Science of the Total Environment 792 (2021) 148403

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Long-term, process-based, continuous simulations for a small, nested rangeland watershed near Tombstone, AZ (USA): Extending model validity to include soil redistribution

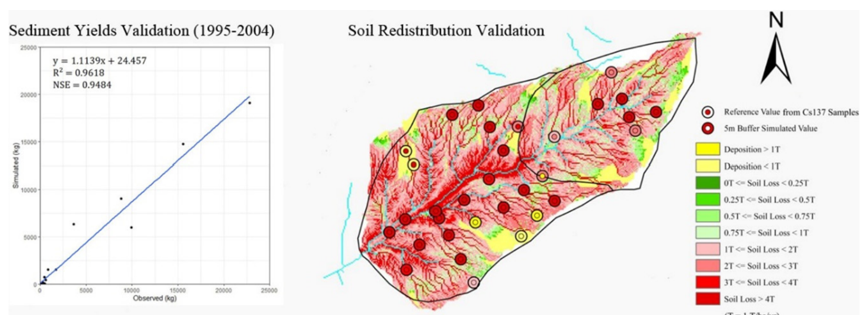
Han Zhang [a,b], Chris S. Renschler [a,b,*], Mary H. Nichols [c], Mark A. Nearing [c]

[a] Department of Geography, University at Buffalo, 116 Wilkeson Quadrangle, Buffalo, NY 14261, USA
[b] Landscape-based Environmental System Analysis & Modeling Laboratory (LESAM), University at Buffalo, 142 Wilkeson Quadrangle, Buffalo, NY 14261, USA
[c] Southwest Watershed Research Center, U.S. Department of Agriculture-Agricultural Research Service, Tucson, AZ, USA

HIGHLIGHTS

- The process-based GeoWEPP for long-term soil redistribution was validated.
- The spatial distribution of soil loss and deposition utilizing fallout ^{137}Cs was generated.
- Model representation was improved using higher resolution input and re-aggregating model output.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 28 March 2021
Received in revised form 3 June 2021
Accepted 8 June 2021
Available online 11 June 2021

Editor: Filip M.G. Tack

Keywords:
Soil redistribution
GeoWEPP
Channel parameter
Soil loss
Deposition
Radionuclide fallout

ABSTRACT

Soil or sediment redistribution prediction along hillslopes and within small watersheds is considered to be a great challenge for the application of watershed erosion models in predicting the impact of soil and water conservation measures as well as for the redistribution of pollution such as radioactive fallout. In this study, long-term soil loss and deposition were estimated for two nested semi-arid watersheds within the Walnut Gulch Experimental Watershed in Southeastern Arizona using the process-based Geo-spatial interface of WEPP (GeoWEPP). While soil parameters were previously parametrized and validated through watershed outlet runoff and sediment yields, the channel parameters were adjusted and validated based on reference values of soil redistribution generated from fallout radionuclide ^{137}Cs samples within the watersheds. Two methods were applied for the soil redistribution analysis by comparing observed and simulated soil loss/deposition rates (a) at single pixels and reference values at the specific location of each ^{137}Cs sample site; and (b) for average values of a 5 m radius around each ^{137}Cs sample site to compensate for measurement and model uncertainties. Surprisingly, soil redistribution predictions improved as topographic data resolution increased from 5 m to 3 m and were best at 1 m without changing key model parameters that were originally derived at the watershed scale.

1. Introduction

While many challenges remain in accurately predicting erosion model parameters (Vente et al., 2007), information gleaned from watershed hydrology-erosion models can be helpful as a guide to local land management, policy implementations, restoration, and rehabilitation

* Corresponding author at: University at Buffalo, USA.
E-mail address: rensch@buffalo.edu (C.S. Renschler).

https://doi.org/10.1016/j.scitotenv.2021.148403

(Maalim et al., 2013). Precise estimations of soil loss are urgently needed for assessing disturbances in rural watersheds (Pacheco et al., 2014) as well as the development of future conservation strategies (Saghafian et al., 2014). Methods and models have been developed to estimate soil redistribution by erosion, and to understand the effect of several parameters of redistribution, including climate, soil properties, land use and landscape structure (Batista et al., 2019; Borrelli et al., 2021). The spatial distribution and connectivity of areas that produce both soil erosion and deposition should be included in studies performed at the landscape or watershed scales (Cerdan et al., 2012; Delmas et al., 2012).

The ability of both empirical models and process-based models to integrate the dominant processes of soil redistribution is uncertain (Kirkby et al., 1996). The validation of such models is also an important need in areas where experimental data are missing (Lacoste et al., 2014), especially when considering detailed spatial distribution of soil loss, because the collection of soil erosion data is a time and resource-consuming exercise, although the process is not considered complicated (Berneard and Laverdière, 1992). This can be solved by utilizing radionuclide fallout Cesium (^{137}Cs), which is an artificial radionuclide with a half-life of 30 years that was produced and deposited globally by atmospheric nuclear weapon tests beginning in 1945, with the highest fallout record occurred in 1963 (Fulajtar et al., 2017). Fallout ^{137}Cs is stored in the upper soil, and its stock decreases due to radioactive decay and fine sediment transfer caused mainly by water and tillage erosion (Mabit et al., 2008), as well as wind erosion (Sutherland et al., 1991). ^{137}Cs redistribution data have been used to estimate the extent and the pattern of long-term soil erosion around the world (Bernard and Laverdiere, 1992). The distribution of ^{137}Cs is relatively spatially uniform and its strong sorption by soil particles make this isotope a reliable indicator of soil movements (Ritchie and McHenry, 1990).

The objectives of this study were (i) to analyze the parameterization, verification and validation of the spatial distribution of soil loss and deposition rate in a semi-arid watershed from 1963 to 2004 using the Geo-spatial interface of WEPP (GeoWEPP), and using soil redistribution results generated based on ^{137}Cs measurement as the reference; (ii) to analyze the simulation performances generated using Digital Elevation Model in the resolutions of 5 m, 3 m and 1 m. This is the second paper in a series following the baseline validation of the watershed simulations using GeoWEPP for long-term and short-term nested watersheds (Renschler and Zhang, 2020).

2. Material and methods

2.1. Water Erosion Prediction Project (WEPP)

The Water Erosion Prediction Project (WEPP), is a process-based, semi-distributed parameter, one-dimensional, continuous model founded on the fundamentals of hydrology, erosion mechanics, plant growth, and open channel hydraulics (Flanagan and Nearing, 1995; Meghdadi, 2013). The model was designed for two approaches: a hillslope and a watershed version, which can be used to model spatial and temporal distributions of net soil loss and sediment deposition (soil redistribution) along a representative hillslope, or across a distributed, watershed on a single event or a time series under various environmental conditions, respectively (Flanagan and Nearing, 1995). It allows the selection of appropriate measures for soil conservation and for soil erosion control (González-Arqueros et al., 2017). Several factors determine the response from soil to water, including climate, irrigation, infiltration, water balance, soil parameters, watershed channel hydrology and erosion processes, as well as the watershed impoundment component. These factors are important parameters that WEPP can be used to study systematic environmental variations and their response to hydrological changes (Yu et al., 2009). However, as a process-based model that can accurately simulate soil erosion condition considering properties and processes at fine spatial and temporal scales, WEPP has an extensive requirement for data (Renschler, 2003).

