UNCERTAINTY AND EFFECTS OF RESOLUTION OF DIGITAL ELEVATION MODEL AND ITS DERIVED FEATURES: CASE STUDY OF SUMBERJAYA, SUMATERA, INDONESIA

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ABSTRACT

Hydrological and erosion studies in Way Besai watershed in Sumberjaya, West-Lampung, Sumatera, Indonesia, require assessment of slope and flow pathways. A Digital Elevation Model (DEM) was generated from aerial photographs (1:24.000) using a softcopy photogrammetry approach. Error of elevation in a DEM affects derived slope, topographic index and catchment boundaries. Propagation of elevation error was evaluated on slopes both in a relatively flat terrain as well as in an undulating one. True elevation is unknown, but error can be estimated from uncertainty assessed with statistical methods following Monte Carlo simulation approach. Statistics grids as well as single parameters resulted were analyzed. Effects of DEM uncertainty on the derived slope is more pronounced in the flat terrain than in the undulating one. Within the scope and assumptions of this study, the effect of resolution on the slope uncertainty shows that higher resolution DEM creates larger slope uncertainty. Incorporation of spatial dependence in the assessment of error propagation has strong effects on the apparent error of slope. Therefore, spatial dependence of DEM uncertainty should be considered when assessing error in spatial data, especially if slope is to be derived from the DEM.

1. INTRODUCTION

1.1 Background

A good assessment of topography is of major importance in quantifying processes of erosion, sedimentation and water flow. Topography is commonly represented in a Digital Elevation Model, which can be produced from various sources and through different methods, and is used as a basis for modeling dynamic processes.

To support hydrological and erosion studies conducted in Way Besai watershed, West-Lampung, Sumatera, Indonesia, two sources of Digital Elevation Model were used for the various levels of those studies. The whole watershed is covered by a DEM derived from Topographical Maps of 1:50,000, while for the sub-catchment level studies, a more detailed DEM was generated from aerial photographs of 1:24,000, which covers about 60% of the Way Besai watershed. The latter was able to capture micro relief in riparian areas that didn't show on the topographic maps, but altered the views on slope and erosion.

Error refers to difference between observed or recorded values and the corresponding true values (Hunter & Goodchild, 1997), supposing the latter is known. Root Mean Square Error (RMSE) is a valid statistical measure to estimate errors with the assumption that errors are random and normally distributed.

In the production of spatial data, the true values are often unknown, or difficult to obtain. When the true value is unknown, uncertainty can substitute for the estimation of error. Uncertainty refers to lack of knowledge about the reliability of a measurement in its representation of the true value (Wechsler, 2000) or simply lack of knowledge of the true value (Hunter & Goodchild, 1997).

Because DEM error propagates to the derived products such as slope, DEM uncertainty also causes uncertainty in the derived products. For hydrological purposes, assessment of the uncertainty of e.g. the derived slope, topographic index and catchment boundaries is more important than uncertainty of the elevation itself.

1.2 Objective of the Study

The objectives of this study were to assess:
1. Effects of DEM uncertainty on the uncertainty of the derived slope,
2. Effects of the DEM cell resolution on the uncertainty of slope,
3. Uncertainty of the derived slope when spatial dependence is incorporated compared to that when error is considered spatially-independent.

2. DATA AND STUDY SITE

The study site is part of Way Besai watershed, which almost coincides with the sub-district of Sumberjaya, located in Lampung Province, Sumatera, Indonesia. It covers a watershed, where large forest areas have been transformed over the past three decades into mosaics of smallholder coffee fields on slopes and rice paddies in the valleys. Ongoing studies of options for managing watershed functions include involvement by local governments and other stakeholders (Verbist, 2003).

A 5km * 5km subset of the watershed was used for this study in Bodong area covering Way Ringkik subcatchment, where various hydrological and erosion studies are conducted.
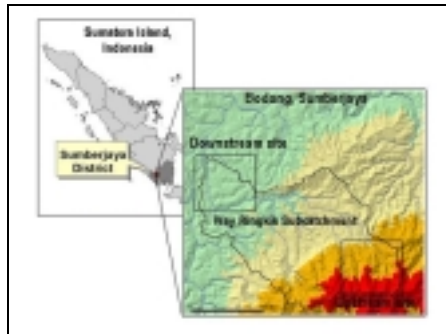
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Figure 1. General location of the study site

Two contrasting sites within the subset were chosen: an 'Upstream site' with undulating terrain, and a 'Downstream site' with relatively flat topography.

