EnMAP Field Guides

Technical Report

Campaign Layout & Sampling Strategies

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Recommended citation:

Danner, M.; Locherer, M.; Hank, T. (2015): Campaign Layout and Sampling Strategies – Theory, Principles, Problems, Practice. *EnMAP Field Guides Technical Report, GFZ Data Services*.
DOI: http://doi.org/10.2312/enmap.2015.012.

Imprint

EnMAP Consortium

GFZ Data Services

Telegrafenberg
D-14473 Potsdam

Published in Potsdam, Germany
December 2015

http://doi.org/10.2312/enmap.2015.012

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Campaign Layout & Sampling Strategies

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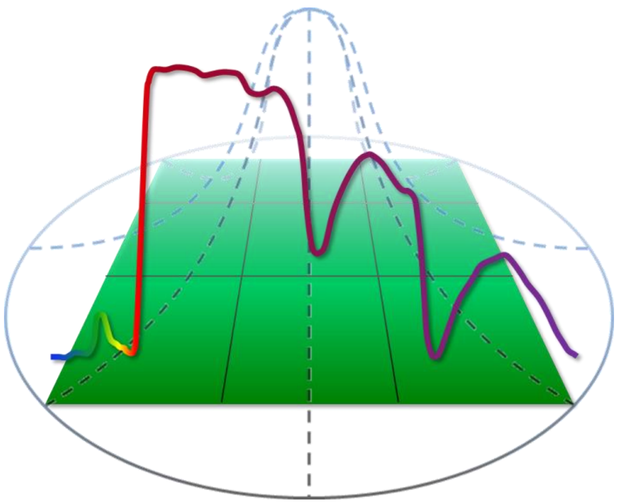

Supported by:
Federal Ministry for Economic Affairs and Energy
on the basis of a decision by the German Bundestag

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1 Introduction: Principles of Measurements

The primary goal of field campaigns is to draw conclusions about natural conditions and processes at the chosen site by taking measurements. In theory it is suggested that environmental systems can be expressed exactly if their physics and interactions are completely understood and all necessary parameters are known. Unfortunately, neither of them can and will ever be achieved. As part of the system theory, in order to be able to deal with earth's complexity, we have to set logical and spatial boundaries and further simplify the underlying problem (Zeigler et al., 1976). This is done by determining key parameters to describe the system or one of its components as accurately as needed and possible. For geographical purposes two different approaches for measuring these parameters have emerged: on the one hand, there is remote sensing making use of the assumption that information about the desired target can be obtained contactless by analysis of electromagnetic waves. These signals are received by sensors varying in construction type, functionality and possible applications. On the other hand, these indirect methods are complemented by *in situ* measurements, i.e. parameters obtained at the exact place where they take effect. Those two procedures, as oppositional they may seem, only represent two different approaches, often dealing with same or similar scientific questions. As an example, ground measurements can serve to optimize possible applications of a sensor in the course of a calibration and validation campaign. At the same time the constant modernization of instrument technology always necessitates new and improved field methods. Before rushing to the test sites and taking measurements linked to the context of e.g. the new EnMAP-HSI, it may be wise to structure individual dates to an organized campaign. This field guide aims to provide a best practice for setting up a campaign layout while putting special emphasis on spatial patterns of variables and the optimal sampling scheme to cover them as accurately as possible.

First of all, we need to understand that it is not possible to observe a process itself, but merely its effects and consequences. The significance of a measurement depends on the spatial and temporal variation of such a process. When planning a field campaign, one should always remember that the layout of this campaign will significantly influence the final results of the project. Gathering parameters over the *entire* region of interest at high resolution appears to be an insurmountable task. Hence a specific sampling scheme is required to optimally represent all occurrences, thus being able to compare them to larger-scale remote sensing data (Webster et al., 1989). The extraction of samples and parameters is conducted with assistance of various instruments. Whereas manuals for the use of these devices can easily be found at the homepages of their producers or in scientific papers, general rules for planning a whole campaign seem to be rare. One of the reasons for that may originate from a general lack of will to scrutinize the origin of readily available data. It seems to be easier to believe in arithmetic means, deviations and quality criterions as quantitative values, than in parameters that have been derived indirectly via remote sensing. Or in other words: when the user reads a number prompted on a display, it might feel unnecessary for him/her to question it any further. Reality shows, however, that we have to face various sources of errors in any kind of geographical measurement – especially when it is taken outside in the field. Curran & Williamson (1986) suggest three attempts to direct the awareness to parameter uncertainty:

a) In common scientific language, replace the expression of *ground truth data* by *ground measurement data* or simply by *ground data*, since the term *truth* contradicts to the nature of taking measurements.
b) Add error bars to plotted values.
c) Incorporate error estimators into mathematical calculations.

Although errors in gathered data can never be eliminated completely, there are several requirements to be met when obtaining values in the field. Most attention is to be paid when handling the respective instruments, but also the shape and frequency of the spatial pattern as well as the mathematical processing of the data is of importance. The latter aspects are those where this field guide shall be applied to.

2 Preliminary Considerations

2.1 Campaign Organization

A well organized campaign might not prevent unforeseen problems in the field completely, but it can reduce the risks of their occurrence. Before a team of scientists starts a series of measurements in the field, preliminary considerations are necessary to guarantee a smooth progression for the entire campaign. The more steps are taken into account prospectively, the fewer eventualities will arise.

