within a remotely sensed window. While this may attain its objective, averaging pixels effectively changes the support of the image data, usually increasing the discrepancy with plot support.

3.2 An illustration of support effects in the remote sensing of canopy cover

Many studies have been done by artificially spatially degrading data from a sensor to examine the effects of different pixel sizes (i.e., Woodcock *et al*., 1988; Marceau *et al*., 1994; Wickham and Riiters, 1995; Hay *et al*., 1997). Support effects can be also be seen in real data from sensors with different supports, such as from the Landsat Thematic Mapper (TM) and the National Oceanic and Atmospheric Administration's Advanced Very High Resolution Radiometer (AVHRR). Though TM and AVHRR differ in many ways, including spectral band passes, scanning system and sensitivity, the largest difference is in the support of the pixels. TM has an approximately 900 m^2 support and AVHRR has an approximately 1.21 km^2 support at nadir. Support effects on the relationship between reflectance data and vegetation amount data are illustrated here in a study in western Montana, USA (Dungan, unpublished data).

Observations on forest composition and canopy structure collected at thousands of locations over a ten year period in the Flathead National Forest (M. Mantas, personal communication) provide many more samples than usually possible in such studies. The region is characterized by conifer forests; with Ponderosa pine, Douglas fir, lodgepole pine and larch being the major tree species in the canopy. One of the observed variables, canopy cover, or the estimated horizontal percent cover of the vertical projection of canopy foliage within a plot, should in theory be related to the visible and near-infrared reflectance of that plot.

A subset of plot data collected in 1988, comprising 335 locations, were compared to spectral data from TM and AVHRR images collected in late August of that year. Here, TM band 3 (0.63-0.69 μm) is compared with AVHRR band 1 (0.58-0.68 μm) and TM band 4 (0.76-0.90 μm) with AVHRR band 2 (0.72-1.10 μm). The support of the ground measurements is approximately 0.05 ha, about half the size of the TM support and 0.04% of the AVHRR support.

The TM scene was georectified using a systematic and terrain correction algorithm (Erdas, Inc., Atlanta, GA) along with ground control points yielding a root-mean-square-error on test locations of 0.49 pixel. A nearest-neighbor resampling was used so as not to further alter the support of the data. Reflectance was estimated from the TM data using an adjustment to the radiometric calibration to account for sensor degradation and a combination of dark targets with atmospheric models to remove the effect of path radiance and approximate irradiance. EROS Data Center (Sioux Falls, SD) provided the AVHRR image and georectified and radiometrically transformed the data to reflectance (Eidenshink and Faundeen 1994).

The distribution of the TM red reflectance (band 3) values from the locations of the 335 samples shows a spread from 3 to 37% (Figure 1a). For the same pixels from AVHRR band 1, the spread of reflectance values is much narrower and the distribution more symmetric (Figure 1b). This happens in the near infrared as well, with a large spread in TM near-infrared reflectance (band 4) from 5 to over 80%, while the AVHRR band 2 distribution lacks the long tail (Figure 2). Change of support models state that the mean value of a distribution should be conserved. The fact that the mean differs in this example likely can be explained by the difference in the sensors' spectral bandpasses and the atmospheric correction algorithms that were used. However, the phenomena of smaller variance and more symmetrical distribution are clearly compatible with a model of support effects.

The relationship between canopy cover versus red and near-infrared reflectance (Figure 3) shows a large amount of scatter. Trends are revealed when the data are summarized using boxplots (Hoaglin *et al*., 1983). Canopy cover indirectly varies with both TM red (r=-0.63, Figure3a) and near infrared (r=-0.48, Figure 3b), a trend that has been observed in several other studies of conifer forests (Franklin, 1986; Peterson *et al*., 1987; Ripple *et al*., 1991). Support effects on these bivariate distributions are less predictable than those on the univariate distributions. In this case, the indirect trends are completely lost at the AVHRR support (Figure 3c and d) for both visible (r=0.05) and near infrared (r=0.06), with variance within each canopy cover class swamping variance among the classes. Support of the ground data is not changed here, just the support of the reflectance variable.

