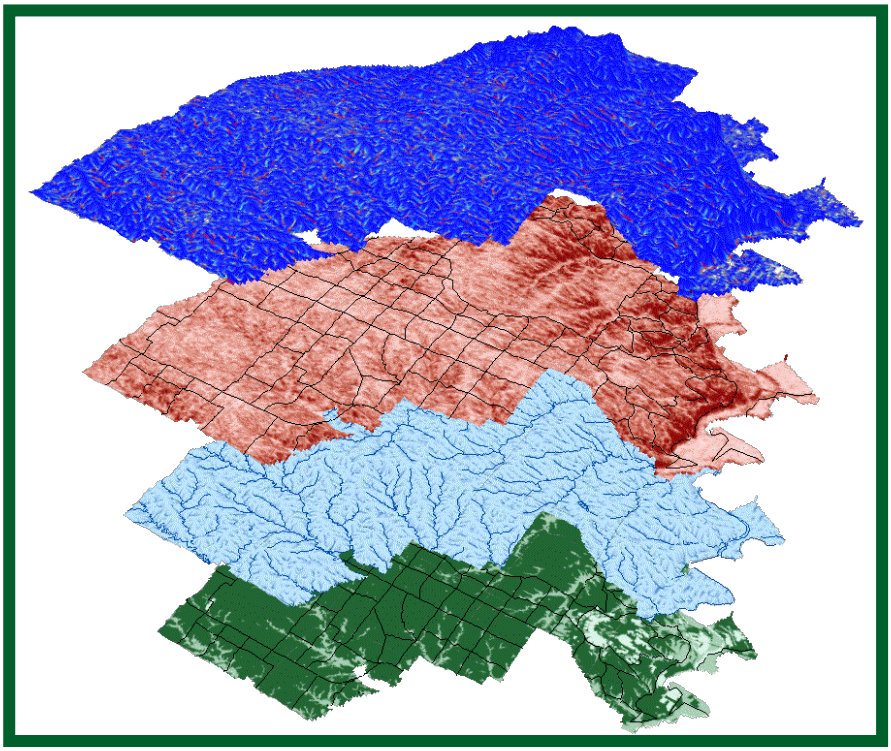
ESTCP
Cost and Performance Report

(RC-200820)



Validating the Kinematic Wave Approach for Rapid Soil Erosion Assessment and Improved BMP Site Selection to Enhance Training Land Sustainability

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COST & PERFORMANCE REPORT
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ACRONYMS AND ABBREVIATIONS

ANOVA	analysis of variance
ATV	all-terrain vehicle
BMP	best management practice
CD	compact disc
CERL	Construction Engineering Research Laboratory
COG	course over ground (heading)
CRP	Conservation Reserve Program
D8	eight direction flow algorithm
DoD	U.S. Department of Defense
DEM	digital elevation model
DSM	digital surface model
DTM	digital terrain model
DVD	digital video disc
ERDC	Engineering Research and Development Center
ESRI	Environment System Research Institute
ESTCP	Environmental Security Technology Certification Program
FGDC	Federal Geographic Data Committee
GIS	geographic information system
GPS	global positioning system
ha	hectares
HSD	honestly significant difference
IS	impact severity
ITAM	Integrated Training and Management
J_δ	Jaccard distance
km	kilometer
L	overland flow length
LIDAR	light detection and ranging
LRAM	Land Rehabilitation and Maintenance
LULC	landuse/landcover
m	meter
mm	millimeters
m/sec	meters per second
n	Manning's surface roughness coefficient