Whereas all other Field Guides of this series deal with procedures during the field survey, this section covers the campaign organization before and afterwards.

2.1.1 Campaign Preparation

Question 1: Who / How many?

- How many people are needed in the project?
  → If the sampling scheme is fixed, think about how many people are needed to meet the requirements
  → If the number of people is fixed, think about what sampling scheme and sampling size can be achieved
- Do further research assistants have to be hired?
  → Depending on the funds available and the knowledge which is needed to work in the field
- Instruction and training of all participants involved
  → Many devices can be used without previous knowledge, but still you might want to have everyone be able to make correct decisions on their own when necessary
- How can participants communicate? E.g.:
  → Exchanging phone numbers,
  → Establishing an intern group on a social network,
  → Setting up a mailing list

Question 2:	Where?

- Where to find an appropriate test site?
  - → Contact persons of former projects and/or existing cooperation
  - → Keep an eye out for suitable sites and try to find the owner to agree on an appointment for a detailed conversation
  - → Contact governmental agencies in the search for a public site
- Inclusion of the field's owner
  - → Report the purpose and the planned procedure as detailed as he/she requests
  - → If possible, share the measured data
- Location and conditions of the test site
  - → How large shall the site be?
  - → How important is an easy reachability?
  - → Will the site be accessible throughout the entire campaign?
  - → Journey time costs money, too. How long will the access route be?
  - → Does the site offer the measurement of the desired parameter in a representative way?

Question 3:	What?

- Which parameter or set of parameters is to be measured?
  - → Make a list of essential parameters
  - → Consider additional parameters, too (e.g. weather conditions, date & time, coordinates of the field, pictures, special occurrences)
  - → The more different parameters you record, the lower the risk of forgetting an important factor
- Which devices are needed for the measurement of the parameter(s)?
  - → Check your devices (batteries, tests, data format & evaluation, possible errors)
  - → Print manuals or brief instructions
  - → Look for alternatives if required devices are not available
- How can an optimal workflow be achieved in the field?
  - → Create a measurement protocol
  - → Test the workflow (e.g. by recording the duration of all steps individually), optimize the procedure and repeat the test

Question 4:	How?

- Which is the optimal measurement layout for the campaign?
  - → Sampling schemes, sampling density & size are explained in the following chapters
- Are preliminary investigations worth the extra effort?
  - → Measuring the spatial auto-correlation of the parameter(s) can contribute to an optimized sampling scheme

2.1.2 Campaign Post-Processing

Question 1:	Where to proceed?

- If there are samples taken from the field…
  - → How can they be transported? Is a special vehicle needed?
  - → Are further implements needed for the post-analysis?
  - → Is there a laboratory available and does it offer the required equipment?
- Documentation and data analysis
  - → Are all workspaces (e.g. for student assistants) provided with computers and access codes?
  - → How can the data be structured? Translate this finding into a standard arrangement of computer folders
  - → Working on a shared directory / network drive prevents file redundancy

Question 2:	How to extract the relevant information?

- Data preparation
  - → A pre-defined input mask speeds up and standardizes the process of data archiving
  - → Which algorithms, regression methods, models (…) are to be used to correct values and extract relevant information out of the data?
  - → Is there specific software needed to be bought, licensed, installed or prepared?
- How to conclude pixel values of punctually measured data
  - → Method of data aggregation
  - → Does a simple spatial average provide sufficient results?
  - → If the ground data is to be compared to remotely sensed data of the same location, regard specifications of the sensor, such as the viewing geometry or the Point Spread Function
- Share the workload
  - → If possible, include student assistants also into data analysis activities
  - → Preparing detailed instructions about the use of software and certain proceedings takes its time, but might pay off in the end

2.2 Geography and Scale Issues

When considering different strategies of sampling a parameter of interest, one inevitably always comes back to problems of geographical scales. The importance of that topic suggests highlighting it in an own chapter.

Scale issues in geography have been increasingly attracting interest since the late sixties (e.g. Harvey, 1969). Especially after the development of powerful computing machines and GIS, the scientific community is hard to imagine dealing without their contribution (Atkinson & Tate, 2010). The term itself, however, is ambiguous with different meanings for cartography versus process description. A global issue, for instance, can be illustrated on a map with *small scale*, whereas the process is considered to be *large-scale* (Atkinson & Tate, 2010). In this field guide, we will refer to the term *scale* as the second of the above mentioned meanings, describing the temporal or spatial extent of a process.

Somewhere in the modelling process – most likely in the course of a validation campaign – theoretical considerations have to be applied to the physical world. The implied conditions vary in spatial and temporal scales. Whenever an observed or modelled process is transferred from one time step or spatial extent to another, this is called *scaling* (Blöschl & Sivapalan, 1995). Upscaling means aggregation of data, downscaling means disaggregating or "singling out" (Blöschl & Sivapalan, 1995). When aggregating model parameters, the user has to make sure that equations and relations are valid for both scales. He further has to find mathematical and/or logical rules for the aggregation in order to keep up the pattern of the distribution. This could happen either in a deterministic or a stochastic framework (Blöschl & Sivapalan, 1995). Taking measurements in the field and applying the extracted information to a larger extent, e.g. the complete scene of a satellite image, is also a process of scaling. Comparison of these data is not trivial, since the natural variation of the parameter in time and space needs to be maintained (Lucht et al., 2000).