All other moments of this multivariate data set will be affected by support, including spatial statistics. For example, the omnidirectional variograms (Isaaks and Srivastava, 1989) of the TM data have much higher apparent sills than those of the AVHRR data (Figure 4). A decrease in sill is expected with regularization (Journel and Huijbregts, 1978; Atkinson this volume). An increase in range with increasing support is also expected (Rendu 1981), but a decrease is instead apparent in the variogram range of the AVHRR data relative to that of the TM data. This may be caused by the decreased radiometric sensivity of the AVHRR relative to the TM.

To summarize, with these data we see a decrease in variance, an increase in symmetry of the univariate distribution, a change in the joint distribution with canopy cover, and a flattening of the variogram as we move from the TM support to the AVHRR support.

3.3 A historical perspective

Though these support effects should not be surprising, the implications were not considered important in the first decade of civilian satellite remote sensing. It was only after the number of satellite sensors proliferated in the 1980's that the idea that image resolution could affect the accuracy of answers obtained using them became widespread (Strahler et al., 1986). Prior to this, experiments were attempted in which field radiometer measurements and vegetation samples from plots were collected simultaneously to generate regression models between spectral reflectance and canopy variables. The hope was to apply the regressions to image data to map vegetation (Tucker, 1978; Wardley and Curran, 1984). The scaling model invoked here entailed a change of extent while ignoring support and assumed a regression equation could be applied to large pixels without modification. Part of the reason this model disappeared is that the strong effect of the atmosphere on satellite observations was realized. But field and satellite radiometer measurements have very different supports, and the comprehension of this fact must also help explain the disappearance of this experimental model. The problem of extrapolating knowledge about vegetation/spectral relationships has proved to be much more difficult than originally envisioned.

One support effect that has received quite a bit of attention in the remote sensing community has been the change in the variance statistic. This has been analyzed by a number of researchers using 'scale variance plots' (Woodcock and Strahler, 1987; Townshend and Justice, 1990). Support effects on semivariance have also been studied using regularization models (Jupp *et al*., 1989; Atkinson and Curran, 1995; Atkinson and Curran, 1999; Collins and Woodcock, 1999). But the corollaries to the change of variance and semivariance with support, changes in distribution shape and bivariate statistics (such as the correlation coefficient) when spectral data are studied jointly with variables measured on the ground, have been comparatively neglected.

The regression models commonly used in remote sensing are derived without reference to space -- they are based on inherently non-geographical assumptions. But when they are applied in a spatial context they require stationarity assumptions (Fotheringham *et al*., 1996) and are tied to the support of the data used to derive them. Given this, any regression model is specific to the support of the data used to derive it, and its usefulness for any other sensor or ground measurement is severely limited without some kind of explicit support effect model. The robustness of any regression model reported in the literature has never been tested because the supports of ground and image data have been unique to each study.

3.4 Support and the MAUP

To this point in the chapter, only the size of support has been emphasized. The additional dimensions of support, shape and orientation, make support effects much more complicated, leading essentially to the Modifiable Areal Unit Problem (Openshaw, 1984; Alvanides et al., this volume). Two parts to the MAUP are generally recognized: the aggregation effect having to do with the *size* of support and the zoning effect having to do with the *shape* of support. GIS software makes it easier than ever to flexibly modify the spatial units of analysis. The fact that support effects like the MAUP can change our interpretations and conclusions from spatial data should require that the original support of data be recorded and preserved in such databases. Remote sensing image data, represented as raster data models, has enforced a limited, though much more consistent, set of supports than is often dealt with in other geographical fields.

3.5 Support effects everywhere[1]

The problems generated by support effects are ubiquitous in Earth science. The seemingly straightforward tasks of quantifying length of a coastline or the area of land that has been

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[1] With apologies to Barnsley (1993)

urbanized, flooded or deforested must be accomplished based on a support. In the case of the coastline length, in an example from Richardson (1961) later made famous by Mandelbrot (1977), the support was the length of an equal-sided polygon used to traverse the line representing a map's coast feature. If all of the lengths are represented as a histogram, the desired total length of the coastline is the integral under the distribution represented by that histogram. As support (length) changes, its distribution changes and therefore its integral can be affected. The fractal model for this process, proposed by Mandelbrot and since tested with mixed results, is simply a power function of the integral with change of support. In the case of area, distributions of patch sizes of urban, flooded or forested land can be considered. Again, it is the integral of that distribution that is needed for the total area calculation.

