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Cost-effective sampling of ^{137}Cs-derived net soil redistribution: part 1 – estimating the spatial mean across scales of variation

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ABSTRACT

The ^{137}Cs technique for estimating net time-integrated soil redistribution is valuable for understanding the factors controlling soil redistribution by all processes. The literature on this technique is dominated by studies of individual fields and describes its typically time-consuming nature. We contend that the community making these studies has inappropriately assumed that many ^{137}Cs measurements are required and hence estimates of net soil redistribution can only be made at the field scale. Here, we support future studies of ^{137}Cs-derived net soil redistribution to apply their often limited resources across scales of variation (field, catchment, region etc.) without compromising the quality of the estimates at any scale. We describe a hybrid, design-based and model-based, stratified random sampling design with composites to estimate the sampling variance and a cost model for fieldwork and laboratory measurements. Geostatistical mapping of net (1954–2012) soil redistribution as a case study on the Chinese Loess Plateau is compared with estimates for several other sampling designs popular in the literature. We demonstrate the cost-effectiveness of the hybrid design for spatial estimation of net soil redistribution. To demonstrate the limitations of current sampling approaches to cut across scales of variation, we extrapolate our estimate of net soil redistribution across the region, show that for the same resources, estimates from many fields could have been provided and would elucidate the cause of differences within and between regional estimates. We recommend that future studies evaluate carefully the sampling design to consider the opportunity to investigate ^{137}Cs-derived net soil redistribution across scales of variation.

1. Introduction

Soil redistribution by the processes of wind, water and tillage is an essential component of Earth System Models (e.g., Shao et al., 2011) and controls soil processes at the nexus of Land Surface Models (LSMs; Chappell et al., 2014). For example, soil erosion and deposition influences soil organic carbon (SOC) stock change which are excluded from SOC cycling and Land Surface Models (LSMs). Soil erosion removes preferentially fine, nutrient- and SOC-rich material which may result in significant change in terrestrial ecosystems (Gregorich et al., 1998). These processes change the soil surface characteristics over time and provide a physical basis for change in energy and water balances. These processes and their dynamics controlled by land use and management change are also excluded from LSMs. The exclusion of soil erosion from these models is likely caused by a lack of awareness by the modelling community of the significance of these processes (Chappell et al., 2014) perhaps compounded by a dearth of soil redistribution information for the initial boundary conditions and/or validation of the models. For example, the largest map of **net** soil redistribution is available only for Australia (5 km pixel; Chappell et al., 2011a,b) and to our knowledge the only global maps provide **gross** soil erosion using the universal soil loss equation (Van Oost et al., 2007; Doetterl et al., 2012). This provides an opportunity for environmental scientists interested in soil redistribution to influence the development of regional and global land surface processes and their significance under a changing climate. The opportunity requires workers to apply their resources across scales of variation

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without compromising the representation of the variation at any scale. Here we support this opportunity by demonstrating how careful consideration of sampling design and objective can be used to produce cost-effective solutions to cut across scales of variation.

The benefits are well-established in this and other journals of the ^{137}Cs technique to estimate net, time-integrated soil redistribution by all processes (Ritchie and McHenry, 1990). When not confined to individual fields, many ^{137}Cs studies have sampled soil using transects (cf. Walling and Quine, 1991; Sutherland and de Jong, 1990; Loughran et al., 1993). In either case, these studies assume that many samples are required to represent adequately the highly variable patterns of soil redistribution by wind, water and tillage (Chappell et al., 2011b). Many studies appear not to separate the requirement to estimate the spatial mean from that of mapping the spatial variability. Consequently, samples within fields are often obtained at the nodes of a regular grid, because little is known *a priori* about the spatial scale of variation in soil redistribution processes (Chappell et al., 2003a,b). However, sampling grids are usually coarse, because the measurement of ^{137}Cs is time-consuming and only few samples may be measured for a given budget and samples may not represent adequately the variation. Use of a fine grid is typically prohibitively expensive with the ^{137}Cs technique and depending on the scale of variation may involve considerable sampling redundancy (Chappell and Warren, 2003). Over areas larger than an individual field, several workers have recognised the difficulty in obtaining sufficient samples of ^{137}Cs to represent the spatial variation in soil redistribution processes (de Roo, 1991; Chappell, 1996, 1998). Chappell et al. (1996, 1998) and Chappell (1999) showed that the sampling design must represent the variability in the spatial scales of soil redistribution processes to provide an unbiased estimate of erosion and deposition. This sampling approach is called ‘design-based’ by de Gruijter et al. (2006) and has been combined with geostatistics for use with the ^{137}Cs technique (Chappell, 1998; Mabit et al., 1998; Chappell and Warren, 2003; Mabit et al., 2008; Chappell et al., 2011a,b). Design-based sampling differs markedly from traditional (grid-based single field) soil ^{137}Cs studies, by sampling to develop a reliable description (model) of the variability in soil ^{137}Cs over space and estimate soil redistribution at unsampled locations. For example, Chappell et al. (2011b) used only 200 samples to map ^{137}Cs-derived net (1950s–1990) soil redistribution and its uncertainty across Australia. This example uses an approach which many workers unfamiliar with geostatistics find unpalatable, but which has a long-established and practical history across the environmental sciences. Notably, design-based sampling for soil redistribution mapping was excluded from the ‘Handbook for the assessment of soil erosion and sedimentation using environmental radionuclides’ (Zapata, 2002). For many, sampling design is not considered further than basic sampling theory, which is somewhat paradoxical given the significant opportunity offered by the broader field of ‘model-based’ sampling (de Gruijter et al., 2006) to estimate ^{137}Cs-derived soil redistribution across scales of variation. Model-based sampling may be considered the antithesis of design-based sampling, but there is much commonality between these approaches and we shall return to them and their hybrid later.