3. METHODS AND PROCEDURES

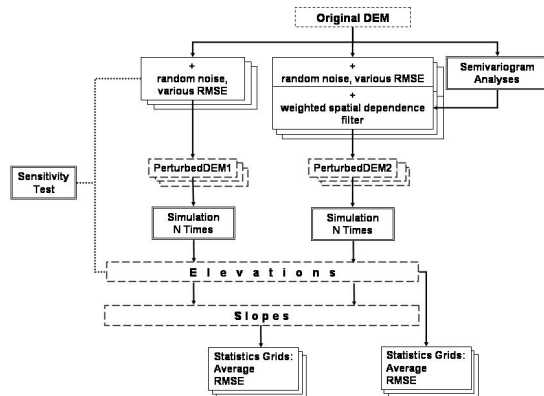The overall methods in this study can be seen in the flow diagram in Figure 2.

Figure 2. Overall flow diagram of the study

The DEM was generated from aerial photos of 1:24,000, using softcopy photogrammetry methods in the Orthoengine Module of PCI Geomatica 8.2.3. The originally-generated DEM is in 5 m resolution.

3.1 Root Mean Square Error (RMSE)

Root Mean Square Error (RMSE) is measured from discrete sample points and is commonly used to estimate error or uncertainty in locations where error was not measured directly (Holmes, 2000). For DEM, RMSE refers to the degree of differences between interpolated values and the "most probable" elevation -- so as not to use the term "true" elevation, which is normally considered unknown--. Methods for obtaining the sample points include GPS measurements, triangulation points, or a DEM of higher accuracy.

In this study, high accuracy GPS measurements were done with carrier phase processing, utilizing Trimble Pro XR as the rover and Trimble Base Station as the base station. The accuracy of this method goes up to sub-meter for horizontal (GPS Tutor, 1998) and approximately 1-2 m for vertical accuracy accordingly. Thirty-five high accuracy elevation points were collected and a subset of 14 points was used to give an error indication of the DEM generated.

3.2 DEM Perturbation using Monte Carlo Simulations

The number of GPS measurements is often limited due to time or budgetary constraints. Modeling offers a way out to assess the effects of error in elevation on the derived products.

To simulate the error over the whole surface of a DEM, a grid of random errors (random field) was generated and perturbed to the original DEM using Monte Carlo method. Monte Carlo method can be loosely described as statistical simulation method that utilizes sequences of random numbers according to a certain statistical distribution. Any statistical distribution can actually be used to generate the random errors, but the Gaussian normal distribution is most commonly used. When additional information is available about the structure of errors in a data set, the Gaussian model should be replaced with a more accurate representation (Hunter and Goodchild, 1997).

In this study, random fields were created with the same geospatial extent of the DEM and with the properties based on the statistics of the error indication of the DEM; mean = 0 and standard deviation = RMSE obtained from validation ($\mu = 0$, σ= RMSE). The random fields were created for N number of times (N simulations) to perturb the DEM.

The 14 samples for elevation validation were considered insufficient to represent the magnitude of error over the whole study site. Therefore in generating the random fields for perturbing the original DEM, instead of using only 10 m as the elevation RMSE, a series of assumed elevation RMSE's of 5, 10, 15 and 20 m were used.

3.2.1 N Optimum. The optimum number of simulations was derived from Wechsler (2000) based on the *Law of Diminishing Return*. A grid of standard deviation values is obtained for each N. From each standard deviation grid, a standard deviation is calculated and kept. The observation is done on the increments of 25. Once the difference of standard deviation estimated from the sequential N falls at 5%, the N optimum (N_{opt}) is reached. This procedure is applied across the perturbed DEMs with different perturbation layers (different assumed RMSEs).

Five hundred simulations were run to each initial DEM RMSEs (5, 10, 15, and 20 m) and then the average values of the resulting RMSE grid for each 25 increments were taken out. Observation was done to see when the 5% difference is reached.

3.2.2 Sensitivity Analysis. Various RMSEs were used as the statistics for the random field. Sensitivity tests (Jorgensen, 1994) were then conducted to observe the effects of the variable DEM RMSEs to the RMSEs of the derived products.

Two types of perturbation layers were used for the simulation, i.e. Random field and Spatially-dependent field. These perturbation filters are explained in the following sections.

3.3 Random Field - Unfiltered

The first approach of perturbation assumes that error is spatially-independent with a normal distribution and mean = zero. The random field generated based on that assumption was added to the original DEM as a single DEM realization to be tested, of which N realizations would be simulated.