Mandelbrot stated that the coastline length problem was 'unsolvable.' It is perhaps impossible to identify a single, correct answer. But integrals and statistics of distributions obviously have real solutions for physical values of support. They have limits and ranges of values for which the answers are useful. Careful consideration must be given to what support is most relevant for the answer to any question.

4 Solutions to change of support problems

There are several geostatistical procedures for predicting the characteristics of a variable at one support given data on another; most deal with univariate problems. The simplest of these is the affine correction, which multiplies a constant with each of the quantiles from the univariate distribution at one support to obtain quantiles of the distribution predicted to exist at another support (Isaaks and Srivastava, 1989). This constant may be obtained through analysis of the variogram. Though this procedure reduces the variance with larger support, it does not concomitantly increase the symmetry of the distribution. A more involved alternative, the indirect lognormal correction, adjusts the quantiles with an exponential equation and produces results that do increase symmetry with increasing support. When maps, not just statistics, are required of a variable at larger support, these aspatial adjustments to distributions must be supplemented with block kriging or averaging blocks from conditional simulations (Goovaerts, 1997).

Geostatistical models rely on a consistent support for each regionalized variable. They do not contain expressions for variables defined on support that changes with space. Therefore, strictly speaking, the geostatistical models that have been developed to date are not amenable to vector models where the data, in essence, have variably shaped supports as is the case with many variables used in GISs.

Solutions to change of support problems in remote sensing have focussed on area calculation. Models to correct area estimates from remotely sensed images were proposed early in the Landsat era (Crapper, 1980) and recently have been receiving increasing attention. Key (1994) examined the effect of increasing pixel size on estimates of total landcover area by explicitly representing the subpixel distribution of that landcover with a parametric distribution function. Hlavka and Livingston (1997) developed parametric distribution models of landscape patch sizes from a landcover of interest. Data from a sensor with large support could be used in a model to estimate the parameters of the actual distribution function and total area, including that contributed by small patches missed by the sensor, could be obtained from the integral of that distribution. Iverson *et al*. (1994) addressed the area estimation problem by developing geographically-varying regression models with AVHRR spectral data as explanatory variables and forested area estimated using TM data as the response variable. Different regression models were created for different regions, depending on general landscape considerations. Other workers have addressed the more complex problem of the areas of multiple landcovers (Mayaux and Lambin, 1995, Moody and Woodcock, 1996). Raffy (1994a) exhorted readers to pay attention to scaling problems and in a series of papers (Raffy, 1994b,c and others) suggested new approaches for dealing with, as the authors called it, the 'spatialization' problem. Progress on dealing with support effects is being made in other fields as well; those dealing with raster data structures may be directly amenable to remotely sensed data. For example, Bindlish and Barros (1996) assumed a fractal model in an attempt to compensate for the loss of extreme values in terrain data when the support represented by digital elevation models is increased. The change of support should receive increasing attention as a larger number of 'multiscale' data sets (those with a variety of supports) become available in the Earth Observing System era (Asrar *et al*., 1992).

5 Conclusion

This chapter has made the case that change of support is one, precisely defined, facet of up- and down-scaling. Recognizing this phenomenon explicitly means acknowledging that increasing support involves decreasing variance and increasing symmetry for univariate distributions and as yet unpredictable effects on multivariate distributions. These effects are clearly seen in an example of optical remote sensing of conifer canopy cover that is typical of the kinds of experiments that have been and continue to be conducted in Earth science. Regression-based approaches to 'calibrate' remotely sensed information to canopy variables or other regionalized variables are contingent on the specifications of support for all variables involved. It does not make sense to discuss the variability of a regionalized quantity without reference to the support on which it was measured.