We contend here that the main hurdle to making estimates of ^{137}Cs-derived soil redistribution at large scales (e.g., regions either within or between continents) is the pre-occupation, evident in the literature, with soil redistribution within fields compounded by (i) the unquestioned assumption that many soil ^{137}Cs samples are required to be measured and hence sampling is too time-consuming/expensive to conduct across scales of variation; (ii) an incomplete or poor understanding of sampling theory and the lack of an explicit decision to estimate a spatial mean or to map the spatial variation. We tackle these contentions here and (a) outline a straight-forward and rigorous statistical hybrid of ‘model-based’ and ‘design-based’ sampling theory based on the recent comprehensive review by de Gruijter et al. (2006); (b) provide a pragmatic application of the hybrid sampling design using a case study in China's Loess Plateau; (c) compare the hybrid design to traditional sampling approaches (transect and arbitrary regular grids); (d) show the benefits of geostatistical mapping and (e) develop an information-cost function for each sampling design to support our recommendation for future sampling of soil ^{137}Cs to estimate net soil redistribution across scales of variation.

2. Sampling and analysis

2.1. Design-based sampling for geostatistics

A variety of statistical and geostatistical methods exist to estimate environmental data on e.g., a fine grid using sparsely sampled data (Isaaks and Srivastava, 1989; Webster and Oliver, 2001). Statistical approaches to interpolate SOC and net soil redistribution, such as a (multiple) linear regression, perform well under some circumstances. Geostatistical approaches account for the spatial dependence (autocorrelation) of the property of interest. This spatial autocorrelation can be quantified using an empirical semi-variogram (or variogram) of the sampled data, where the semi-variance is plotted as a function of the separation distance. For a dataset $z(x_1)$, $z(x_2)$, …, $z(x_n)$, with separation distance (lag h) the semi-variance:

$$\gamma(h) = \frac{1}{2m(h)} \sum_{j=1}^{m(h)} \left\{ z(x_j) - z(x_j + h) \right\}^2, \tag{1}$$

where $m(h)$ is the number of paired comparisons for a given lag, and $\gamma(h)$ is the semi-variance of the lag distance h. Prior to the calculation of the variograms ^{137}Cs was transformed using $\log_{10}$ to standardise the spatial variance. The net soil redistribution was approximately normally distributed with a skewness coefficient less than 1 and it was deemed unnecessary to transform these data. We calculated the experimental variograms for these two variograms using the average semi-variance. These variograms were fitted, using weighted least squares, with several models authorized for kriging. The model that fitted best, in the least squares sense, was selected using the square root of the mean squared difference (RMSE) between the model and the observations. The parameters of the fitted models describe the structure of spatial variation (e.g., Chappell and Oliver, 1997) and were used with kriging to make estimates at unsampled locations. Due to the limited number of samples it was assumed that the variation was isotropic and only an omni-directional variogram was calculated and fitted.

We evaluated the performance of the OK predictions using cross-validation because we had too few samples to create an independent validation dataset. We used R-squared, the mean error (ME), the root mean square error (RMSE) of prediction as criteria for the comparison.

2.2. Model-based statistics

The measurement costs of each sample at one location (e.g., 3–4 depths) make it prohibitively expensive to obtain and measure ^{137}Cs at many locations across a field. A straightforward solution to represent adequately the mean ^{137}Cs and net soil redistribution for the field, is to create a composite of a given number of soil samples hereafter called aliquots (n). Since only the composite soil is measured the number and hence cost of analyses is reduced. The key is to ensure that samples are representative of the spatial variation. Simple random sampling may be adopted across a field prior to creating a composite. However, a single composite does not in itself convey information about variability in that compositing approach. The compositing should be repeated a number of times to provide an estimate of the sampling variance. With simple random sampling the sampling variance is usually larger than with most other types of design at the same costs (Brus et al., 1999; de Gruijter et al., 2006). With stratified simple random sampling the field may be divided into equal area strata and simple random sampling applied to identify soil collection locations within each stratum. The strata should be approximately uniform in area to maximise the benefits. In common with all randomised or probability-based sampling, locations may fall within previously excluded zones e.g., rivers, area around trees etc. In these situations procedures must be used to safeguard against the introduction of bias due to the relocation of a sample location to within the sampling area. Prior information may be used to stratify e.g., soil type, topography etc. In the absence of any other information, a regular grid may be used to stratify the field prior to sampling. In this case, the strata have equal area and therefore equal volumes of soil material can be collected at the locations. In practice, stratification is formed from strata that are as homogeneous as possible. Two, or preferably more, aliquots may be placed within each stratum and these aliquots can form composites with their counterparts in the remaining strata. Once the composites are formed, well mixed and sub-sampled, they can be measured and used to estimate the variance of the composite samples. Following de Gruijter et al. (2006), the mean of the study area for each composite is estimated by:

$$\hat{\bar{z}}_{\mathrm{St}} = \sum_{h=1}^{H} a_h \hat{\bar{z}}_h, \tag{2}$$

where H is the number of strata, a_h is the relative area of stratum h, $\hat{\bar{z}}_h$ is the sample mean and St indicates the stratified simple random sampling design. The sampling variance of $\hat{\bar{z}}_{\mathrm{St}}$ can be estimated by

$$\hat{V}\left(\hat{\bar{z}}_{\mathrm{St}}\right) = \sum_{h=1}^{H} a_h^2 \hat{V}\left(\hat{\bar{z}}_h\right), \tag{3}$$

where $\hat{V}(\hat{\bar{z}}_h)$ is the estimated variance of $\hat{\bar{z}}_h$ and is given by

$$\hat{V}\left(\hat{\bar{z}}_h\right) = \frac{1}{n_h(n_h-1)} \sum_{i=1}^{n_h} \left(z_{hi} - \hat{\bar{z}}_h\right)^2, \tag{4}$$

and n_h is the sample size in stratum h. The standard error of the estimated mean is estimated by $\sqrt{\hat{V}(\hat{\bar{z}}_{\mathrm{St}})}$. An unbiased estimator of the spatial variance $S^2(z)$ is:

$$\widehat{S^2} = \widehat{\overline{z^2}}_{\mathrm{St}} - \left(\hat{\bar{z}}_{\mathrm{St}}\right)^2 + \hat{V}\left(\hat{\bar{z}}_{\mathrm{St}}\right), \tag{5}$$

where $\widehat{\overline{z^2}}_{\mathrm{St}}$ denotes the estimated mean of the target variable squared (z^2), obtained in the same way as $\hat{\bar{z}}_{\mathrm{St}}$ (Eq. (5)) but using squared values (de Gruijter et al., 2006). Notably, the total variance includes the measurement error which here we assume includes the measurement of ^{137}Cs and the calibration to estimate net soil redistribution and set constant $V_{\mathrm{lab}} = 5\ (\mathrm{t\ ha^{-1}\ yr^{-1}})^2$.