This pure random approach is a "worst case uncertainty assessment", as also suggested by Wechsler (2000).

3.4 Spatially-dependent Field – Filtered

In reality, elevation error is not purely random because of the spatial autocorrelation nature of elevation and so is the error (Hunter and Goodchild, 1997; Holmes, 2000; Wechsler, 2000).

3.4.1 Semivariograms: Semivariogram analysis can characterize spatial data by relating the semivariance between two sample points to the distance that separates them. The distance interval is called *lag*. The important properties of semivariogram for the characterization of spatial dependence are: *sill* and *range*. *Range* is the value of lag (h) when it levels off, which shows the distance that the data are spatially dependent. *Sill* is the semivariance value in the maximum distance of spatial dependence (range) (Figure 3a).

However, for topographic surface, it is very unlikely that the semivariogram will reach sill, unless the strength of the geologic properties limits the maximum elevation (Holmes, 2000). In the semivariogram of topographic data, very likely the variability increases infinitely within the area under study (Figure 3b).
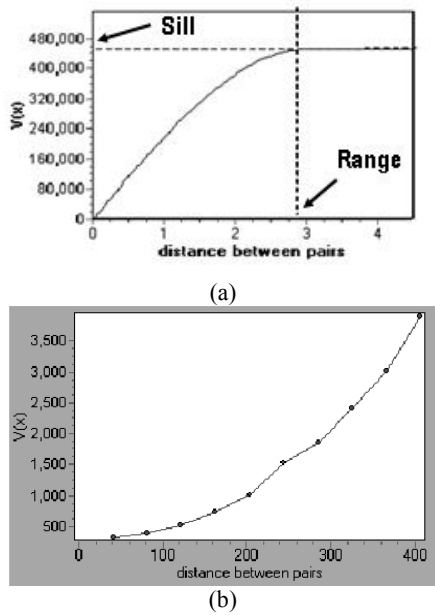

(a)

(b)

Figure 3. (a) Range and Sill in a semivariogram; (b) semivariogram with infinite increase of spatial variability (picture courtesy of The Idrisi Project)

In the case of topographic data, directional semivariograms can be calculated to obtain distance of spatial dependence. By simultaneously plotting them, the distance over which all the semivariograms show similar behavior can be used as the distance of spatial dependence.

Semivariogram Analysis was conducted using Spatial Dependence Modeller under Idrisi32. Both Upstream and Downstream sites were analyzed and the directions applied were omni directions, 45°, 90° and 180 °.

3.4.2 Weighted-mean filter. The perturbation layer developed in this second approach is called **"weighted-mean filter"** which is developed following a method by Wechsler (2000). This filter is composed of several layers, with the original values being from the random field generated. Each layer is like a 'square ring' surrounding the central cell which uniformly contains the values of 'mean * weight'. The weight assigned to each layer becomes decreasing as the layer moves farther away from the central cell. The size of the filter comes from the spatial dependence distance (SDD) obtained from semivariogram analysis. For example, if the SDD is 50 m, which means the SDD from the central cell is 50 m, then the filter size is 100 m. The total weighted-mean values are obtained as the sum of the total layers.
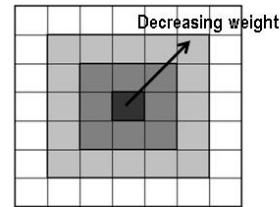

Figure 4. Example of weight layer, of 4*4 window

The formula for this method is as follows (Wechsler, 2000):

$$\text{Weighted mean filter} = \sum_{i=1}^{TL} \left(\mu(L)_i * \frac{TL - i + 1}{\sum_{i=1}^{TL} i} \right) \tag{1}$$

where: $\mu(L_i)$ = mean of the values in layer i, i.e. mean of the random field cells in the ring
i = layer number
TL = total number of layers

3.5 Slope as a DEM-derived Topographic Feature

The derived topographic parameter to be tested in this study is **slope**. Slope is defined as the increase in vertical direction (dz) per distance in horizontal direction (dx). The calculation of slope takes the eight neighboring cells or 3x3 cell window. The method follows 'third-order finite difference' by Horn (1981) (PCRaster Environmental Software).

Error in elevation propagates to the slopes derived and the uncertainty of the slope is observed by deriving the perturbed DEM into slope grids and calculating the slope RMSE by the end of the simulation.

3.6 Simulation Procedures

In conducting the simulation, the dynamic modeling tool of PC Raster was used.