2.2. Geospatial interface for WEPP

The use of Geographic Information Systems (GIS) technology enables the efficient and effective preparation of spatially-distributed parameters within watersheds. GeoWEPP is a user-friendly geo-spatial interface for the WEPP model that combines the process model with ArcGIS (Renschler, 2003) enabling researchers and practitioners to utilize a complex process-based model for land management decision-making. It was also developed to overcome the limitation of WEPP with the advanced characteristics of GIS (Yu et al., 2009). GeoWEPP provides a platform for processing and generating digital data outputs at a watershed scale and the visualization of the production of soil erosion and the deposition of sediments in a time series (Renschler and Zhang, 2020). The preparation of parameters for the simulation using the GeoWEPP interface was independent from the pixel sizes over the range from 1 m to 3 m and 5 m. This follows the approach of a minimum of adjustments of parameters across pixel sizes for the same process-based model approach. The interface allows input parameters for WEPP to be well-prepared by processing publicly available data sources to the required inputs for WEPP watershed simulation (Singh et al., 2020), which in turn provides an excellent tool to simulate the runoff and sediment yields at a watershed scale. GeoWEPP has emerged as an important tool in soil erosion studies, especially at the watershed scale, and has made a contribution to the development of appropriate soil conservation strategies.

While both WEPP and GeoWEPP do not belong to landscape evolution models, they cannot adjust the terrain based on each soil redistribution event. Landscape evolution models are defined as models that operate on a two-dimensional (planform) surface aiming to model different processes that detach and transport sediment in natural landscapes (van der Beek, 2013). For landscape evolution models, there is a distinction between short-term processes that act on hill-slopes and transport sediment from drainage divides toward the drainage net, and long-term fluvial processes that export sediment from the model domain (van der Beek and Braun, 1998). In contrast, steady-state models are defined as models that take net soil loss or changes in storage of material eroded from the landscape as constant (Montgomery, 2001). For stead-state models (including WEPP and GeoWEPP), one need to assess the generalized consequences of a series of erosional events throughout the landscape change rather than the dynamics of discrete, stochastic erosional events (Fernandes and Dietrich, 1997).

Corresponding with the two methods in WEPP, there is a watershed method and a flow-path method in GeoWEPP. While the validation for the GeoWEPP watershed model for multiple, nested watershed outlets was the focus of the initial paper in this series (Renschler and Zhang, 2020), this second paper features the validation of the flow-path method simulating the spatial distribution of long-term soil loss and deposition within a watershed.

2.3. Study area

The study was conducted on two sub-catchments within the Lucky Hills study area on the semi-arid USDA-ARS Walnut Gulch Experimental Watershed (WGEW) near Tombstone in southeastern Arizona. Within the Lucky Hills study area is a 47-ha watershed that is shrub-dominated, primarily by creosote bush, tarbush, and acacia (Fig. S1 (Supplementary Information)) (Canfield and Goodrich, 2003; Ritchie et al., 2005). Runoff has been measured with a Santa Rita supercritical flume (SRSF) at the outlet of sub-catchment 103 since 1963. Runoff was measured from 1962 to 1986 with a V-notch weir at the outlet of sub-catchment 101 (Stone et al., 2008). The elevation ranges from about 1354 m to 1376 m above sea level. The major soil is mainly gravelly sandy loam with a high fraction of fragmented rocks (Ritchie et al., 2005).

Canopy cover in Lucky Hills during the rainy season is approximately 25%, and the ground area is mainly covered with rock and bare soil (Nearing et al., 2007). The Lucky Hills area is classified as rangeland, which has historically served as grazing land for cattle and horses. The shrubland was severely eroded by the early 1900s because it experienced overgrazing from 1880 to 1930 (Nearing et al., 2007). Grazing has been eliminated since 1963 when the area was fenced, although smaller herbivores may still graze within the watershed (Minkowski, 2012; Abercrombie et al., 2019). Long-term average precipitation at Lucky Hills is 350 mm per year, and potential evapotranspiration is 260 mm per year, which is approximately 75% of the annual precipitation (Becker et al., 2018). GeoWEPP was used for the study of soil redistribution estimation (Minkowski, 2012), and radionuclide fallout ^{137}Cs was used to measure soil loss and distribution in the study area (Ritchie et al., 2005). Soil redistribution simulation using GeoWEPP has not been parameterized and validated using the measurement samples of fallout ^{137}Cs. No comparison has been made between the output of the GeoWEPP and fallout ^{137}Cs for long-term soil redistribution simulation, as well as analyzing the influence of model input resolutions to model performance of GeoWEPP in this study area.

2.4. GeoWEPP input data preparation

2.4.1. Digital elevation models

The research-grade 1 m-LiDAR DEM data was sourced from the USDA – Agricultural Research Service. The data were created in 2003 (Fig. 1). The DEM was resampled into 3 m and 5 m resolutions for the purpose of comparing simulation results using model inputs in different resolutions.

2.4.2. Watershed delineation

GeoWEPP integrates the WEPP model and TOPAZ (TOpography PArameteriZation) software via ArcGIS. A DEM provides the required input data for the delineation of the watershed and sub-catchments extraction. The channel network is defined using TOPAZ based on the steepest down slope path, considering eight adjacent cells of each pixel (Garbrecht and Martz, 1997). The channel network can be adjusted by changing values of Mean Source Channel Length (MSCL) and Critical Source Area (CSA). The MSCL defines the shortest channel length and the CSA is the minimum drainage area (Garbrecht and Martz, 1997). Sub-catchments are explicitly defined based on the channel network and prepared for further processing (Flanagan and Nearing, 1995). The runoff and sediment yield simulated for each event are listed in text files or in grid outputs. The flow-path outputs are generated as grid layers representing soil loss and deposition in relation to a Target Soil Loss (TSL).

2.4.3. Climate file

The climate file consisted of 10 parameters, including day, month, year, the number of daily break point (nbrkpt), daily maximum and minimum temperature (tmax, tmin), as well as solar radiation (rad), wind velocity (w-vel), wind directions (w-dir) and dew-point temperature (dew). Daily break point precipitation records from 1963 to 2004 for the climate file were obtained from rain gauge 83 (Fig. S1 (Supplementary Information)), which was installed in 1963 within the study area, and can be accessed from the USDA-ARS Southwest Watershed Research Center (SWRC). The remaining parameters within the same time period were obtained from the nearest climate station located in Tombstone, AZ. Data above are formatted to a Breakpoint Climate file with 42 years of climate records following the standard formats (Zeleke et al., 2019). For each day with precipitation records, the break point precipitation was formatted into two columns, the time and precipitation, following the general climate information of the day. The time is described as decimal hour for each break point, followed by the accumulated precipitation at the respective break point (Renschler and Zhang, 2020). The number of break points in each day is listed as the fourth column. For those days with no precipitation, the number of break points is 0.