A general distinction has to be made between what happens and what is observed, i.e. *process scale* versus *observation scale*. An ideal measurement layout would capture any process at the scale it occurs and would thus make this differentiation obsolete. The urge for the definition of an observation-scale emanates from the restriction that only a limited number of samples can be extracted for a given site and set of parameters. Hence sampling is also an act of filtering.

In order to employ an appropriate sampling strategy, it is necessary to keep in mind the different aspects of a sample's scales, introduced by Blöschl & Sivapalan (1995) and illustrated in Figure 2-1:

a) The spatial or temporal **extent** of series of measurements.
b) The **spacing** between individual samples or a series of measurements.
c) The integration time or integration volume of a sample, known as **support** (Matheron, 1965).

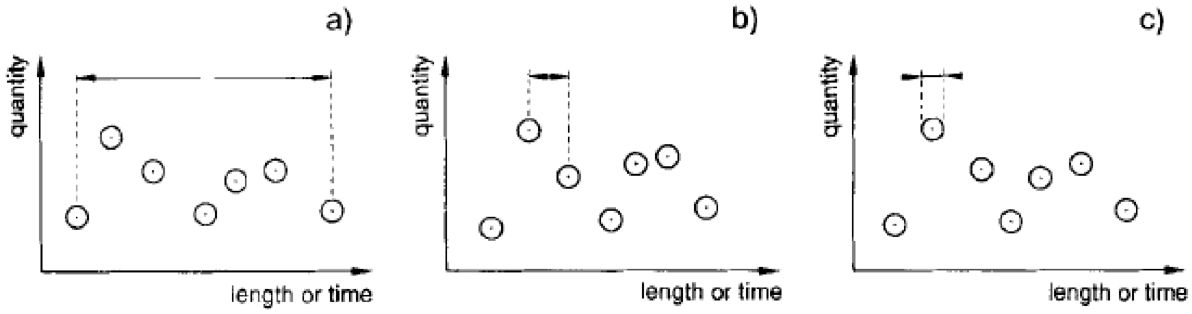
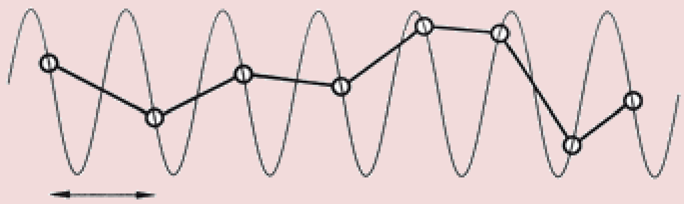


Figure 2-1: Illustration of the triplet of scales for a series of measurements, separated in time or space (Blöschl & Sivapalan (1995).

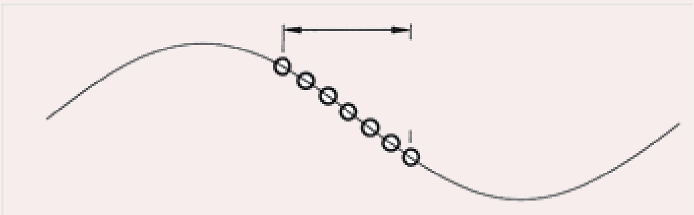
Keeping this principle in mind, the implicated error sources can be explained as follows:

Disregard of the triplet of scales and its expected consequences

- Spacing too wide or support too large
  - ➔ *Pattern turns into noise*
  - ➔ *Smoothing*



- Extent too short
  - ➔ *Misleading trend*



Errors in capturing spatial or temporal patterns, as illustrated above, of course only account for variables that undergo periodic cycles. They do, however, work similar for different kinds of trends. What appears to be a perfectly linear trend might turn out to be of spherical or exponential behavior, once the extent is set large enough to realize.

The other Field Guides of this series provide information about how to measure the particular variables of interest with given instrumentation. They also contain suggestions about how many measurements have to be taken in order to best represent the true value for this very sample unit. Extending the scale from sample unit to sample site, this yields the necessary information about the support of the desired sampling scheme. The other two aspects, **extent** and **spacing**, are then to be discussed in the following chapters.

Generally, there are two ways to approach the scale issue for field campaigns (Atkinson & Tate, 2010):

a) What scales are the processes on that I detect with measurements for the given layout of my campaign?
b) What is the natural spatial/temporal variability of the parameter, so that I can adapt my campaign layout?

The first approach reveals that the validity of the measured data comes second behind the restrictions of a sampling scheme. It can only contribute to a better assessment of the data, but not for their improvement. The second approach is the one suggested in this Field Guide. Preliminary considerations about the scales involved will lead to an optimized sampling scheme and an efficient compromise between cost and benefit even for large validation sites (Tian et al., 2002).

2.3 Distribution of Variables

One of the most important skills of geo-scientists is the comprehension of the spatial distribution of processes. For the organization, procedure and post-processing of a field campaign, it is therefore indispensable to gain knowledge about the spatial extent of a natural process, the area of which a measurement of this process is usually representative and how they can be acquired from satellite data and models.