For each N, a random field of normal distribution ($\mu = 0$, $\sigma =$ RMSE) was generated and was added to the original DEM, each time with a non-repetitive random field perturbation. After N_{opt} times, a grid of elevation RMSE was obtained as the simulation output. The same procedures were applied in assessing the uncertainty of the derived product, in this case, slope. For each N, after the perturbation, slope grid was calculated, and after N_{opt} times, the final slope RMSE grid was obtained.

To see the effects of resolution, the DEM was tested in three cell sizes: 5, 10 and 20 m.

Similar procedure of simulation in PC Raster was applied to the filtered-perturbed DEM. At the end of N_{opt} simulation, similarly, the statistics grids of DEM as well as of slope were obtained. Due to computational limitations, for this method, only DEM with 20 m cell size was used.

3.7 Assessment of Output

To comply with the objectives, the following statistics were used to evaluate the level of uncertainty:

1) Grids of elevation RMSE and slope RMSE, which are defined as:

$$\text{RMSE:} \quad \sqrt{\frac{\sum_{i=1}^{N}\left(\hat{Y}_i - Y_i\right)^2}{N}} \tag{2}$$

where: $\hat{Y}_i$ = estimator of the parameter Y_i. In this study, the Y_i is the original data, DEM or slope.

N = number of simulations.

To avoid confusion between the RMSE as the input of assumed error for perturbation layer with the RMSE as the statistics for uncertainty, the term 'initial DEM RMSE' is used for the first and 'output RMSE' for the latter.

2) Average value of each RMSE grid (from **1)** above) was used to observe the trends and effects of tested parameters on the variables of interests, i.e.:
- Effects of initial DEM RMSE on slope RMSE
- Effects of resolutions on slope RMSE

3) The average grids of slope at the end of N simulations were also analyzed visually to see the resulting derived slope, and to compare those resulted from unfiltered perturbation and from filtered perturbation with the original DEM.

4. RESULTS AND DISCUSSION

From the elevation validation using GPS measurements, the difference in elevation resulted was an RMSE of 10.7 m.

The simulations to determine N optimum for perturbation simulations gave result that across different initial RMSEs, the 5% difference occurs between N =125 and N = 175. Therefore, the number of simulations considered to be optimum was 150 (Figure 5).
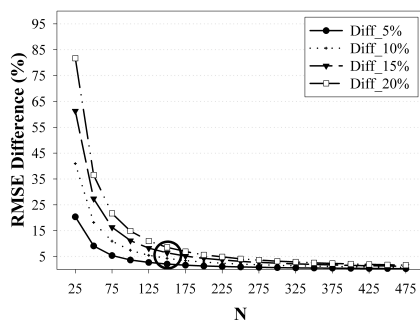
Figure 5. N optimum of the simulation

4.1 Semivariogram Analysis.

The results of Semivariogram show that for the Upstream site, similar behavior of the semivariance is shown within the distance of approximately 375 m while for the Downstream site it is within the distance of approximately 130 m (Figures 6 and 7). Those distances were then used as the distances of spatial dependence (SDD) in filtering the random field to obtain "weighted-mean" filter.
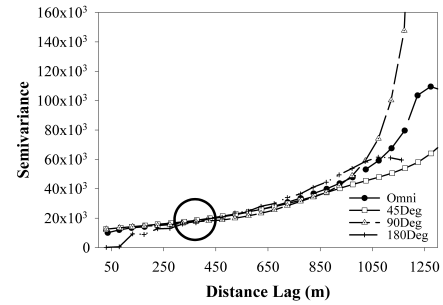
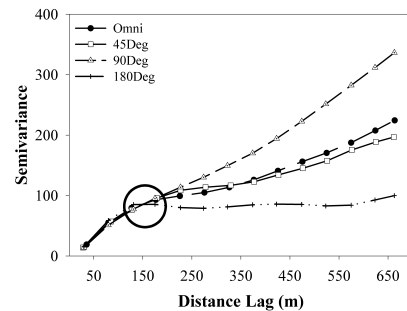Figure 6. Semivariogram of the Upstream site

Figure 7. Semivariogram of the Downstream site

4.2 Sensitivity Analysis – effects of initial RMSE on slope RMSE

The result shows that the increase of initial DEM RMSE affects the increase of slope RMSE following linear trend (Figure 8). For the higher resolution (5 m), the trend appears to be curvilinear, as the slope of the graph is smaller for the higher initial DEM RMSE.