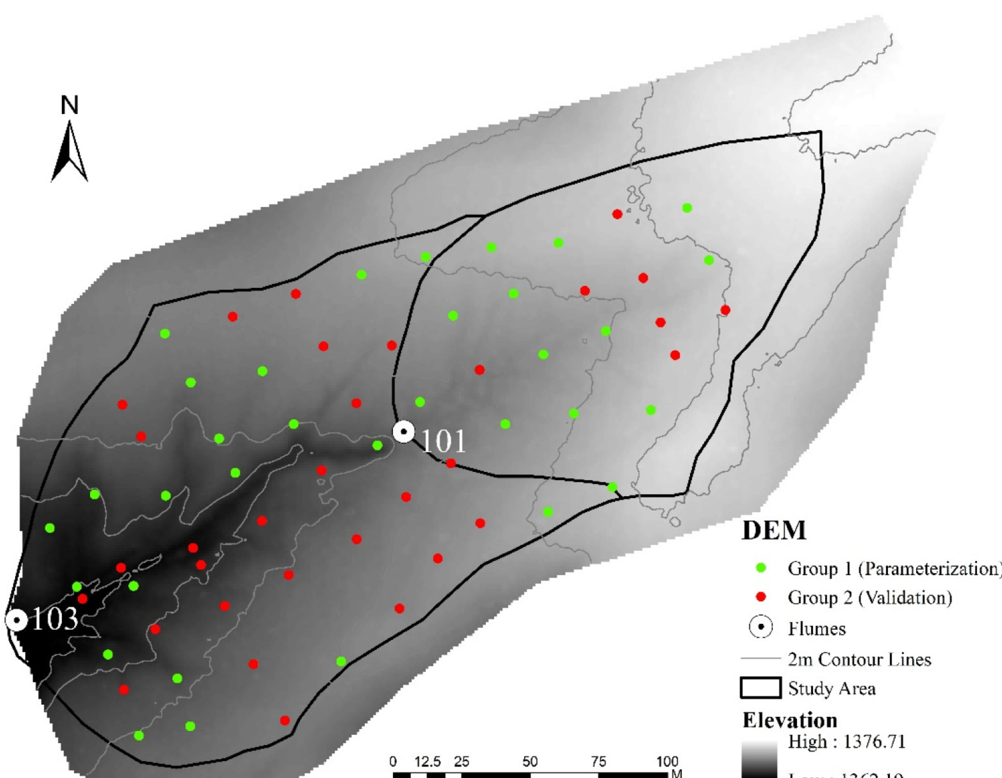


Fig. 1. DEM with 2 m contour lines and 65 sample sites of fallout ^{137}Cs (Ritchie et al., 2005) randomly divided to two groups in the study area.

2.4.4. Soil and vegetation files

The soil model parameters for the Lucky Hills-McNeal Sandy Loam (Breckenfeld, 1995) were initially developed for selected individual events in 1982 and 1984 (Nearing et al., 2005). Minkowski (2012) adjusted these two parameters – hydraulic conductivity and shear stress, to reflect the hydrologic and sediment yield responses, respectively – for a continuous, but also a short-term simulation over three years. In contrast to these short-term parameter adjustment and validation, Renschler and Zhang (2020) re-evaluated the same two parameters and used a verification and validation period of a much longer time period of 52 years (1965 to 2017). Please note, that while these parameters are much more stable, for this study it was assumed that there was no spatial distribution of soil and vegetation parameters within the Lucky Hills watersheds. Raster files in 1 m resolution for both the soil and vegetation were generated and further resampled into the resolution of 3 m and 5 m for the comparison of simulation results using model inputs for these three different resolutions.

2.5. GeoWEPP model application

Required input data, including the DEM, soil and land use were derived to generate an ArcMap project for 1 m, 3 m, and 5 m resolution using the GeoWEPP interface. The critical source area (CSA) and the minimum source channel length (MSCL) were adjusted to meet the identified channels in the study area. According to the composition of the soil in the study area, the channel parameters were set as the default values of gravel for previous studies of the analysis of long-term, event-based runoff and sediment yields (Renschler and Zhang, 2020). However, the channel parameter has a great impact on the soil redistribution and the default values of gravel cannot lead to an accurate spatial distribution of soil loss and deposition. Thus, the channel parameters needed to be estimated and validated. The outlet points of each watershed were specified based on Google Earth images of 2016 and the satellite base map of ArcMap (undated), combining with the shapefile of sub-watersheds obtained from the SWRC. The sub-catchments within each watershed were defined based on the outlet points. The data above were accepted and then input into GeoWEPP with the climate data to generate the spatial distribution of soil loss and deposition created in 42 years from 1963 to 2004 using the flow-path method. Both the general information about the soil erosion patterns, runoff and sediment yields by events were simulated and a map of the average annual soil loss and deposition rates with value in each pixel were generated: soil loss as a positive value, and deposition as a negative value.

Because the data available for model verification and validation was gathered in 2004, the time period of 1963 to 2004 was used for the study. The simulation results for both runoff and sediment yield for the time period from 1963 to 2004 were different using flow-path method and watershed method. Because the original input parameters that affect runoff and sediment yields, hydraulic conductivity (K_{eff}) and critical shear stress, were determined based on the watershed method, the two parameters needed to be readjusted for the flowpath method following the same process as the watershed method (Renschler and Zhang, 2020). Observed event-based runoff and sediment yields for the same time period were extracted from measurement records of flume 103 (Fig. S1 (Supplementary Information)), which locates at the outlet of the study area. Input data of 5 m resolution were used to do the parametrization of K_{eff} and critical shear stress. Channel parameters were then adjusted based on the new critical shear stress obtained in the previous step. Both K_{eff} and critical shear stress values are set as the same for 1 m, 3 m and 5 m resolution.

2.6. Model verification and validation

Soil loss and deposition rates calculated using the distribution of fallout ^{137}Cs from 74 samples in the study area (Ritchie et al., 2005) were used as the reference values for the verification and validation of soil redistribution simulated using GeoWEPP. Among the 74 samples, seven samples were located outside of watershed 101 and 103, one sample was located in a delineated channel without simulation output, and one sample was an outlier (^{137}Cs concentration was more than double the next highest concentration measured according to Ritchie et al., 2005). Thus, these nine samples were not used in this study. In order to do the parametrization, verification and validation of soil redistribution, the remaining 65 samples were randomly separated into two groups, with 33 samples for parametrization (group 1) and 32 samples for validation (group 2) (Fig. 1).

Two methods were used for the verification and validation of soil redistribution: (a) comparison between simulated soil loss/deposition rate in single pixel and reference value at the specific location of each sample site; and (b) a 5 m radius was created for each sample site,

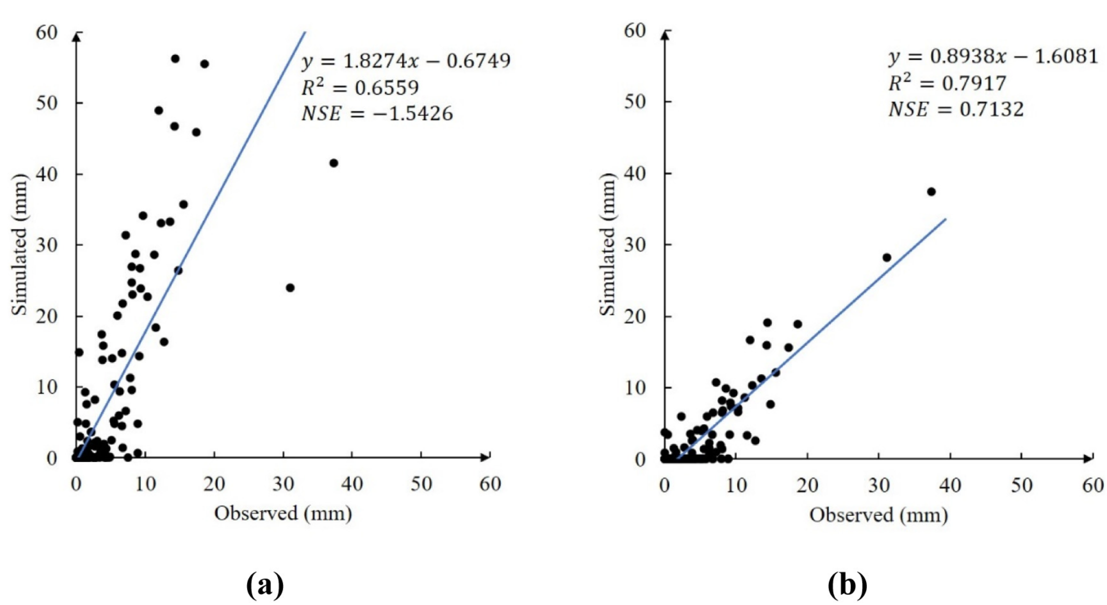


Fig. 2. Runoff (mm) simulation performance by flow-path method using the K_{eff} adjusted by the watershed method (K_{eff1}) (Renschler and Zhang, 2020) (a), and using the new K_{eff} (K_{eff2}) for the time period of 1963 to 2004. All of the relationships between simulated and observed runoff are significant (Pr(>|t|) < 0.001).

and the average value of simulated soil loss/deposition rate in each pixel that fell in the radius was calculated and compared with the reference value generated using ^{137}Cs.