If prior information on the spatial variability is available in the form of a variogram, Domburg et al. (1994) demonstrated how it may be used to estimate the sampling variance of the sample mean of an area. Brus and Noij (2008) showed how the sampling variance may be estimated from stratified simple random sampling using composites:

$$V_{\mathrm{St}}\left(\hat{\bar{z}}\right) = \sum_{h=1}^{H} w_h^2 \frac{\overline{\gamma}_h}{n_h} = \frac{1}{H^2} \sum_{h=1}^{H} w_h^2 \frac{\overline{\gamma}_h}{n_h}, \tag{6}$$

where H is the number of strata (the number of aliquots per composite), w_h is the relative area of stratum h, $\overline{\gamma}_h$ is the mean semi-variance within stratum h and n_h is the number of sample points per stratum (number of composites). Since the strata have equal area and in this case are assumed to be as compact as possible, Brus and Noij (2008) suggest that the mean semi-variances within strata are approximately equal for the strata. They approximated the mean semi-variance using the mean semi-variance within a square of the same area.

There are two approaches to calculating the mean values $\overline{\gamma}$ of the point variogram $\gamma(h)$: numerically using a computer or by analytical solutions in successive stages (Journel and Huijbregts, 1978). We used the former approach, assumed that the sample support was square (as in our case study below) and calculated the mean values $\overline{\gamma}$ of the point variogram $\gamma(h)$ for a range of block sizes which represented the subdivision of a field into smaller strata. Notably, an approximation to the mean values $\overline{\gamma}$ is available to simplify for practitioners this stage of the analysis (cf Chappell and Viscarra Rossel, 2013).

In the absence of spatial information on the soil ^{137}Cs and/or net soil redistribution the sampling design is ill-informed. The practitioner can choose to either approximate the spatial information or proceed without the spatial information. In the former case, information may be used from other studies on the spatial variability. This is a form of chronosequence and may introduce an uncertainty depending on the unknown similarity in the spatial structure between study sites. In the latter case, the practitioner will at the outset allocate resources to sampling, largely unguided. However, after the measurements have been made using the stratified simple random sampling design above, the performance of the design can be examined and used to form the basis for the adaptation of future sampling, perhaps as part of a monitoring design or a second stage. This is possible because the variance of the composite means provide an estimate of the sampling variance. This estimate of the sampling variance can be used with the actual number of strata and composites to estimate the $\overline{\gamma}_h$ and to subsequently predict the sampling variance (rearranging Eq. (6)). If the predicted sample variance is smaller than the measured estimate of the sample variance then the sampling was adequate. If the predicted sample variance is larger than the measured estimate of the sample variance, more composites can be obtained. In the extreme case where the predicted sample variance is substantially larger than the measured estimate of the sample variance more strata and potentially more composites must be used. It can be difficult to adapt the sampling strategy in this case. It is better to avoid its occurrence at the outset by using as many strata and composites as can reasonably be afforded.

2.3. Optimising sampling using cost

In many cases it may be desirable to optimise sampling by minimising the variance for a given maximum allowable cost or to minimise the cost for a given maximum allowable variance. We followed Brus and Noij (2008) simple cost model (C) to demonstrate how cost depends on sampling design:

$$\begin{aligned} C &= C_0 + C_{\mathrm{fld}} + C_{\mathrm{lab}}, \\ C_{\mathrm{fld}} &= 2 \times H \times n \times t \times c_{\mathrm{fld}}, \\ C_{\mathrm{lab}} &= 2 \times H \times c_{\mathrm{lab}}, \end{aligned} \tag{7}$$

Table 1
Approximated values for the cost parameters for sampling and measurement.

Parameters	Cost
Fieldwork fixed cost (C_0)	1000 USD
Time (t per hour) to sample one aliquot	0.33
Fieldwork costs (c_{fld} cost per hour)	60 USD
Laboratory costs (c_{lab} cost per sample)	50 USD

where C_0 are the fixed costs which are independent of the number of composites (H) and aliquots (n) i.e., costs of preparing the fieldwork, travel costs, equipment costs, etc., t is the time in hours needed to sample one aliquot, c_{fld} are the costs of fieldwork per hour and c_{lab} are the costs of the laboratory measurement per composite. The optimal combination of n and H is independent of C_0, so this was separated from the processing. The C_{lab} cost is that associated with the receipt, preparation and measurement of soil ^{137}Cs, soil bulk density and the calibration of ^{137}Cs to net soil redistribution. In the absence of definitive information for these parameters, we estimated the parameter values in Table 1.

3. Case study

3.1. Study area

To determine the variogram, we chose to use soil samples collected from the cultivated land of the Chinese Loess Plateau, located near Nanwang village, Shaanxi province in China (35° 3.369′N, 109° 38.973′E). The loess soil is highly erodible and has been highly dissected by gullying in the past leaving steep slopes. Since 1998, widely adopted terrace construction (<1 ha) in the steep slopes has reduced soil erosion. The entire region of the Loess Plateau is divided into fields of this typically small size. Although small relative to other regions, the field provides results of significance for other scales of sampling design, resource allocation and research objectives.