When comparing the two sites, for each initial DEM RMSE and each cell size, the slope RMSE is higher in the Downstream site than in the Upstream site. This result shows perturbation has stronger effects in adding variability to the original elevation variability in the flat area than in the undulating area.
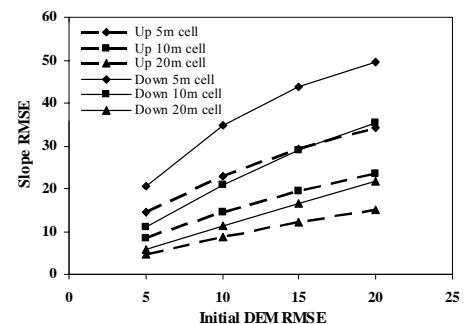
Figure 8. Sensitivity of initial DEM RMSE on Slope RMSE

In this case study, taking the RMSE of 10 m, for the Upstream site (undulating terrain), the slope uncertainty is 9° (for 20 m cell size) up to 22° (for 5m cell size), and for the Downstream site (flat terrain) 11° (for 20 m cell size) up to 35° (for 5 m resolution).

4.3 Effects of Resolution on Slope RMSE

Slope RMSE decreases with increase of cell size following a negative power trend (Figure 9) but less strong than expected if all effects are due to the large number of random variables involved.

Because in this case error is assumed to be randomly distributed, more slope variability occurs for the surface with smaller cell size than that with bigger cell size. The increase of cell size to some extent brings smoothing effects and with similar error of the elevation, the slope RMSE is lower.
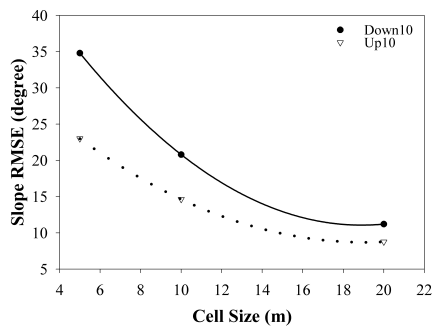

Figure 9. Effects of resolution on slope RMSE, example of initial DEM RMSE = 10 m

4.4 Effects of Spatial-dependence

4.4.1 Perturbation layer - unfiltered and filtered. An example of unfiltered layer for perturbation (Figure 10a) shows randomly distributed error. In the filtered layers (Figure 10b and 10c), clustered values are seen, with "decreasing" values as the function of distance. This effect is more clearly seen in the Upstream site (Figure 10b), because the distance of spatial dependence is bigger in this site than in Downstream site (Figure 10c).
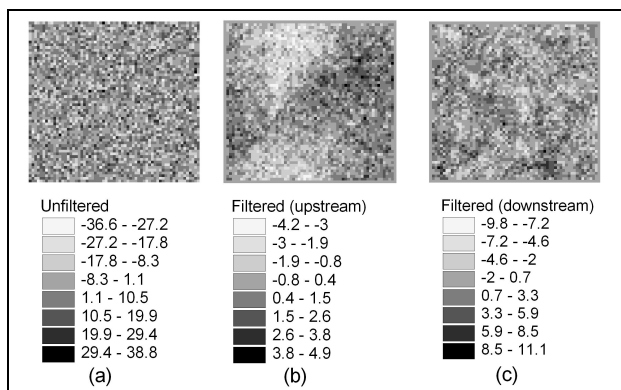

Figure 10. Perturbation layer (a) unfiltered; (b) filtered for Upstream site; (c) filtered for Downstream site

4.4.2 Effects of spatial dependence on the slope grids. The final average slope grids by the end of simulations, both the unfiltered and filtered and in comparison with the original one are shown in Figure 11. Frequency distributions are shown in

Figures 12 & 13. From the unfiltered approach, there is an increase of low slopes into steeper slopes, which is the effect of "added" error. With the incorporation of spatial dependence, slopes are less elevated and the distribution is closer to that of the original slope grid.
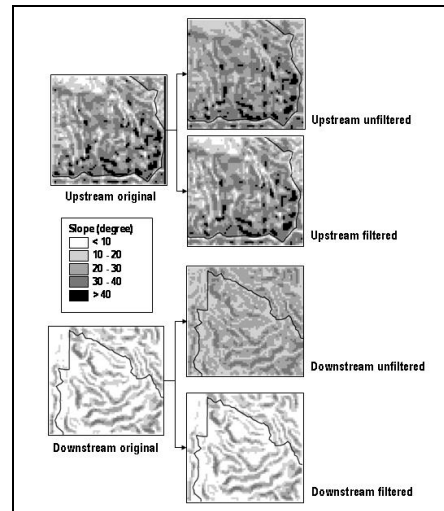