2.7. Model performance evaluation

Traditionally, the correlation coefficient and standard error of estimate have been used to measure the fitness of a model. However, the correlation coefficient can be a poor estimator of goodness of fit because of model bias (McCuen et al., 2006). The correlation coefficient assumes that the model being tested is unbiased, but a fitted power model can be significantly biased in contrast (McCuen et al., 1990). Nash and Sutcliffe (1970) proposed an alternative goodness-of-fit index, Nash-Sutcliffe Efficiency (NSE), which overcomes the limitation of the traditional correlation coefficient. The total variation of the random variable potentially can be explained by the model that will be used to predict values of the random variable (Lamontagne et al., 2020).

$$\mathrm{NSE} = 1 - \frac{\sum_{1=1}^{n} (\hat{y}_i - y_i)^2}{\sum (y_i - \overline{y})^2}$$

in which y_i= simulated values, $\hat{y}_i$ = observed values, $\overline{y}$ = mean of the observed values, and n= sample size.

If the predictions of a linear model are unbiased, then the NSE will lie in the interval from 0 to 1. For biased models, the NSE index may actually be algebraically negative. The NSE index can be applied to a variety of model types, which indicates its flexibility as a goodness-of-fit statistic. (McCuen et al., 2006). For hydrological models, values with NSE > 0.5 are considered as good fits (Moriasi et al., 2007).

3. Results

3.1. Parameters adjustment

The simulation performance of runoff by the flow-path method using the K_{eff} adjusted by the watershed method (K_{eff1}) (Renschler and Zhang, 2020) for the time period of 1963 to 2004 is shown in Fig. 2(a). The relation between observed and simulated runoff for events during 1963 to 2004 was $y = 1.83x$, with the coefficient of determination (R^2) and Nash-Sutcliffe Efficiency (NSE) equal to 0.66 and −1.54, respectively. Runoff was significantly over-estimated with a relatively low R^2 and a negative NSE, which indicated that K_{eff} needed to be

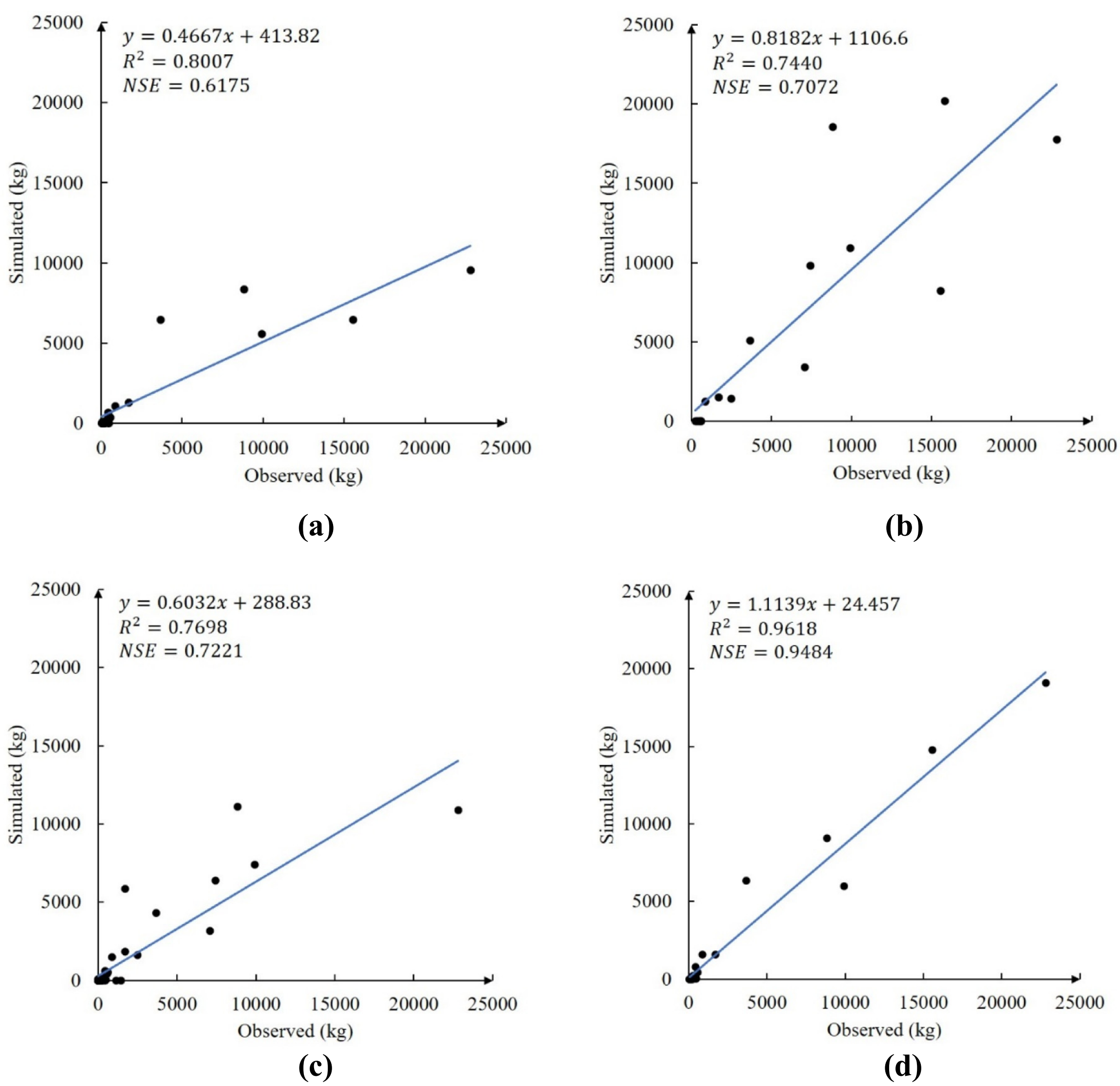


Fig. 3. Sediment yields (kg) simulation performance by flow-path method using the critical shear stress adjusted by the watershed method (C_1) (Renschler and Zhang, 2020) in 5 m resolution (a), and using the new critical shear stress (C_2) in 5 m (b), 3 m (c) and 1 m (d) resolution for the time period of 1995 to 2004. All of the relationships between simulated and observed runoff are significant ($\Pr(>|t|) < 0.001$).

decreased for the flow-path method. The simulation performance of runoff using the decreased K_{eff} (K_{eff2}) is shown in Fig. 2(b). The relation between observed and simulated runoff for events during 1963 to 2004 was $y = 0.89x$, with R^2 and NSE as 0.79 and 0.71, respectively. The model efficiency was high, which indicated that the simulated runoff was well represented by using K_{eff2} for flowpath method.