It is possible to look at support effects as a class of unified scaling problems affecting integrals and other statistics of distributions of length, area and value. The Modifiable Areal Unit Problem arises from complicated change of support problems. The recognition of the definition of support and its implications for all sorts of spatial problems should help to transfer knowledge across disciplines about how to address support effects, potentially borrowing solutions from one field and modifying them for another. Geostatistical theory already gives some potential paths to follow for change of support corrections. The abundance of remotely sensed data should be useful to build upon these models.

6 Acknowledgments

Great appreciation extends to Maria Mantas and her colleagues at the Flathead National Forest, Kalispell, Montana for their generosity in sharing procedures and data.

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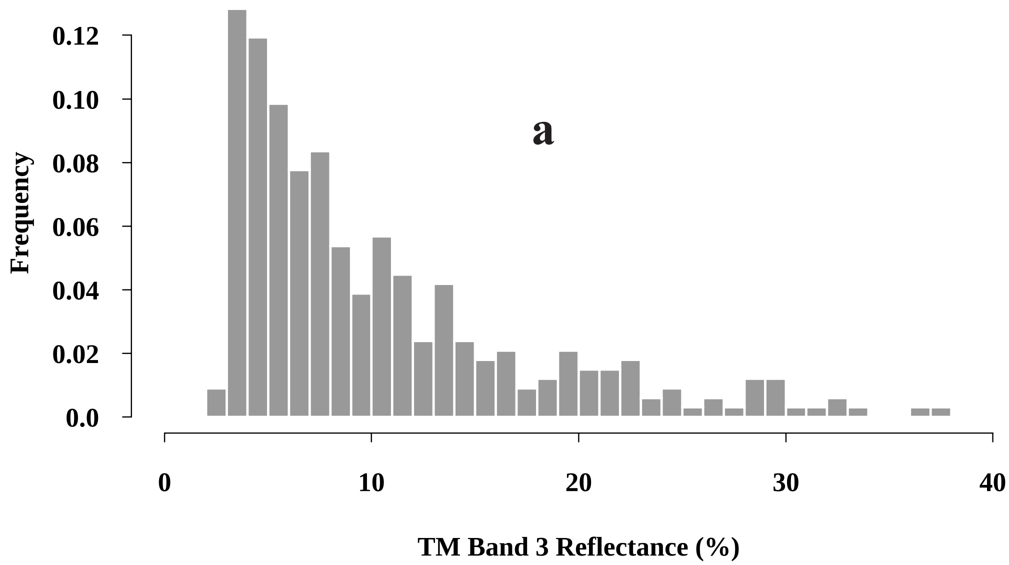
Figure 1 a) Histogram of TM band 3 reflectance values from 335 ground measurement locations b) Histogram of AVHRR band 1 reflectance values from the same 335 locations.

Figure 2 a) Histogram of TM band 4 reflectance values from 335 ground measurement locations b) Histogram of AVHRR band 2 reflectance values from the same locations.

Figure 3 Boxplot representation of a) scatterplot between TM band 3 and canopy cover b) scatterplot between TM band 4 and canopy cover c) scatterplot between AVHRR band 1 and canopy cover and d) scatterplot between AVHRR band 2 and canopy cover, all from 335 measurement locations

Figure 4 a) Omnidirectional variogram of visible reflectance values at two different supports and b) Omnidirectional variogram of near-infrared reflectance values at two different supports