Our field site (35 m × 30 m) had a slope with an average angle of 9° (range: 2°–19°) and was surrounded by other similarly sized terraced fields. The site covers an area of 721 m^2 and its altitude ranges from 723 m to 730 m (Fig. 1). The annual temperature is 9.2 °C and the average annual precipitation reaches 500 mm with 70% occurring from July to September (Li et al., 2003, 2007). The soil type is Calcaric-Cambisols with an average texture involving 6% sand, 63% silt and 25% clay. Corn (*Zea mays* L.) and winter wheat (*Triticum aestivum* L.) are the major crops cultivated in the study area.

3.2. Traditional (regular grid node) soil sampling

In April 2011, we established an approximately regular square 3 m grid using six transects parallel to the main downslope direction of the field. Along each transect, 7–8 locations (grid nodes) for sampling were identified. Soil sampling was conducted at each grid node using a hand operated core sampler (8 cm internal diameter). A total of 50 samples were collected to a depth of between 30 cm and 45 cm and a composite of the sampled soil was produced. In addition, three soil cores were collected at 5 cm depth increments to provide detailed soil profile information at selected locations (upper, middle, lower). A reference site for determining the initial ^{137}Cs inventory was selected in uncultivated grassland near the

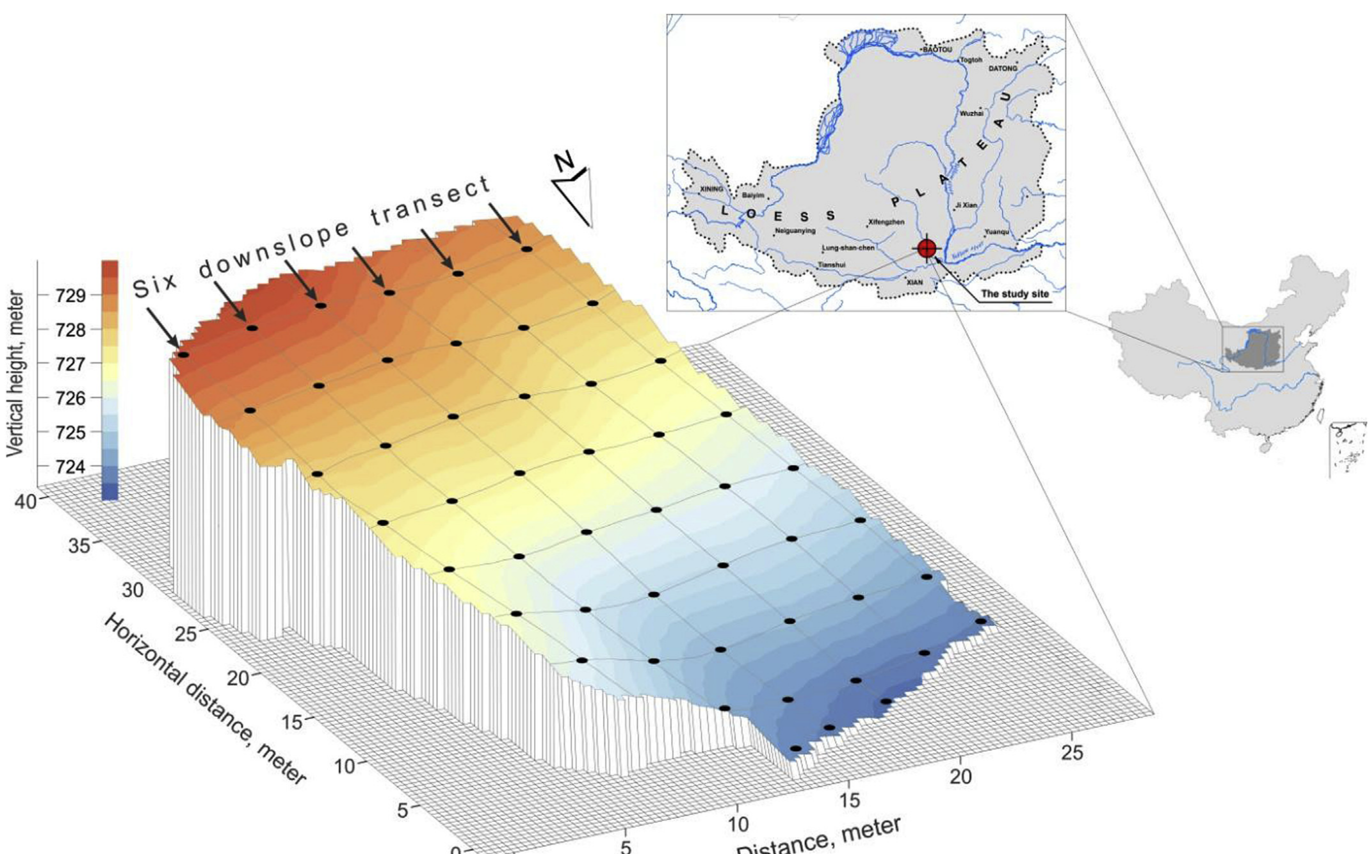

Fig. 1. Location of the study site in the Loess Plateau of northern China and a digital elevation model (DEM) of the topography showing the sampling locations.

study area. All sampling points were geo-referenced by differential Global Positioning System (dGPS) in the field to produce a digital elevation model (Fig. 1).

For clarity, we do not advocate this form of sampling because of the vagaries described above associated with grid spacing (cf Introduction). It is used here as one approach to provide the variogram of ^{137}Cs and net soil redistribution to enable the demonstration of the hybrid design-based and model-based sampling design.

3.3. Sample analysis

Soil samples were air-dried, weighed, and divided into two parts, one passing through a 0.15 mm sieve for measurement of soil chemical and physical properties as part of a larger study. The other part was passed through a 2 mm sieve for measurement of ^{137}Cs. The mass activity of ^{137}Cs (Bq kg^{-1}) was measured by gamma spectrometry at 662 keV using a hyper-pure coaxial Ge detector coupled to a multichannel analyser (Li et al., 2003). Counting time was set at 40,000 s to provide a measurement precision of ±5% (Li et al., 2006). Calibration and quality control were performed following the protocol of Shakhashiro and Mabit (2009). The results of ^{137}Cs (Bq kg^{-1}) activities were converted to areal activities (Bq m^{-2}) using the total weight of the bulked core sample and the sampling area of the corer.