For sediment yields, due to the limited availability of observed records in the study area, events during the time period of 1995 to 2004 were used for parameterization. Similar to the runoff simulation, the simulation performance of sediment yields by flow-path method using the critical shear stress adjusted by the watershed method (C_1) (Renschler and Zhang, 2020) for the time period of 1995 to 2004 in 5 m resolution are shown Fig. 3(a). The relation between observed and simulated sediment yields for events during 1995 to 2004 was $y = 0.47x$, with R^2 and NSE as 0.8007 and −0.62, respectively. Although the R^2 and NSE were relatively high, the simulated sediment yields were significantly under-estimated. Thus, critical shear stress that controls the model output of sediment yields needed to be decreased for flow-path method. The simulation performance of sediment yields using the new critical shear stress (C_2) in 5 m resolution is shown in Fig. 3(b). The relation between observed and simulated sediment yields for events during 1995 to 2004 was $y = 0.82x$, with R^2 and NSE as 0.74 and 0.71, respectively. The model efficiency was high, which indicated that the simulated sediment yields were well predicted by using C_2 for flow-path method. The same parameter value was also used to generate sediment yields using model inputs in 3 m and 1 m resolution, the

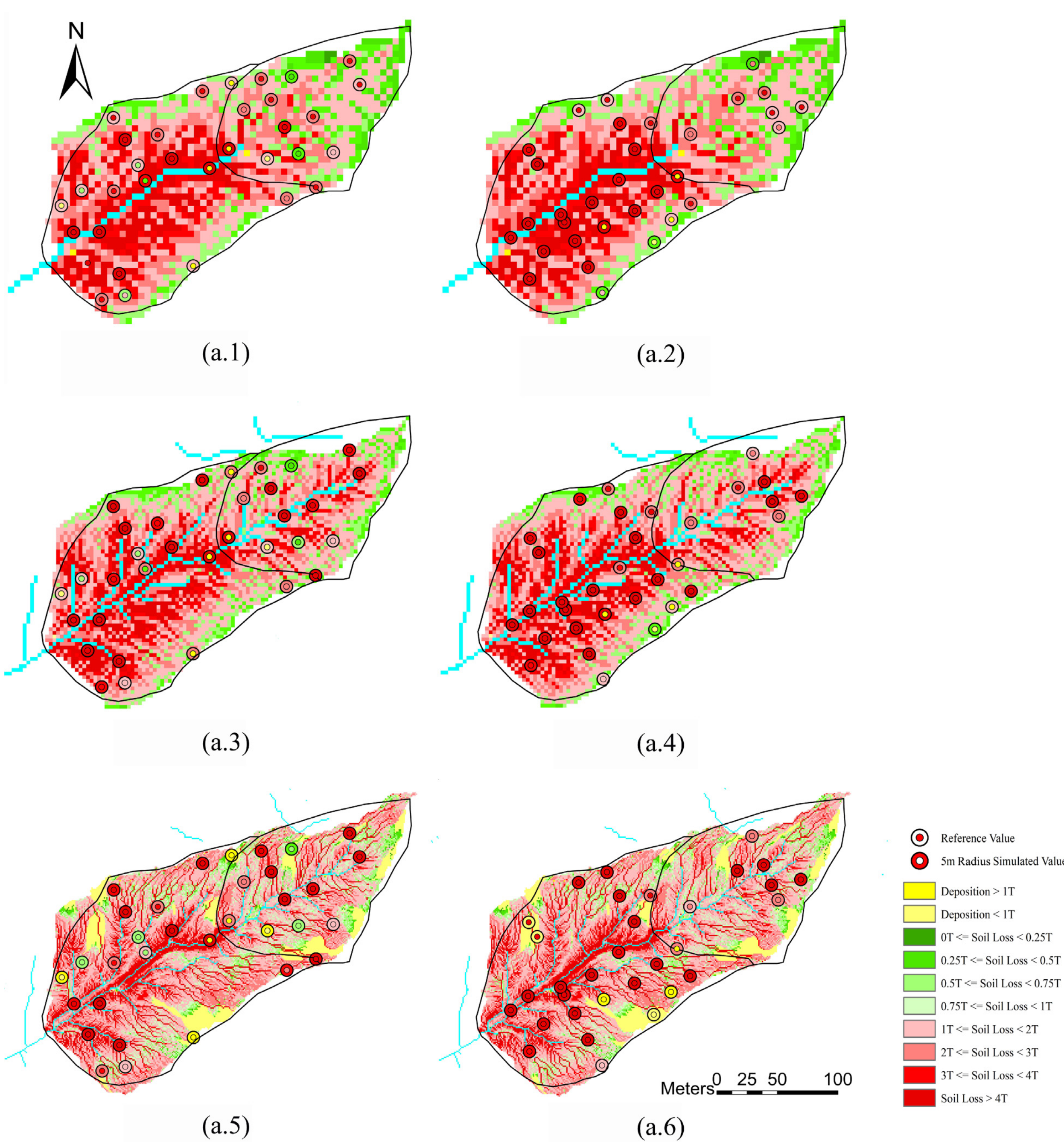


Fig. 4. Two groups of soil loss/deposition rate (T/ha/yr) from ^{137}Cs samples (Ritchie et al., 2005) (inner points) and aggregated simulation value within 5 m radius of ^{137}Cs samples (outer rings), Group 1 for parametrization and the spatial distribution of simulated soil loss/deposition in 5 m (a.1), 3 m (a.2) and 1 m (a.1); Group 2 for validation and the spatial distribution of simulated soil loss/deposition in 5 m (b.1), 3 m (b.2) and 1 m (b.1). T represents the tolerance value as 1 T/ha/yr.