When talking about the distribution of variables, there are many similar and occasionally identical terms that need to be understood. They are explained in Table 2-1.

If we wish to quantify the distribution of variables, we can only do that with the use of theoretical models which follow the assumption of the *Regionalized Values Theory* (Matheron, 1963). According to this theory, a parameter is distributed continuously while subjected to a spatial distribution as well as an autocorrelation. A desired parameter value Z located at x accordingly consists of the summand f(x) as a function that spatially distributes the variable, and a second summand ε(x) which is the random portion. ε(x) has an expectancy value of zero and an expected variance of

$$E \mid \{\varepsilon(x) - \varepsilon(x+h)\}^2 = 2\gamma(h)$$ *Equation 2-1*

(Webster et al., 1989)

In Equation 2-1, h represents the *lag*, i.e. the spatial remoteness between a pair of measurements in direction and distance. γ(h) then is called the *semi*-variance, since division of Equation 2-1 by two delivers:

$$\gamma(h) = \frac{1}{2m} \sum_{i=1}^{m} [z(x_i) - z(x_i + h)]^2$$ *Equation 2-2*

(Curran, 1988; modified)

Table 2-1: **Explanation of Terms**	
▪ Homogeneity	The degree of uniformity, mostly on local scale (Gonzalez & Wintz, 1987; Cheng et al., 2003). On a perfectly homogeneous surface, any local measurement would equal its spatial average.
▪ Heterogeneity	Antonym of homogeneity. Different values of a parameter occur in close vicinity to each other, due to smaller-scale processes.
▪ Randomness	"[…] is not predictable in detail, but predictable in terms of statistical properties" (Blöschl & Sivapalan, 1995)
▪ Organization	Antonym of randomness. Regularity, mostly related to complex structures (Blöschl & Sivapalan, 1995)
▪ Disorder	"[…] erratic variation in space or time similar to randomness, but it has no probability aspect" (Blöschl & Sivapalan, 1995)
▪ Discontinuity	"Within the zones, the properties are relatively uniform and predictable, whereas there is disparity between the zones" (Blöschl & Sivapalan, 1995)
▪ Spatial variation	Is statistically described via the mean value and (co-)variance of a data set (Atkinson & Tate, 2010)
▪ Stationarity	Spatial variation is constant over time or space (Atkinson & Tate, 2010)

If we put Equation 2-2 in words, it means that $\gamma(h)$ is a function which assigns half the variation of all possible pairs of values to a lag h which is also the distance of that respective pair. This function is called *Semi-Variogram* or simply *Variogram* (Curran, 1988). It yields valuable quantitative information about the shape and strength of the distribution within the sampled field. First, a theoretical model is fitted to the experimental variogram to improve the interpretation of the graph. This is best done by minimizing the sum of squared errors (SSE) between experimental and theoretical variogram in different forms until the best solution is found and then used for any further analysis. An example for the fitting of a theoretical variogram is shown in Figure 2-2.

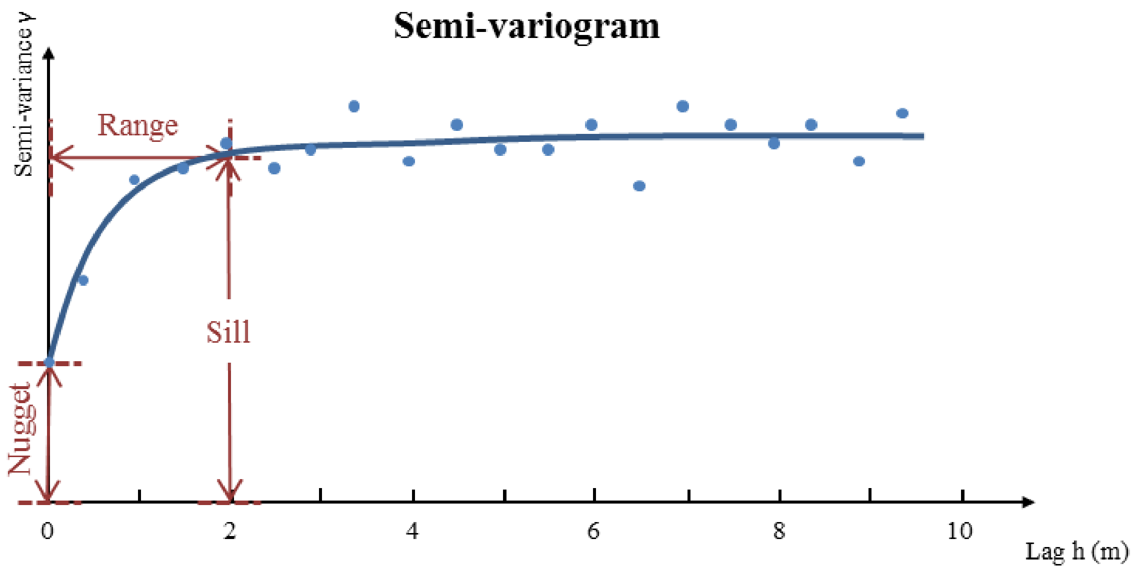


Figure 2-2: Example for an experimental variogram (blue dots) with an exponential fit (blue curve). Illustration of Nugget, Range and sill.