3.4. ^{137}Cs-derived net (1954–2011) soil redistribution

The anthropogenic radionuclide ^{137}Cs (half-life of 30.2 years) produced during the atmospheric testing of nuclear weapons has been used successfully as a tracer of net soil redistribution for more than 50 years all over the world (Mabit et al., 2013). This radioisotope is non-exchangeable and strongly fixed by fine soil and sediment particles (Mabit et al., 2008). This ^{137}Cs technique estimates net, time integrated soil redistribution by all processes of wind, water and tillage. It is commonly used with a single visit to a study area by establishing a reference ^{137}Cs inventory at an undisturbed nearby location for use in the conversion of ^{137}Cs areal activities (Bq m^{-2}) into net soil redistribution (t ha^{-1} yr^{-1}). However, awareness and requirements are growing for the use of the ^{137}Cs technique as part of a repeated sampling or monitoring design (Kachanoski and de Jong, 1984; Chappell et al., 2012; Porto et al., 2014). Our study used the traditional approach to the use of the ^{137}Cs technique and we established a ^{137}Cs reference inventory from uncultivated grassland to provide an estimate of the initial ^{137}Cs fallout.

The Mass Balance Model II (Walling and He, 1997; Walling et al., 2003, 2011) was used to estimate net soil redistribution at each sampling location. The parameters of this model were determined based on local conditions and available information as follows: particle size factor (1), proportion factor (0.5), relaxation depth (4 kg m^{-2}), and the year tillage commenced (1954). A tillage depth factor of 306.5 kg m^{-2} was established by multiplying the tillage depth (0.25 m) by the bulk density (1226 kg m^{-3}). The mass balance model assumes that a sampling point with a total radionuclide inventory A (Bq m^{-2}) less than the local reference inventory A_{ref} (Bq m^{-2}) represents an eroding site, whilst a point with a total radionuclide inventory greater than the local reference inventory is assumed to be a depositional site (Walling et al., 2011; Porto et al., 2011). For an eroding point ($A(t) < A_{ref}$), the change in the total ^{137}Cs inventory $A(t)$ with time t can be represented as:

$$\frac{dA(t)}{dt} = (1-\Gamma)I(t) - \left(\lambda + P\frac{R}{d}\right)A(t) \quad (8)$$

where $A(t)$ = cumulative ^{137}Cs activity per unit area (Bq m^{-2}); R = erosion rate (kg m^{-2} yr^{-1}); d = cumulative mass depth representing the average plough depth (kg m^{-2}); λ = decay constant for ^{137}Cs (yr^{-1}); $I(t)$ = annual ^{137}Cs deposition flux (Bq m^{-2} yr^{-1}); Γ = percentage of the freshly deposited ^{137}Cs fallout removed by erosion before being mixed into the plough layer; P = particle size correction factor. For a depositional point ($A(t) > A_{ref}$), assuming that the excess ^{137}Cs inventory A_{ex} (Bq m^{-2}) (defined as the measured total inventory $A(t)$ less the local direct fallout input A_{ref}) at an aggrading point is due to the accumulation of ^{137}Cs associated with deposited sediment, the excess ^{137}Cs inventory can be expressed as:

$$A_{ex} = \int_{t_0}^{t} R' C_d(t') e^{-\lambda(t-t')} dt' \quad (9)$$

where R' (kg m^{-2} yr^{-1}) is the deposition rate and $C_d(t')$ (Bq kg^{-1}) is the ^{137}Cs concentration of deposited sediment.

4. Results

4.1. ^{137}Cs reference inventories

Soil profiles were collected for the reference inventory at an uncultivated site where no net soil redistribution had occurred since the mid 1950s (Fig. 2). The ^{137}Cs activity soil profile showed a monotonic (exponential) decline with depth. The shape of this profile conforms to that expected for an undistributed location, with 80–90% of the ^{137}Cs inventory concentrated in the top 15 cm. The reference inventory of this study sites was established as 1266 Bq m^{-2}.

4.2. Spatial variability of ^{137}Cs-derived net soil redistribution

A statistical summary of the measurements of ^{137}Cs and soil erosion is shown in Table 2. The net soil redistribution derived from the ^{137}Cs measurement relates to 50-years since the onset of the main period on the bomb fallout (Zapata, 2002), whereas the measured sediment eroded and deposited within the field is based on measurements undertaken during the period 1954–2011. The estimated net soil redistribution (NSR) between 1954 and 2011 ranged from a soil loss of 110 t ha^{-1} yr^{-1} to a deposition of 30 t ha^{-1} yr^{-1} with a mean 50.09 ± 7.43 t ha^{-1} yr^{-1}.

Variogram parameter values for the soil properties are shown in Table 3. Variogram models for ^{137}Cs and $NSR_{1954-2011}$ exhibited similar spatial structure with a small nugget and small nugget/sill ratio (Fig. 3) which indicated their suitability for mapping using ordinary kriging (OK). The root mean square error (RMSE) of ^{137}Cs computed from the cross-validation of OK is smaller than for

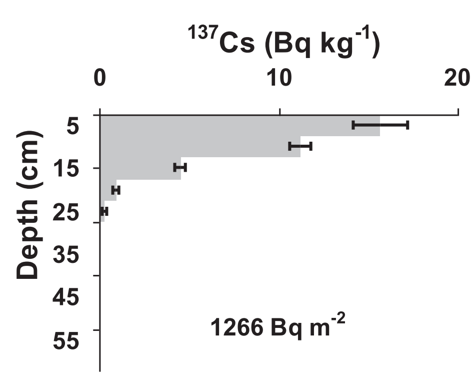

Fig. 2. The depth distributions of ^{137}Cs activities at the reference site.