NED	National Elevation Dataset
NEPA	National Environmental Policy Act of 1969
NGA	National Geospatial Intelligence Agency
NLCD	National Landcover Database
nLS+	GIS-enabled kinematic wave model
NPS	non-point source
NRCS	Natural Resource Conservation Service
PTA	Pohakuloa Training Area
R	rainfall erosivity factor
RBF	radial basis function
RD	rut depth
RTLA	range and training land assessment
S	slope
SD	standard deviation
SQL	structured query language
SRA	Sustainable Range Awareness
TMDL	total maximum daily load
TRI	Training Requirements Integration
URL	uniform resource locator
USDA	U.S. Department of Agriculture
USEPA	U.S. Environmental Protection Agency
VEL	velocity
WWF	World Wildlife Fund

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EXECUTIVE SUMMARY

OBJECTIVES OF THE DEMONSTRATION

Based on the concept of accumulating overland flow energy, an erosion potential model *(nLS+)*[1] was calibrated and validated for five military installations (Fort Benning, Fort Hood, Fort Riley, Schofield Barracks and Pohakuloa Training Area [PTA]). By integrating data from digital elevation models (DEM) and landuse/landcover (LULC) assessments in a geographic information system (GIS) environment, the *nLS+* model determines where surface water runoff transitions from overland sheet flow to concentrated flow and, as a result, where the potential for soil erosion and gully formation is highest.

Three quantitative performance objectives were identified for this project: (1) identify the critical threshold for accumulated *nLS+* values for each study installation, (2) determine whether a single critical threshold for accumulated *nLS+* values is adequate for all installation study sites, and (3) use the *nLS+* model in a predictive mode to forecast areas where gullies are likely to form in response to future military training events.

TECHNOLOGY DESCRIPTION

The *nLS+* model is designed as a series of four sub-models to predict the current location of gullies or forecast the formation of new gullies in response to a training event. Data sets required for gully prediction include LULC and DEM inputs. From these data layers, the Manning's n, slope, profile curvature, and other required intermediate data products are computed. In forecast mode, input data include a filled (i.e., depressionless or pit-removed) DEM and Manning's n grid (output from the model in prediction mode) and a form of vehicle tracking data from Global Positioning System (GPS) devices that includes, at minimum, vehicle coordinates and velocity. Model LULC and DEM inputs can be obtained from nationally available geographic datasets such as the National Landcover Database (NLCD) and National Elevation Dataset (NED) to minimize data acquisition and preparation times.

DEMONSTRATION RESULTS

At the NED DEM resolution 131 of 222 total validation gullies (59%) were predicted to within 10 meters (m) of their actual location. This percentage increases to 79% and 89% for distances within 20 and 30 m, respectively. Mean distance to the correct location ranged from a low of 4.93 m (Keamuku Parcel) to a high of 14.73 m (Fort Hood). Percentage correct predictions (# 10 m) for individual installations ranged from a high of 85% (Keamuku Parcel) and a low of 50% (Fort Benning), with the total range in distances varying from 20 m (Keamuku Parcel) to nearly 96 m (Fort Hood). Only the predictions for Keamuku Parcel met the success criteria of having more than 80% of gully locations correctly identified using installation-specific accumulated *nLS+* thresholds within the required distance precision. Overall model accuracy was 86%, though commission error for the predicted gully class was nearly 100%. Although the model suffered from extreme overprediction of gully locations, the total land area identified as likely erosion sites ranged from a low of 496 hectares (ha) (Kahuku Range) to a high of

[1] The *nLS+* model acronym represents Manning's n (*n*), slope length (*L*), slope (*S*), and profile surface curvature (+).

16,862 ha (Fort Hood), with the total installation area susceptible to predicted gully erosion falling between 12% (Fort Riley) and 21% (Keamuku Parcel).

The *nLS+* model was developed with the ArcGIS 10.0 (Esri, Redlands, CA) suite of GIS software applications routinely utilized across Department of Defense (DoD) agencies and installations. The model is packaged as a "toolbox" with multiple sequenced tools than can be downloaded and used on a local computer workstation running ArcGIS version 10.0. The toolbox and associated modeling tools also includes an integrated help system to explain the underlying processes, data requirements, and recommendations for default settings or values as they apply to execution of the model. Feedback from installation Integrated Training Area Management (ITAM) GIS technicians helped shape the final form of the modeling tool as a sequence of smaller and quicker performing submodels rather than one large model. Comments and questions generated during site visits were very useful during creation of the integrated help system to guide users through the geoprocessing procedures.