Interpretation of the semi-variogram			
(1)	Nugget	→	The semi-variance at lag h=0 does not always happen to be 0
		→	When the variogram does not run through the origin, the function is subject to an offset whose value is called *Nugget variance*
		→	This value represents the sum of errors of a measurement and the model fitting as well as sampling uncertainties (Atkinson & Tate, 2010)
(2)	Sill	→	Commonly, the semi-variance increases with the lag until it reaches a constant value
		→	This value is called *Sill* and can be considered as the *global variance* of the spatial data (Tian et al., 2002)
(3)	Range	→	The lag at which the sill is reached is called *Range*
		→	It represents the maximum statistical distance of a value to affect another

Since the model curve follows theoretical rules, it can be mathematically described and analyzed. The interpretation of a variogram consists of examination of three parameters: nugget, sill and range. They are depicted in Figure 2-2 and explained below.

Out of those three variogram parameters, the range contributes most to the spatial measurement schemes. It represents the maximum scale which a process can be observed at and thus defines the largest spacing allowable between individual sample points. A large range of influence suggests that one measurement also inherits information about a rather bigger surrounding spot, whereas a short range indicates the parameter to occur more isolated.

For a proper interpretation of a variogram, it is important to find the best model fit for the experimental data. There are different approaches of functions the data can be tested against. The most famous ones are the spherical model, the exponential model, the Gaussian model and various kinds of power models. The latter are known as *unbounded* variograms, since their semi-variances increase infinitely with lag. They neither have a sill nor a range, i.e. the more separated by distance a pair of values is, the less similar it becomes. The opposite of this effect would create a *bounded* variogram. The variable of interest then does not exceed a specific value of semi-variance and is then called *weak stationary* or *second-order stationary*. For an exhausting overview about different models and their interpretation, please refer to Atkinson & Tate (2010).

Only if weak stationarity is ensured, large-scale measurements can be examined together in one data pool (Journel, 1993). In practice, however, this premise is very often not the case. Variances are subject to a spatial trend, increasing with the chosen extent (Haining, 1989). This again calls for a well-considered sampling scheme and appropriate methods of interpolation and aggregation.

2.4 Sample Size & Sample Density

The *sample size* quantifies the number of measurements to be taken for a specific site or cluster. Assuming the extent of this site to be pre-set by sensor characteristics or constraints in the field, the sample size will also determine the *sample density*, i.e. the number of measurements per area or the length of a transect. In the process of finding borders for a site in which to conduct a field campaign, the most important question is the ground resolution of the corresponding sensor. In the context of the EnMAP-HSI a simulated pixel would have an edge length of 30m. If, however, observations in the field are to be compared with airborne data, the extent of the test site ought to be at least four times the size of the pixel in order to avoid spectral mixing with features located in close vicinity to the actual cluster (Justice & Townshend, 1981). Alternatively, only a central area of 30x30 meters can be sampled, while keeping a distance of another 30 meter from each of the four square sides to surrounding features. This principle is illustrated in Figure 2-3.

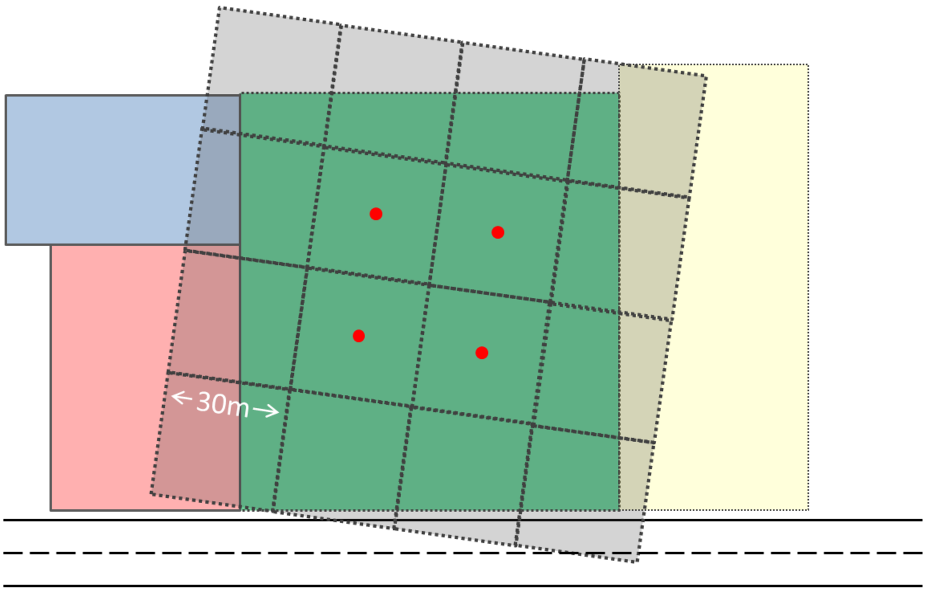


Figure 2-3: Potential areas at which samples of the test site (green) can be taken. The only pixels not revealing mixed spectra are those indicated with a red dot.