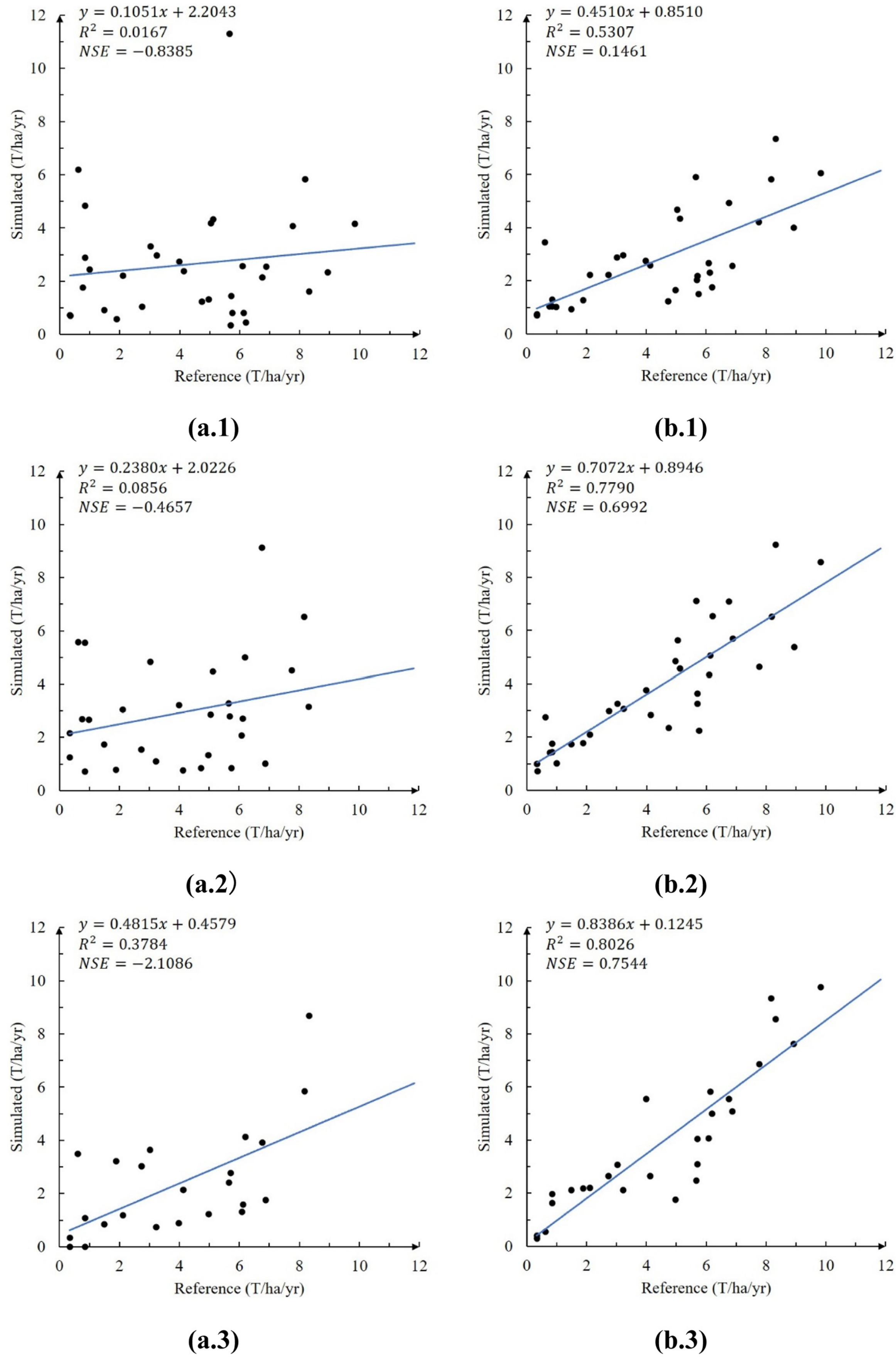


Fig. 5. Soil loss (T/ha/yr) simulation performance for Group 1 (parameterization) at the specific locations of sample sites (method a) in 5 m (a.1), 3 m (a.2) and 1 m (a.3) resolution, and for aggregated values within 5 m radius (method b) in 5 m (b.1), 3 m (b.2) and 1 m (b.3). All of the relationships between simulated and observed runoff are significant (Pr(>|t|) < 0.001).

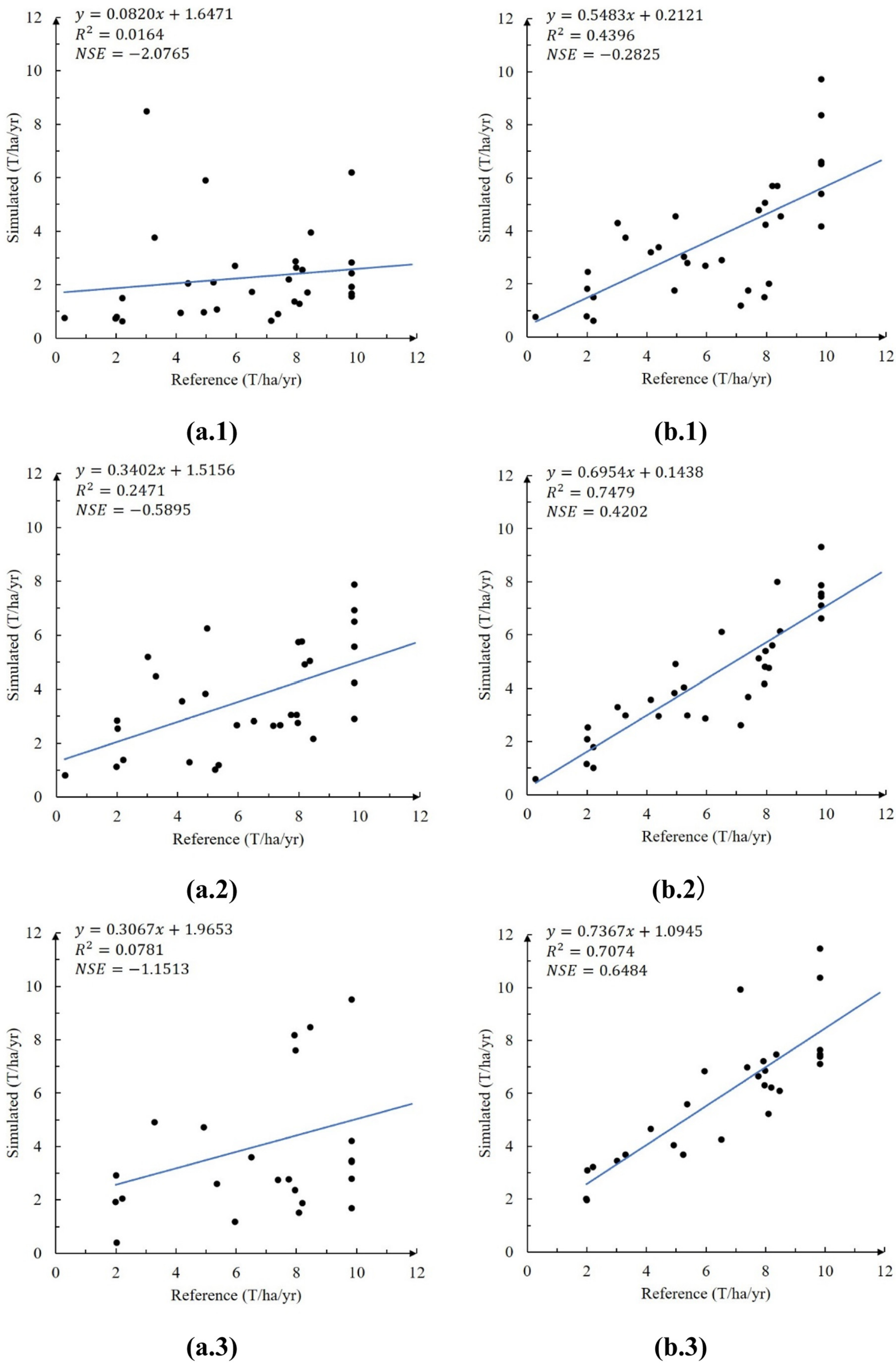


Fig. 6. Soil loss (T/ha/yr) simulation performance for Group 2 (validation) at the specific locations of sample sites (method a) in 5 m (a.1), 3 m (a.2) and 1 m (a.3) resolution, and for aggregated values within 5 m radius (method b) in 5 m (b.1), 3 m (b.2) and 1 m (b.3). All of the relationships between simulated and observed runoff are significant (Pr(>|t|) < 0.001).

simulation performances are shown in Figs. 3(c) and 4(d). Comparing the model performance among three different resolutions (Fig. 3(b), (c), (d)), there was a significant increase of both R^2 and NSE with the increase of topographic resolution. Sediment yield and runoff were simulated for events during a 42-year period. Sediment yield was predicted for 17 events out of 35 runoff events when topography was represented at 5 m resolution. When topographic resolution was increased to 3 m and 1 m sediment yield was predicted for 30 and 35 runoff events, respectively.