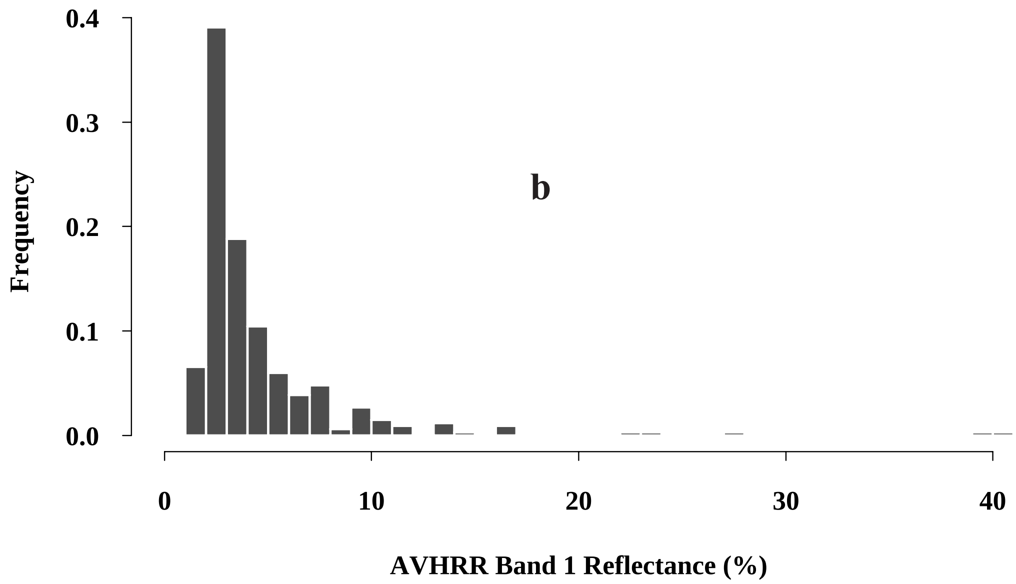


Figure 1 a) Histogram of TM band 3 reflectance values from 335 ground measurement locations b) Histogram of AVHRR band 1 reflectance values from the same 335 locations.