Table 2
Summary statistics for measured ^{137}Cs and net soil redistribution within the field.

Variable	Number	Min	Max	Mean	StDev[a]
^{137}Cs (Bq m^{-2})	50	113.69	1730.34	677.65	472.21
Estimates of net soil redistribution (t ha^{-1} yr^{-1})	50	−114.10	35.17	−34.65	38.04
Interpolated net soil redistribution (t ha^{-1} yr^{-1})	2891	−124.69	24.38	−57.65	38.41

[a] The standard deviation.

Table 3
Fitted variogram parameters and cross-validation results using ordinary kriging (OK) for ^{137}Cs (Log$_{10}$(Bq m^{-2})) and net (1954–2011) soil redistribution (NSR$_{1954-2011}$, t ha^{-1} yr^{-1}).

Variables	Model	Range (m)	Nugget	Sill	Nugget/Sill (%)	R^2	RMSE
^{137}Cs	Exp	38.79	0.022	0.796	0	0.506	0.238
NSR$_{1954-2011}$	Sph	37.53	82	1786	6	0.491	38.08

NSR$_{1954-2011}$. The R^2 computed from the cross-validation of OK are 0.51 and 0.49 for ^{137}Cs and NSR$_{1954-2011}$, respectively. This indicates unbiased prediction of ^{137}Cs and a small tolerable bias in the prediction of NSR$_{1954-2011}$.

Most of the soil ^{137}Cs cores (42 points) have a reduced inventory relative to the reference site, suggesting that net soil loss significantly dominates this agricultural site. However, eight soil cores had larger amounts of ^{137}Cs than the local reference value, indicating net soil deposition. They are located along the northeast boundary of the lowest slope position and in a depression situated in the middle slope. Large amounts of soil erosion are evident on the divergent middle slope and upper slope area within the field. Locations with most deposition are near the outlet area of the lower slope along the northeast boundary and the depression on the middle slope. The map of net soil redistribution provided 2891 estimates at unsampled locations and the mean and standard deviation were −57.65 t ha^{-1} yr^{-1} and 38.41 t ha^{-1} yr^{-1}, respectively. We note that spatial variability on uncultivated land is likely larger than our case study on cultivated land.

4.3. Cost

In the absence of definitive information about sampling cost, we used the values of the cost parameters in Table 1 to estimate the total cost (C; excluding fixed costs) for stratified random sampling for a range of composites and strata. The results show that the cost of taking more composites increases at a faster rate than the cost of using more strata (see Fig. 4).

4.4. Model-based sampling statistics

We calculated the point variogram $\gamma(h)$ for net soil redistribution and estimated the mean values $\overline{\gamma}$ for a range of strata size (Fig. 5) which subdivide the field into smaller strata. We estimated the number of composites to achieve the measured variance of net soil redistribution (1447 t ha^{-1} yr^{-1})^2. The results showed that when stratifying the study area into blocks of 5.5 m size (approximately the size of our regular grid) only 1 composite was required to achieve the variance. However, dividing the study area into

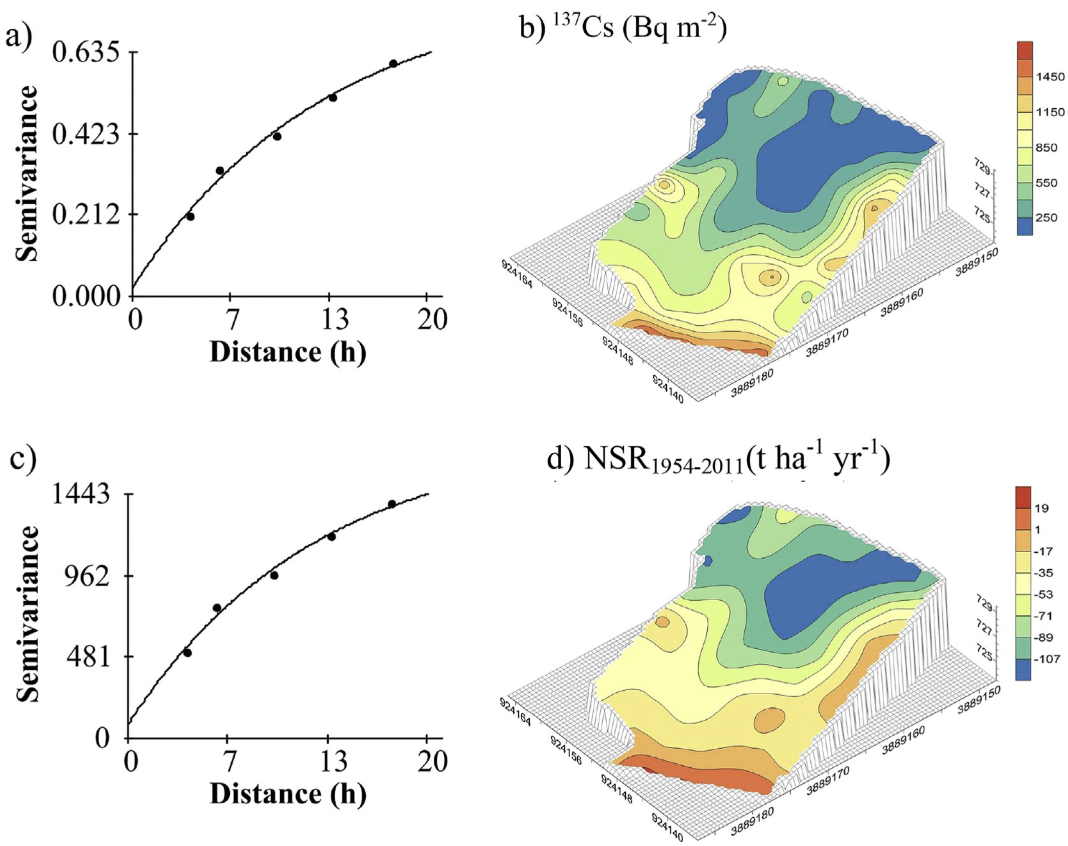

Fig. 3. Experimental (dots) and fitted (line) semivariogram for ^{137}Cs inventory (log$_{10}$(Bq m^{-2}); a) and NSR$_{1954-2011}$ estimated from ^{137}Cs measurement (t ha^{-1} yr^{-1}; c). Predicted maps using ordinary kriging for ^{137}Cs (Bq m^{-2}; b), and net soil redistribution estimated from ^{137}Cs (NSR$_{1954-2011}$, t ha^{-1} yr^{-1}; d).