3.2. Soil redistribution

The output of GeoWEPP for soil redistribution was in the format of raster map with each pixel value representing soil loss as a positive value and deposition as a negative value. The spatial pattern of soil redistribution in the study area simulated by GeoWEPP using adjusted channel parameters using model input in 5 m, 3 m and 1 m resolutions are shown in Fig. 4. The model results based on 5 m and 3 m resolutions failed to simulate any deposition; however, the model based on 1 m resolution topography successfully simulated deposition. The spatial pattern of soil loss and deposition shared a pattern similar to the soil redistribution generated by Ritchie et al. (2005) using fallout ^{137}Cs. Deposition happened mostly in relatively low elevations, while soil loss happened mostly in higher elevations.

3.2.1. Soil loss

Data from Group 1 (Fig. 1) were used for the parameterization of channel parameters used in the GeoWEPP model. The critical shear value in the channel parameter file used for previous study was decreased from 3.11 pa to 1.94 pa, and was used in the GeoWEPP model to simulate soil loss for the time period of 1963 to 2004. The model outputs of soil distribution in three resolutions were shown in Fig. 4(a). The simulation performance for soil loss in 5 m, 3 m and 1 m resolutions using (a) value at the specific pixel where sample sites are located, and (b) aggregated values of pixels within 5 m radius of sample sites are shown in Fig. 5. At the specific location of sample sites (Fig. 5(a)), the correlations between model output and reference value for three different resolutions were all relatively low. The highest R^2 was 0.3784 in the 1 m resolution model output. However, the correlations between aggregated value of model output within 5 m radius for the three different resolutions (Fig. 5(b)) were significantly higher compared to the results of method (a). The highest R^2 among the three resolutions was 0.8026 and the highest NSE was 0.7544. Comparing the performance across different resolutions, the model results improved from 5 m, 3 m to 1 m resolution for both method (a) and method (b). The level of soil loss/deposition under-estimation decreased significantly as resolution decreased from 5 m to 3 m and 1 m.

To validate the accuracy of the channel parameter values for simulating soil loss, Group 2 (Fig. 1) was used to be the reference and was compared with the model output in three resolutions for both method (a) and method (b) (Fig. 4(b)). The simulation performance for soil loss based on 5 m, 3 m and 1 m resolutions using method (a) and method (b) are shown in Fig. 6. Both R^2 and NSE for method (a) were relatively low, and comparatively higher for method (b) for all three resolutions. Also, there was an increase of both R^2 and NSE with the increase of input resolution, along with the decrease of the level of model under-estimation.

3.2.2. Deposition

Deposition was only simulated using the 1 m-resolution model. In the Group 1 (Fig. 1), locations of two of six sample sites with deposition were mis-simulated as soil loss. Fig. 7(a) shows the simulation performance of the remaining four deposition values for Group 1. Similar to the simulation performance of soil loss, at the specific location of each sample site, the model errors showed no significant pattern of spatial distribution. However, by aggregating values within 5 m radius for each sample site, R^2 was as high as 0.9245 and the NSE was 0.7641, indicating the simulation results were also highly representative. The channel parameter adjusted based on the soil loss simulation was fitted to model deposition, although there were two locations inaccurately simulated.

Group 2 (Fig. 1) was used to validate the accuracy of the channel parameter values for both methods. In Group 2, locations of one out of four sample sites with deposition rates were mis-simulated as soil loss. Fig. 7 (b) shows the simulation performance of the remaining three deposition values for Group 2. The performance followed the same patterns with deposition rates in Group 1, with relatively low correlation for method (a) and significantly higher correlation for method (b).

3.2.3. Spatial distribution of model errors

The spatial distribution of relative errors between each corresponding simulated and reference value for method (a) and method (b) for

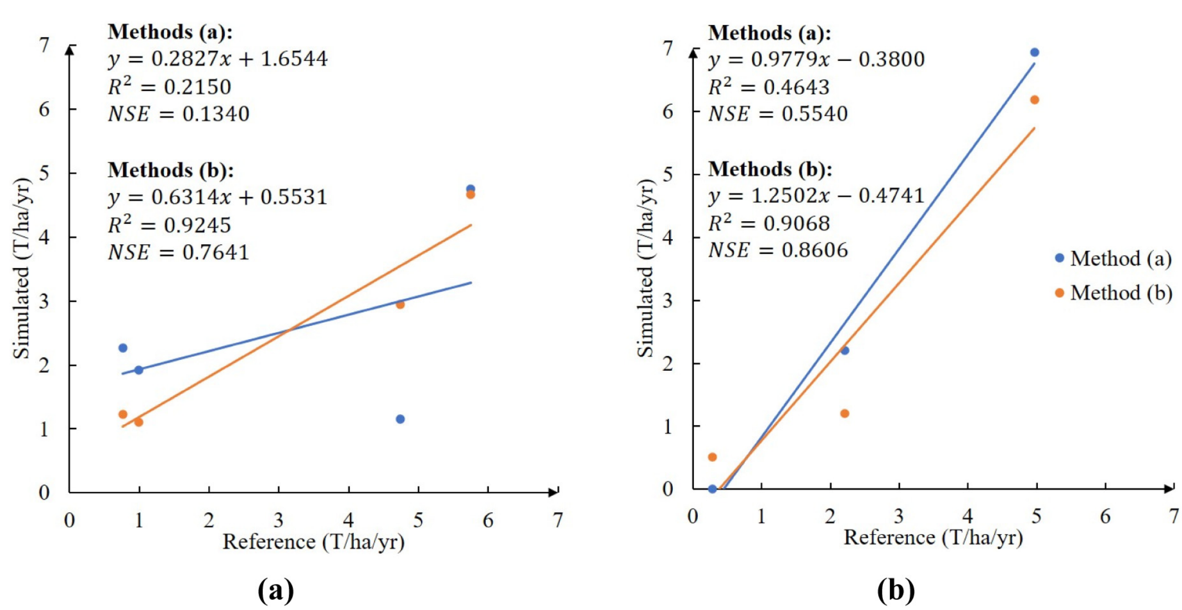


Fig. 7. Deposition (T/ha/yr) simulation performance for Group 1 (a) and group 2 (b). Method a: value comparison between reference value and simulation output at the specific location of each sample site; and method b: value comparison between reference value and simulation output of aggregated value within 5 m radius of each sample site.

the three resolutions are shown in Fig. 8. Errors are classified by one order of magnitude for under-estimated and over-estimated sample points, as well as sample points with errors less than one order of magnitude. For 5 m-resolution data, the majority of sample points have under-estimated errors greater than one order of magnitude. The number of under-estimated samples decrease with the increase of model resolution. For models based on 5 m and 3 m resolution data, the over-estimated samples concentrate near the main channel. For the model based on 1 m resolution data, the three classifications of errors are comparatively randomly distributed.

The three mis-simulated values of deposition - GeoWEPP determined them as locations with soil loss (Fig. 8) - were located near the main channel as well as the outlet of the nested smaller watershed 101 within the study area.