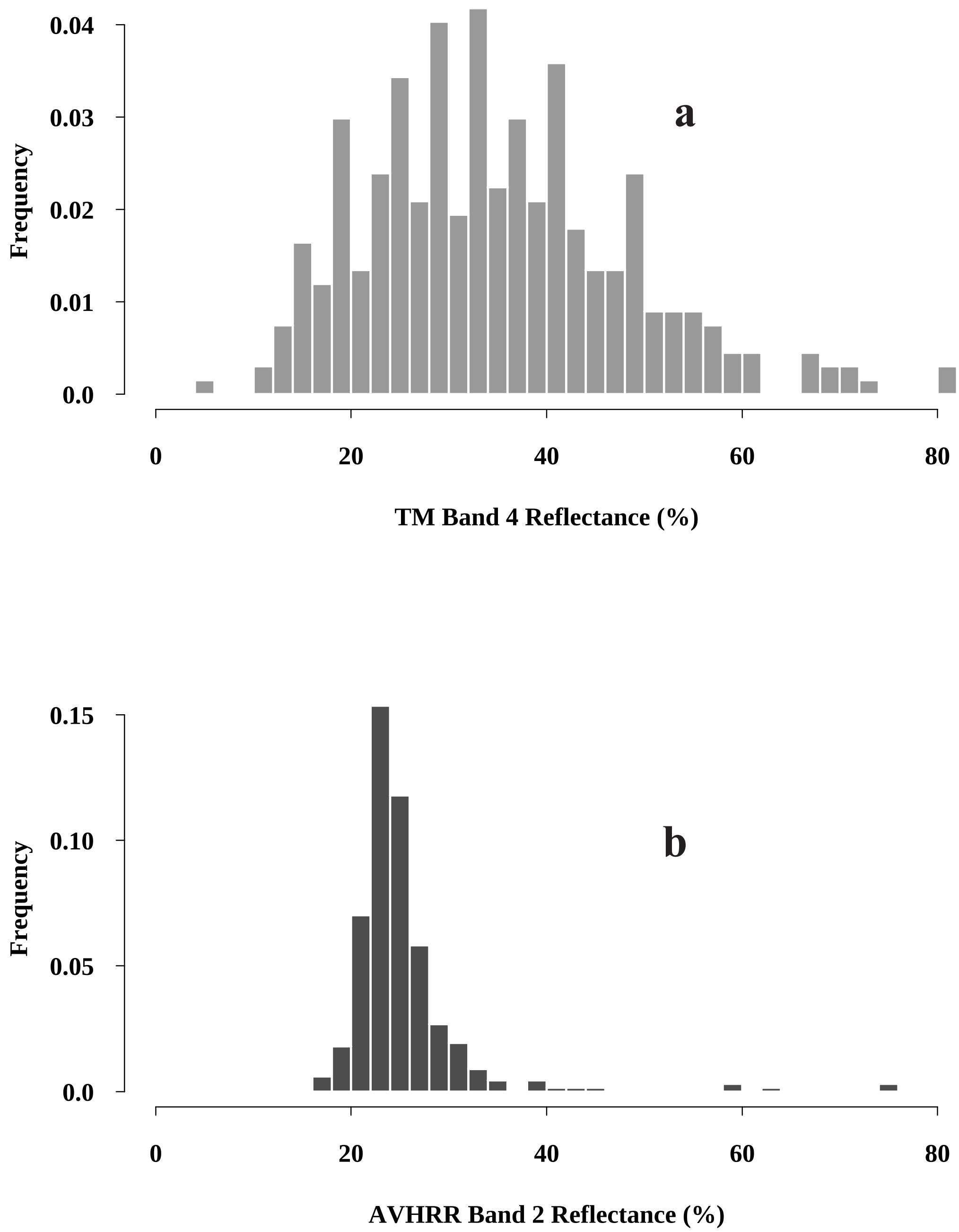


Figure 2 a) Histogram of TM band 4 reflectance values from 335 ground measurement locations b) Histogram of AVHRR band 2 reflectance values from the same locations.