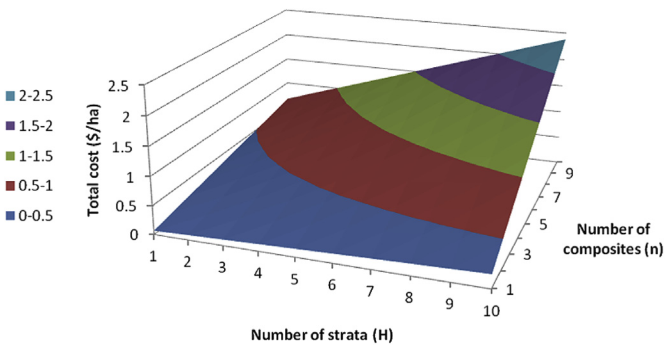

Fig. 4. Cost (excluding fixed cost) of fieldwork using the stratified simple random sampling design and laboratory measurements using compositing.

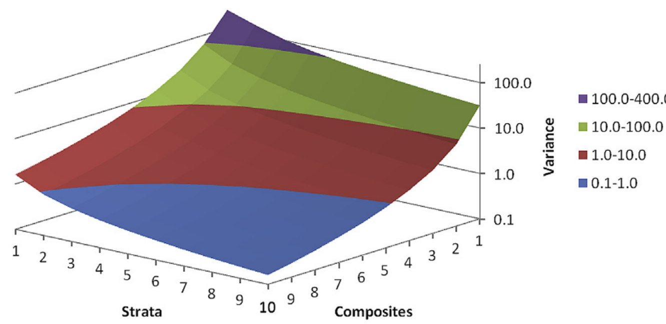

Fig. 6. Variance of net soil redistribution (t ha^{-1} yr^{-1})^2 for stratified simple random sampling with various combinations of strata and composites. Note the vertical axis is on the log scale.

larger strata required many more composites to achieve the same measured variance.

We used equation (8) to estimate the sampling variance of stratified simple random sampling for various combinations of strata and composites (Fig. 6). The smallest variance is associated with the most strata (areas which divide up the study area) or most composites (number of samples within each strata which are subsequently combined). In practice, the only likely reason to have many more composites than strata would be if the measurement cost is many times larger than the fieldwork costs. In our situation and most other situations many strata and few composites would provide adequate sampling. Conversely, these results show that few strata and few composites produce a very rapid increase in the sampling variance which would undermine the ability to adequately represent the true variance.

We used the above formulae (Eqs. (7) and (8)) to estimate the sampling variance of various sampling designs (Table 4). The original set of samples (on a regular grid) is equivalent to 50 composites within 1 strata and the sampling variance is consequently small but the measurement cost is large. For comparison the estimates made by geostatistical mapping on a fine grid produced a very small sampling variance for the same cost. Unsurprisingly, random samples across the study area produced a sampling variance and measurement costs similar to those of the regular grid. Of perhaps greater interest, is the finding that stratifying the study area using a coarse grid (11 m) and taking only one composite from each strata provided a substantially smaller sampling variance and measurement cost than random sampling and the original samples on a regular grid. The use of this design with more composites reduced the sampling variance by an order of magnitude. Stratifying the study area in to a fine grid (7 m), similar to that of the original sampling, and randomly sampling with only 18 samples, produced a sampling variance which is equivalent to using 45 samples with a coarse grid.

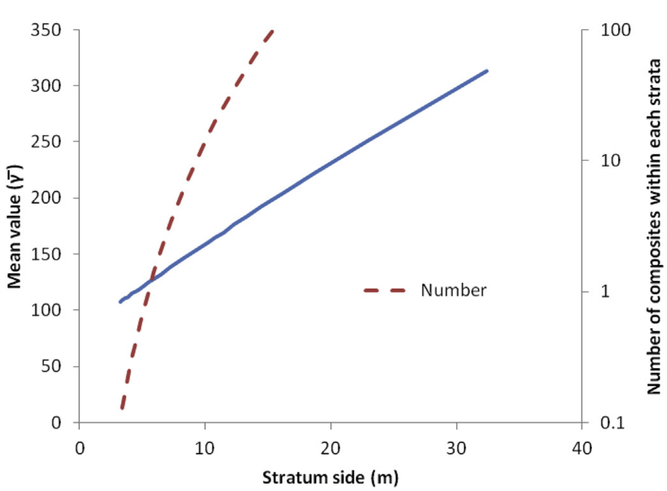

Fig. 5. The mean values $\overline{\gamma}$ of the point variogram $\gamma(h)$ for net soil redistribution are shown for a range of stratum sizes which subdivided the field (30 m × 35 m) into smaller strata. To achieve the net soil redistribution variance (1447 t ha^{-1} yr^{-1})^2 of the study area requires the displayed number of composites within each stratum. Note the secondary y-axis is on the log scale.

5. Discussion and conclusion

The hybrid sampling design required the spatial auto-correlations or variograms which describe the spatial structure of ^{137}Cs and net soil redistribution. The variogram enabled us to demonstrate the rigorous nature of the sampling design and the cost-effective benefits it confers, particularly for time-consuming environmental properties like radioactive nuclides. The variogram could be borrowed from nearby or related studies or approximated based on prior knowledge. We chose to use recent soil samples and subsequent ^{137}Cs measurements to calculate the variogram. Those samples were obtained from the nodes of a regular grid using a traditional sampling approach. For clarity, we do not advocate this sampling design because of the vagaries of choosing the grid spacing which can have considerable implications for sampling performance. Instead, there are many examples in the literature of design-based sampling to establish the variogram and to subsequently map net soil redistribution (cf Chappell and Warren, 2003).