In most cases, sampling units (or ESU = elementary sampling unit) are significantly smaller than the whole pixel or site, which in theory leads to an excessive sample size. Neglecting this fact and sampling at larger spacings can cause problems when the spatial variability of the parameter is too high (Curran & Williamson, 1986). Considerations like the validity of samples are essential before starting the actual campaign. For this reason, most authors suggest to organize a preliminary investigation on-site with the goal to assess the variability of the desired parameters. A simple rule of thumbs was first introduced by Yates (1981) and later adapted by Curran & Williamson (1986):

$$n = \left(\frac{\sigma_S \cdot t}{e}\right)^2 \qquad \textit{Equation 2-3}$$

(Curran & Williamson, 1986)

with

n = desired sample size

σ_s = standard deviation of the measured parameter

t = t-value for a two-sided test with n_{pre}-1 degrees of freedom for a preferred level of confidence, e.g. 95%

e = tolerable error (same unit as σ_s)

Mind that Equation 2-3 requires normally distributed input parameters and assumes that n is of similar magnitude as the sample size for the preliminary investigation n_{pre} out of which σ_s originates (Webster et al., 1989). Another idea would be the determination of an empirical index of heterogeneity for the derivation of the appropriate sample size (Curran & Williamson, 1986). Such an index could lead to a more efficient measurement procedure, but on the other hand requires proper calibration and validation.

Another way to determine an optimal sample size is the evaluation of semi-variograms which are fitted to experimental field data (s. chapter 2.3). The range of that variogram would be the maximum spacing allowed between sample points. It was shown that the use of variograms for an optimization of the sampling process led to a 3.5 to 9-fold reduction in sample size at given level of error (McBratney & Webster, 1983).

2.5 Sampling Schemes

By selecting a suitable sampling scheme, the spatial pattern of a sample observation is defined. Basically there are four different approaches which are listed in Table 2-2, sorted by increasing evenness.

Table 2-2: **Sampling Strategy, sorted by their degree of evenness**

▪ Simple Random Sampling	→ Sampling units are picked randomly over the complete site
▪ Stratified Random Sampling	→ The site is divided into natural zones of different area → Within each zone, samples are chosen randomly → The number of samples per zone is proportional to its spatial contribution to the whole area
▪ Unaligned Sampling	→ The site is divided into equally spaced zones → For each of these zones, sample units are chosen randomly
▪ Systematic Sampling	→ Sample units are chosen by a predefined measurement pattern

(Stehman & Czaplewski, 1998)

In most cases, natural parameters tend to be spatially auto-correlated (Curran & Williamson, 1986). This means that each value also carries information about its neighbors. With a plain random sampling strategy applied, this information is multiplied on the one hand, while on the other hand other information is being missed out (Curran & Williamson, 1986). This assumption is confirmed by Webster & Burgess (1984) who were able to show that for any regionalized variable with a monotonically non-decreasing variogram, the estimated variances were minimal for measurements with given effort when they were obtained in a regular pattern. Negative aspects of organized sampling strategies, however, are the difficulty of estimating the sampling error out of these samples, plus the risk of committing a systematic bias (Dixon & Leach, 1978). Nevertheless the random sampling of auto-correlated parameters is increasingly considered as inefficient and inaccurate (Webster et al., 1989).

If a systematic sampling strategy is chosen, it is necessary to pre-define a certain pattern. There are no general rules about which design is best, but there are some aspects of experience that might help with the decision. One of the most effective measuring schemes, especially for exponential variograms, is the setup of sampling units per triangulation (Matérn, 1960). If the variance of the parameter shows distinct isotropic behavior, it is recommended to make these triangles equilateral (Matérn, 1960) as is the case in Figure 2-4.

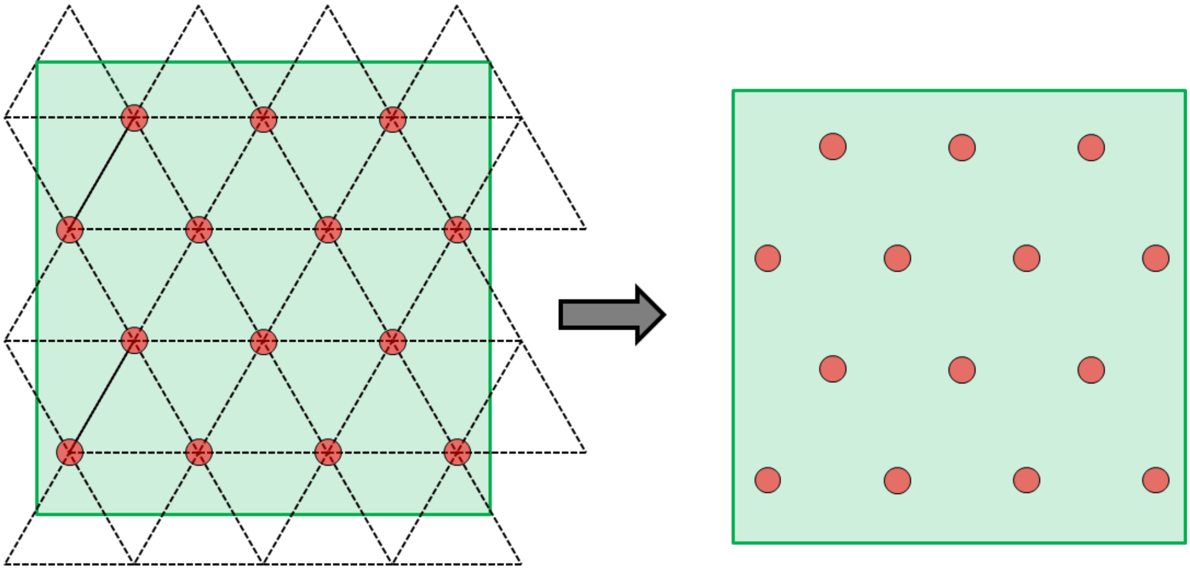


Figure 2-4: Measuring networks of equilateral triangles are considered one of the most effective sampling schemes.