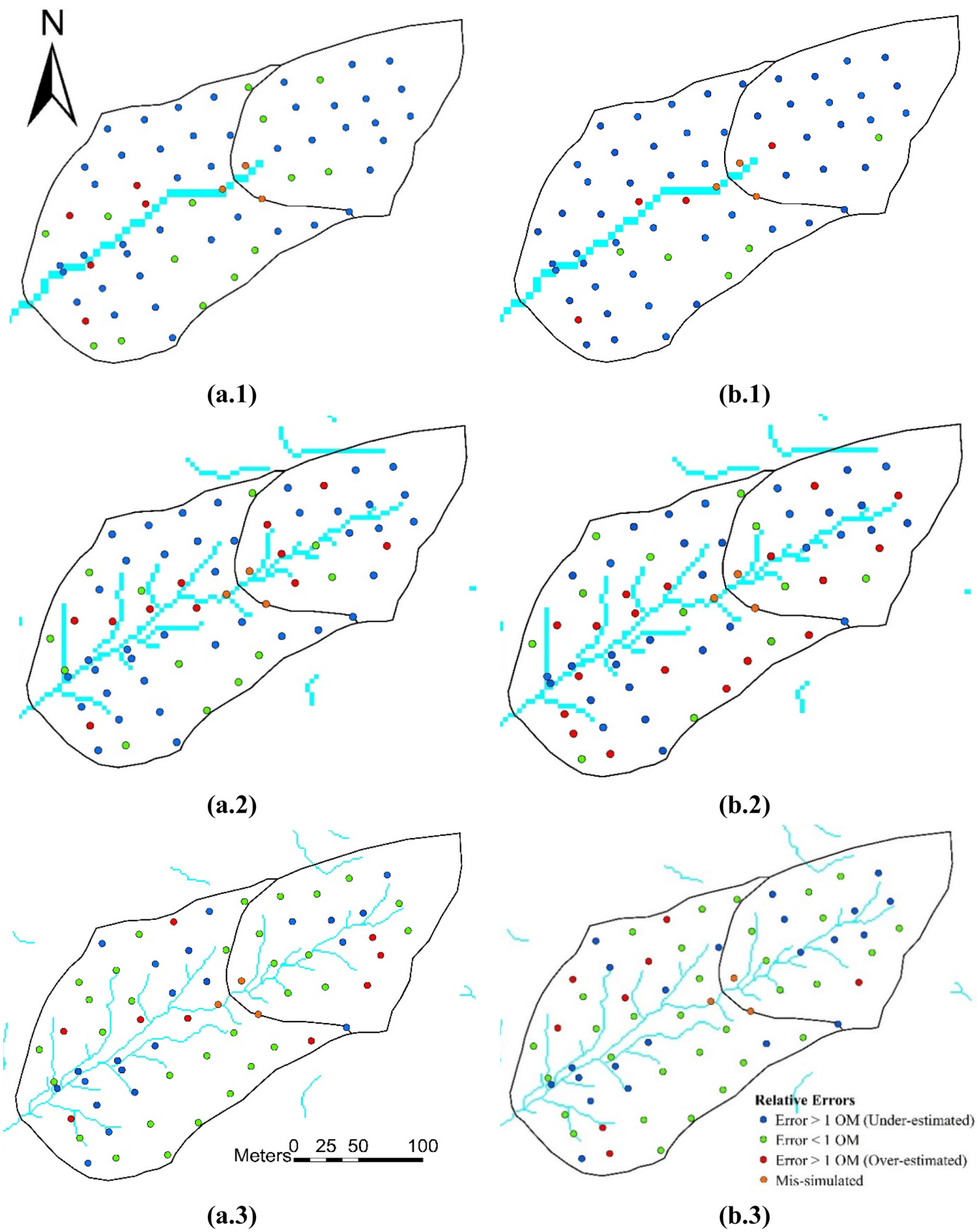


Fig. 8. Spatial distribution of relative errors between corresponding simulated and reference value for method a in 5 m (a.1), 3 m (a.2) and 1 m (a.3) resolution, as well as method b in 5 m (b.1), 3 m (b.2) and 1 m (b.3) resolution. Errors were classified by one order of magnitude (OM) for over and under estimated sample points.

4. Discussion

The simulation of soil redistribution is affected by many factors and it is a challenge to accurately simulate fine resolution soil loss and deposition rates. By adjusting the channel parameters, the model was adjusted to be as highly representative as possible. At the specific locations of sampled sites, the simulated soil redistribution was comparatively less representative. However, aggregated values of soil redistribution rates within 5 m radius of sample sites had considerably strong correlation with the measured values. Comparing the model performance across 5 m, 3 m and 1 m resolutions, the model was increasingly representative with the increase in resolution when considering both a single pixel at the sample sites and multiple pixels with 5 m radius around sample sites. Therefore, including more detailed micro-topographic features into consideration by using higher resolution data as model input, and re-aggregating the values within a specific radius, it is possible to generate representative simulated soil redistribution. For event-based models of runoff and sediment yields using the watershed method, the simulation with 5 m resolution's input had the best model performance instead of higher resolutions (Renschler and Zhang, 2020). In contrast, the validation patterns of soil redistribution simulation using flowpath method illustrated much better results for the 1 m resolution as part of this study.

5. Conclusion

In this study, long-term annual soil loss and deposition rates for sub-catchments within the Lucky Hills area in the Walnut Gulch Experimental Watershed, southeastern Arizona, were simulated using GeoWEPP. In order to increase the accuracy of the model output, hydraulic conductivity and critical shear were readjusted using the same method described in the previously published companion describing runoff and sediment yield simulation, and channel parameters were then adjusted. Soil redistribution rates at 65 sample sites calculated based on fallout ^{137}Cs data were used as the reference for the parametrization, verification, and validation of soil loss and deposition simulated using GeoWEPP. Topographic data of three resolutions were used to analyze the influence of model resolution on the output performance. The spatial distribution of soil loss and deposition generally had the same patterns as the spatial soil redistribution measured using ^{137}Cs. Deposition occurred mostly in relatively low elevations, while soil loss occurred mostly in higher elevations. Although the model performance at the specific pixel associate with each sample site was not ideal, aggregated values of multiple pixels within 5 m radius around each sample sites had significant high correlation with the measured reference values. In addition, the model is more accurate with input data in higher resolutions. Three out of ten sample sites with deposition were mis-simulated. These sites were concentrated at the outlet of the nested smaller watershed within the study area. The locations of remaining sample sites with deposition were successfully simulated and the model performance was highly acceptable, especially by aggregating values within 5 m radius around each sample site. This paper demonstrates the benefit of using detailed micro-topography as model input, and re-aggregating the output results to minimize potential errors. One needs to be aware, that model input resolution impacts runoff and sediment yields simulation results for the watershed method, as well as the soil redistribution simulation results for the flow-path method. Soil redistribution processes vary in space and time and would be influenced by the spatial variability of land use and soil loss, although in this paper, soil properties and land use were considered to be uniform across the study area. Future work will focus on the impact of spatially distributed vegetation and roads that influence connectivity of soil redistribution within the study area.

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2021.148403.

Funding

This work was not supported by a specific funding source.

CRediT authorship contribution statement

CSR: Conceptualization; MAN & MHN: Data collection; HZ & CSR: Data curation; HZ & CSR: Formal analysis; CSR & HZ: Methodology; HZ: Project administration; CSR: Software; CSR: Supervision; HZ & CSR: Validation; HZ & CSR: Visualization; HZ: Roles/Writing - original draft; HZ, CSR, MHN & MAN: Writing - review & editing.

Declaration of competing interest

The authors declare no conflict of interest.

Acknowledgments

The authors would like to thank Martin Minkowski and Lu Meng when they spent time as graduate students for the initial preparation of some of the soils and climate files, respectively. We acknowledge the US Department of Agriculture (USDA) Agricultural Research Service (ARS) Southwest Watershed Research Center: Tucson, AZ, for providing the freely available online data sets. Special thanks go out to Mark Nearing and the late Jerry Ritchie for being such great mentors for the next generations of soil and water conservation. They provided the senior author with the fallout ^{137}Cs measurements and related documentation a long time ago and with the newly available elevation data and updated software the authors could finally put this dataset to use.

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