The data we used are a special case in that many samples have been obtained from a small area with relatively similar soil texture and soil redistribution processes, typical of fields in the Chinese

Table 4
Summary statistics for sampling ^{137}Cs-derived net soil redistribution.

Variable	Composites	Strata	Stratum size (m)	$\overline{\gamma}$	Sampling variance (t ha^{-1} yr^{-1})^2	Cost ($/$m^2$)
Original samples (regular grid)	50	1	5.0	314.15	6.28	3.3
Mapping (regular grid)	2100	1	0.7	87.34	0.04	3.3
Random	9	1	32.0	319.09	35.45	0.6
Random	27	1	32.0	319.09	11.82	1.8
Random	45	1	32.0	319.09	7.09	3.0
Stratified random	1	9	11.0	164.71	2.03	0.2
Stratified random	3	9	11.0	164.71	0.68	0.7
Stratified random	5	9	11.0	164.71	0.41	1.1
Stratified random	1	18	7.6	140.17	0.43	0.4
Stratified random	2	18	7.6	140.17	0.22	0.8

Loess Plateau. Consequently, the use of a fine regular grid (50 sample locations) adequately represented the spatial variation of ^{137}Cs and net soil redistribution at this scale. Although a smaller number of samples than recommended, the variograms showed a smooth monotonic pattern consistent with those produced by reliable variograms (Webster and Oliver, 1992). The similarity in the spatial structure of variograms for ^{137}Cs and net soil redistribution is likely due to the scale of the data used in this case study. Other workers have found differences in the spatial structure of variograms for ^{137}Cs and net soil redistribution which is likely associated with the scale of the sources and magnitude of the variation. These variograms produced maps which had tolerable cross-validation statistics. The maps showed patterns of ^{137}Cs and net soil redistribution consistent with control by topography and removal from the upslope and accumulation at the base of the slope. These patterns are consistent with water erosion as the main factor driving the overall decline in soil quality on this steep cultivated hillslope. It is likely that tillage erosion has a comparable contribution to overall soil quality on terraces over the last 50 years (Li and Lindstrom, 2001). The interpretation of the spatial variability of net soil redistribution is not the focus of this paper. Our results demonstrate that the spatial variation of net soil redistribution can be produced using design-based geostatistics and produce valuable understanding of processes (e.g., Chappell, 1999). However, the production of these maps comes at considerable cost because soil from each location must be measured for ^{137}Cs. With limited resources, we contend here that this has created a focus on processes at the field scale and the neglect of net soil redistribution across scales (Chappell and Warren, 2003; Chappell et al., 2011a,b).

Using the hybrid of design-based spatial variation information (variogram) and model-based statistics demonstrates that sampling variance can be reduced considerably relative to sampling for mapping. This sampling approach provides for a robust estimate of the mean ^{137}Cs and net soil redistribution for the field at a fraction of the cost of sampling for mapping. Sampling to estimate the mean and minimise sampling variance is best performed using stratification to avoid clustering and ensure that spatial variability from across the field is represented in the sampling. Here we provide a very basic stratification to demonstrate its utility using a regular grid which assumes no prior information on how to stratify. However, stratification can make use of more or less sophisticated spatial information e.g., topography, vegetation, soil property spatial classifications etc. The compositing of spatial samples considerably reduces measurement cost/time which is important for ^{137}Cs, particularly in the southern hemisphere and as its measurement becomes more demanding over the next decade or so.

We suggest that future studies redress the balance in the focus of ^{137}Cs-derived net soil redistribution at the field scale by adopting the hybrid sampling design to estimate the mean and variance for individual fields or catchments. For example, the resources that were used to obtain soil and measure ^{137}Cs from 50 separate locations within the field could be applied to 50 fields within a catchment. This ability to refocus the nature of the study is provided by sampling design. To demonstrate the limitation of current field scale estimates for regional and global assessments we extrapolate our estimate of ^{137}Cs-derived net soil redistribution. Soil erosion observed on cultivated steep lands in the Loess Plateau was 50–80 t ha^{-1} yr^{-1} prior to 1998 (Zhang et al., 1998). Since 1998, widely adopted terrace construction (<1 ha) in the steep slopes was used to reduce soil erosion. Our results show net (1954–2011) soil erosion of 50 t ha^{-1} yr^{-1}, consistent with previous estimates in the region (Li et al., 2007). We multiplied this estimate of net soil redistribution by the area of this region of the Loess Plateau (4.6 Mha) to estimate a net soil redistribution of 250 Tg soil yr^{-1}. Doetterl et al. (2012) revised previous estimates of global soil erosion (year 2000). Their extrapolation using gross erosion from the Universal Soil Loss Equation suggested that for the Loess Plateau water erosion and tillage erosion (combined) varied spatially between 5 and 15 t ha^{-1} yr^{-1}. This soil erosion is considerably smaller than previously published estimates in the region and the results from this study. Doetterl et al. (2012) found that previous regional estimates of soil erosion, some based on extrapolation of erosion plot data, were between two to five times larger than their estimates. The differences in magnitudes were partly attributed to bias in the extrapolation due to the use of unrepresentative intensively eroding areas. Within the context of our study and the region of the Loess Plateau, we suspect that erosion has been under-estimated by Doetterl et al. (2012) due to their use of ca 10 km resolution topographic data and/or that their estimates for the year 2000 are after the majority of soil erosion occurred (prior to 1998) and after terracing reduced soil erosion in the region.

If the resources expended on our individual field had instead been allocated to 50 fields across the region we would have a better understanding of, and be better able to interpret, the differences in magnitudes and at least make recommendations for alternative modelling for estimates of soil erosion across scales.

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