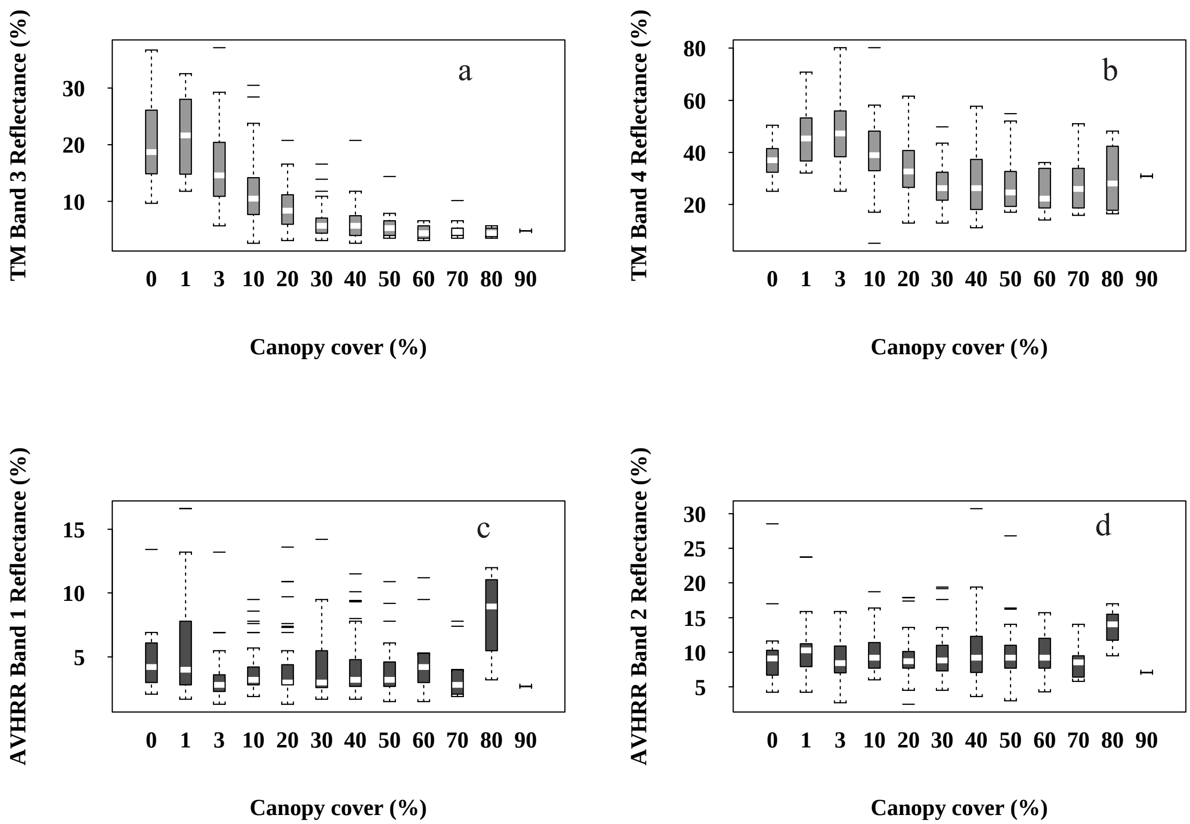


Figure 3 Boxplot representation of a) scatterplot between TM band 3 and canopy cover b) scatterplot between TM band 4 and canopy cover c) scatterplot between AVHRR band 1 and canopy cover and d) scatterplot between AVHRR band 2 and canopy cover, all from 335 measurement locations

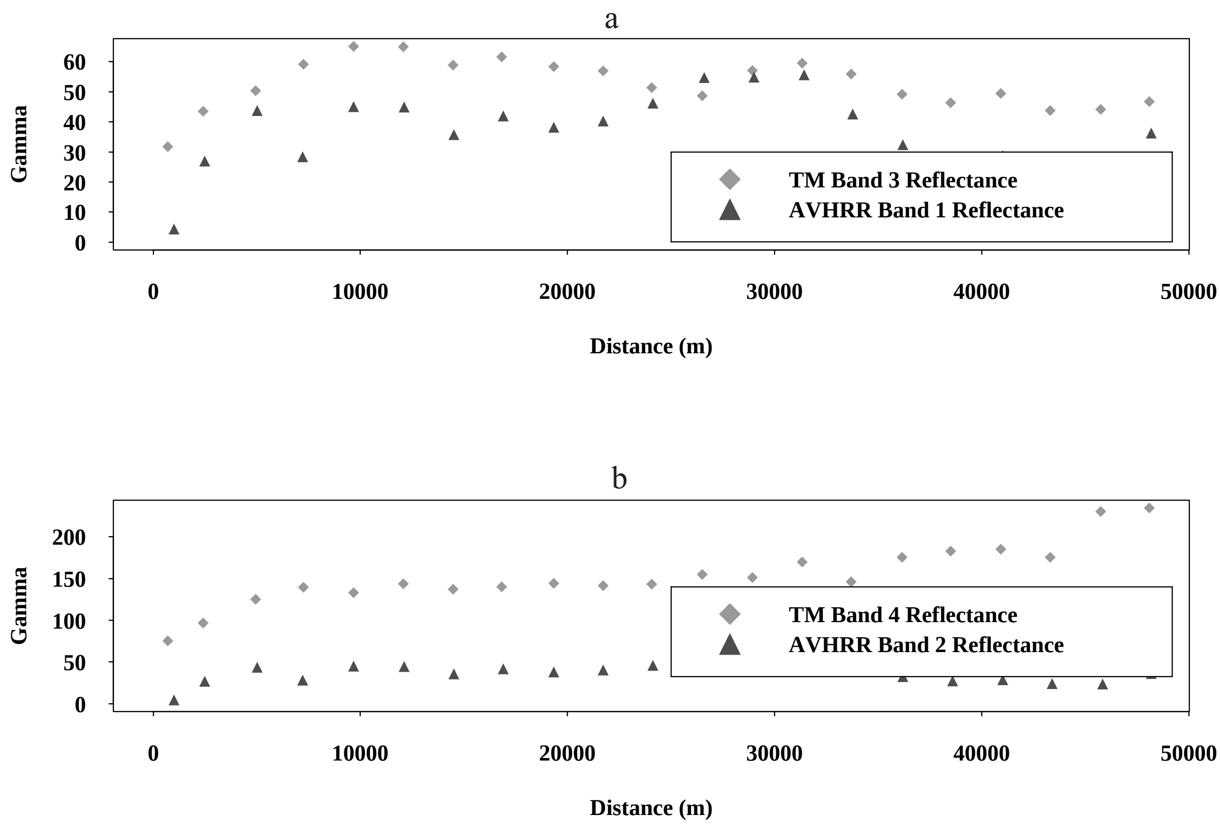


Figure 4 a) Omnidirectional variogram of visible reflectance values at two different supports and b) Omnidirectional variogram of near-infrared reflectance values at two different supports