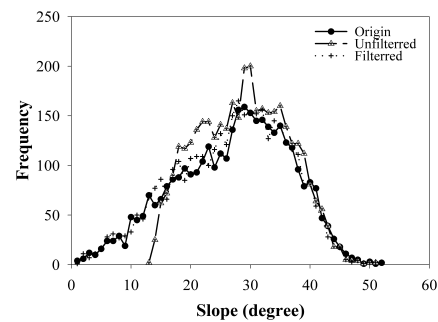Figure 11. Original slope grids and the resulting slope grids

Figure 12. Frequency distribution of original slope, and slopes of unfiltered and filtered approaches in the Upstream site
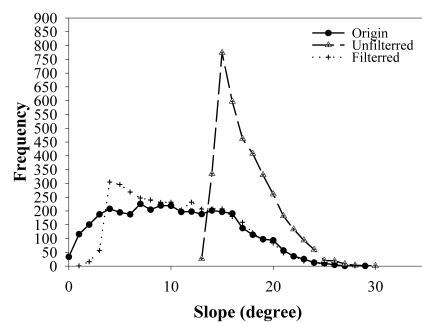

Figure 13. Frequency distribution of original slope, and slopes of unfiltered and filtered approaches in the Downstream site

Despite the different magnitude, both perturbations create a larger frequency of steep slopes. However, the slopes of filtered-perturbed DEM stay closer to the original slopes than the unfiltered-perturbed ones. The shape of frequency distribution of slopes is maintained, i.e. normal for Upstream site and left-skewed for the Downstream one

4.4.3 Effects of spatial dependence on the slope RMSE. The incorporation of spatial dependence, i.e. by applying weighted-mean filter, decreases slope RMSE in the Upstream site into

12% of the unfiltered one, and in the Downstream site into 27% (Figure 14). This result shows that the incorporation of spatial dependence of elevation error reduces the estimated error of slope.
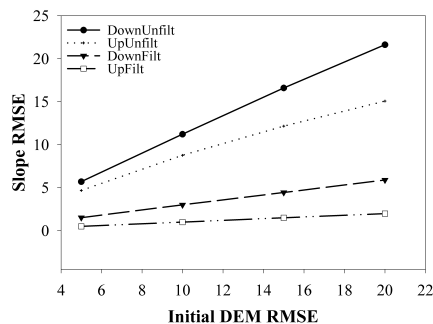

Figure 14. Effects of spatial dependence on slope RMSE

5. CONCLUSION

The increase of initial DEM uncertainty affects the increase of derived-slope uncertainty following a linear trend although for the higher resolution (5 m), the trend appears to be curvilinear, as the slope of the graph is smaller for the higher initial DEM RMSE. The slope uncertainty is larger in the Downstream site than in the Upstream site because the effects of similar magnitude of error to the original elevation variability are stronger in flat area than in undulating area.

Slope RMSE increases by the increase of resolution (smaller cell size), which means that with a similar magnitude of error indicated, higher slope uncertainty occurs in higher resolution slope grids. This result shows the importance of choosing the optimum resolution so as to minimize big slope uncertainty. And as the result shows that higher slope uncertainty occurs in the flat area than in the undulating area, the decision of resolution is more crucial if the terrain under study is relatively flat than if it is undulating.

The approach which considers that elevation error is random shows that initial DEM uncertainty affects derived-slope uncertainty in a much higher degree than if elevation error is considered spatially-dependent. Assuming that error is spatially-dependent, error propagation from DEM to the slope error occurs in a lower magnitude compared to the propagation when error is considered random. And the magnitude of the reduction is bigger in the undulating terrain than in the flat terrain.

This study is still in the preliminary stage, a few points for further improvement are considered important to note:
1. With the spatial dependence assumption, the relationship between the spatial dependence of elevation and that of the error is yet to be studied further. The question should be whether spatial dependence of elevation error is linearly correlated with that of the elevation.
2. Comparison of slope RMSE obtained as the DEM-derived feature with that obtained from field observation may result in a different magnitude of uncertainty.
3. For overall outcomes of erosion and river flow, the frequency distribution of slopes, and thus of the error, is important to assess. However for spatially-explicit intervention, the demand is on the location aspects of the error/uncertainty.

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