Setting up a triangular network serves the purpose of a highly systematic sampling scheme, yet it is difficult to establish. According to Burgess et al. (1981) a *rectangular* pattern is way easier to arrange and only slightly less accurate. Considering the cost-benefit ratio this means that a rectangular sampling scheme is most likely to achieve best efficiency for most field campaigns. Still, thoughts have to be given to the detailed array of sampling units within the sampling area. Distances between sampling units, for example, could be equal over the complete field, or only within their cluster. By squeezing them closer together, there is an accumulation of information and special emphasis is put on that location, but it inevitably also leads to a disregard of peripheral spots. For a pattern of absolute evenness, the site is divided into zones of the same area and one sampling unit is placed into the middle of these fractions. The X-shaped sampling scheme is a simplification of the zonally centered scheme in regard to the sampling points that are being left out at the sides of the rectangle. For this reason, this measuring process can be treated like two transects crossing in the middle of the sampling area (Chen et al., 1997).

Apart from the above mentioned sampling schemes, it can also be decided to apply an experimental design: either in a regular pattern that suits the field conditions and the spatial variation of the parameter best, or as a mixture between systematic and random sampling. By now, for the choice of an adequate sampling scheme only boundary conditions of the measurement principle have been taken into account. Further consideration is necessary depending on the state of the field and the purpose of the data. If the gathered information is to describe the distribution of the variable of interest within the site, then one of the above mentioned sampling schemes can be picked and applied directly. Sampling units are placed in such a way that their spatial average represents the aggregated value for the whole site. If, however, this value is to be compared to remotely sensed data, the optimal pattern might differ to correspond to the sensor's within-pixel sensitivity. The intensity of the signal in the focal plane is a function of the position [x,y] within one elementary sampling unit, called *Point Spread Function* (PSF) (Cracknell, 2010). In an ideal case, the response equals 1 within the pixel and 0 beyond. In practice, this response, which is sometimes called the support of the remotely sensed measurement, is described by a 2D-Gaussian curve, assigning more weight to the positions located centrally than to those at the edges of the distribution (Atkinson & Tate, 2010). As a substitution for the PSF, Figure 2-5 shows the Linear Spread Function (LSF) of EnMAP which constitutes the breakdown of a PSF in along-track and across-track pixel sensitivity.

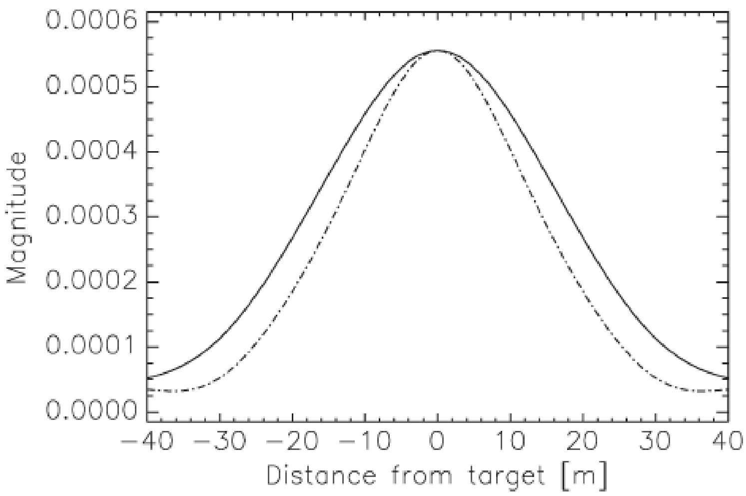
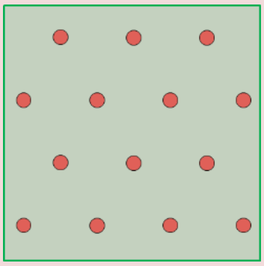
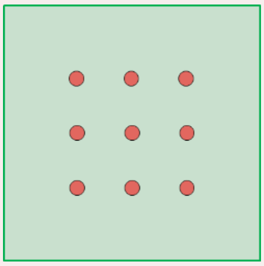
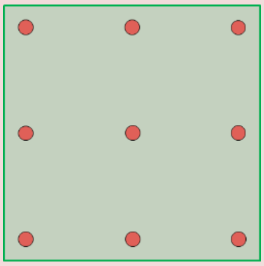
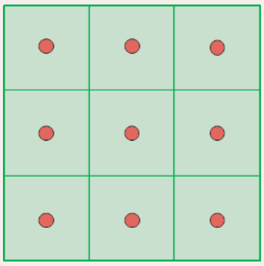
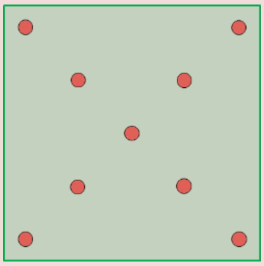


Figure 2-5: Illustration of the PSF for the EnMAP-HSI, divided into the LSF along-track (solid line) and across track (dashed line) (Segl et al., 2010).

If ground data is used to calibrate or validate those taken by an airborne or space borne sensor, measurements for positions where the PSF approaches 0 are unprofitable. Even if there is a sub-scale feature within this sensor pixel but located near its edges, this information will not contribute to the gray value of the image. In conclusion, this means that for the selection of suited sampling units, a clustered scheme is preferred with emphasis on the central area of the related pixel. In the context of EnMAP it should be noticed that satellite data is not yet measured from space but by airborne sensors with similar characteristics and aggregated on a later date. Hence, an orbital view onto earth is only simulated and the PSF refers more to the airborne sensor rather than to the EnMAP-HSI. The PSF could then consequently be ignored, since the original spatial resolution of the airborne sensor ought to be much higher than the resolution of the sampling scheme, i.e. the density of sampling units.

Table 2-3 summarizes different approaches and examples of sampling schemes as well as their weaknesses and benefits.

Table 2-3: **Examples for rectangular Sampling Schemes**

a)		*Triangulated scheme* → Equilateral arms suggested, but not compulsive for most layouts → Best coverage → Difficult to set up
b)		*Clustered scheme* → Emphasizes the center of the sampling area → In accordance to the common point spread function of spaceborne sensors → Misses out information at the edges of the field
c)		*Spread scheme* → Emphasizes the borders of the sampling area → Covers the complete extent of the site → Sampling units contain much information about adjacent features → Low density at the center of the field
d)		*Zonally centered scheme* → Equal distances towards every direction → Maximum level of evenness → Recommended for linear variograms, but also suited for other spatial variations
e)		*X-shaped scheme* → Treated like two crossing transects → Emphasis on the center and coverage of the complete area → Uncertainties for interpolation due to distinct gaps
f)		*Experimental scheme* → Maximum flexibility allows adaptation to the specific field conditions → No knowledge about the quantity of the sampling error → Pattern should first be tested and validated if possible

3 Practical Accomplishment

Between the theoretically best solution and the accomplishment that is practically possible, there is often a more or less large gap. Preliminary considerations and detailed planning of sampling schemes and sizes are worthless if they cannot be performed in the field.

In the easiest case, a site would reveal perfectly homogeneous parameters which only require one single measurement representative for the complete field, but in reality, uniformly distributed variables are rare. The second easiest case would be a site at which the heterogeneity of the parameters is already known. Nortcliff (1983), for instance, was hoping that one day there would be a database of universally valid semi-variograms a campaign could be based on. Unfortunately, more than 30 years later, this vision has not come true. Every setting is unique and so the spatial auto-correlation differs from site to site, type to type, species to species, etc. (Davis et al., 1991). The ecosystem is structured hierarchically creating interactions between individual stages and thus between processes on different scales (Urban et al., 1986). It is therefore recommended to perform a pre-study, measuring at different scales, keeping a narrow pattern, e.g. spacing of 40cm (Webster et al., 1989) and experimenting with different schemes. Afterwards, the experimental variograms are calculated and fitted mathematically (e.g. McBratney & Webster, 1986).

Time and financial constrains as well as hard accessible terrains or disturbed natural conditions are only some factors that might lead to cutbacks and the final selection of a sub-optimal measurement layout. Hence a pre-survey should always test how long a single measurement takes, how much time there is available and affordable and what the resulting sampling size then is. When there are several different parameters to be obtained, it might not be obligatory to find single variograms for each one of them. Many variables are connected in such a way that their spatial distributions highly correlate. Furthermore, the sampling density is determined by the parameter with the highest heterogeneity, but not every parameter necessarily has to be measured at each individual spot. Let parameter P_1 reveal a range of influence of 5m and 10m for parameter P_2: in this case, the value of P_2 only has to be taken at every other sampling unit.

Since the ground resolution of a sensor is indicated by pixel length, the sampling area by comparison behaves quadratic. For the EnMAP-HSI a simulated nadir pixel covers an area of 900m². Mixed pixels theoretically necessitate three times the technical cell size to be sampled (Curran & Williamson, 1986) and thus nine times its area which is 8100m² or 0.81ha. On the other hand sampling units at the edge of the field are less important when compared to remotely sensed data due to the point spread function. A more practical approach would be to keep a distance of at least 30 meters to any surrounding features of the test field and then only measure within the designated 30x30m area. When no data from airborne or spaceborne sensors are involved, e.g. for the comparison between ground data and spectra measured with a field spectrometer, a smaller field without restriction of the adjacent geometry will work just fine.

When a measurement layout is optimal in theory, but impracticable in accomplishment, the results of the field campaign will not be satisfying. Quantity of the sampling units is a key factor to quality of the data set, but it is not the only one. The more boundary conditions of the whole campaign are taken into account, the more valuable the data will be.

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