The final model—Rapid Soil Erosion Assessment Toolbox—is comprised of six total submodels labeled within the toolbox by number and title. Users run the model and arrive at final results by executing each sub-model in numeric sequence from #1 (Prepare Filled DEM) to #4 (Predict Gully Locations). Sub-models #5 to 6 can be used to forecast future gully locations by modifying the installation DEM and Manning's *n* grid with GPS-derived vehicle tracks. Average run time for the model, including all sub-models and assuming a non-light detection and ranging (LIDAR) DEM and satellite resolution LULC grid for the installation is already on hand, ranged between 1.1 and 8.3 minutes on a typical desktop computer workstation. When working with spatial data at the spatial resolution of installation LIDAR datasets (3 m), processing time was three to four times longer in duration.

IMPLEMENTATION ISSUES

Project results were largely positive, despite not meeting the success criteria established for all performance objectives. One issue that remains with interpreting model results is the large rate of false positive gully predictions (i.e., errors of commission). Despite this issue, when used as a guide to identify areas with the most potential for gully erosion, the model results support time and cost savings by significantly reducing the total area of land being considered for more frequent and/or intensive field monitoring.

If the *nLS+* model finds widespread use across installations, it is important that an organization be identified to maintain the model and make any updates and/or revisions necessitated by future GIS software versions. As with any GIS-based model for which installation use is expected, the *nLS+* model is an ideal candidate to be delivered to end-users as a Web-based geoprocessing service made available and maintained by a central environmental organization. Uniform data and information products could then be delivered on a scheduled basis to installations for action. All data products required by the *nLS+* model, and other environmental/sustainability indicators, could be stored in a geospatially-enabled relational database to facilitate access to current data. Storing data in the geospatially enabled relational database supports distributed viewing and editing by land managers and their staff, as well as distribution via mapping and geoprocessing

web services similar to the “ITAM Map Viewer” web application used by Fort Riley (http://services.geog.ksu.edu/frk_rtla).

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1.0 INTRODUCTION

This section is intended to provide a general overview of the project. Specific subsections, including project background, demonstration objectives, and regulatory drivers are described.

1.1 BACKGROUND

The 2000 National Water Quality Inventory reported that 40% of the nation's water bodies do not meet water quality standards and identified non-point source (NPS) pollution as the leading cause of surface water degradation (USEPA, 2000). Military training maneuvers have the potential to significantly alter land surfaces, reduce quality and promote NPS pollution, resulting in a reduction of training land quality and the inability of military installations to meet water quality standards as defined by current, and future, total maximum daily load (TMDL) mandated in Section 303(d) of the 1972 Clean Water Act.

Military readiness depends upon high quality training. A prerequisite of effective maneuver training is repetition and a large land base, which creates intense stress on military lands. Environmental protection requirements place additional restrictions on land use and availability. Because military training schedules are set well in advance to make the best use of installation training facilities and National Training Centers, there is little flexibility to modify training events while maintaining readiness. Management practices are required that allow for high military training tempos while protecting surface water quality and reducing NPS pollution generation.

In order to meet this need, the military initiated the Integrated Training and Management (ITAM) program with the overall goal to achieve optimum sustainable use of military lands. The ITAM program provides Army range officers with the capability to manage and maintain training lands while supporting mission readiness. ITAM integrates mission requirements with environmental requirements and environmental management practices, and establishes the policies and procedures to achieve optimum, sustainable use of training and testing lands. There are multiple components of ITAM including Training Requirements Integration (TRI), Range and Training Land Assessment (RTLA), Land Rehabilitation and Maintenance (LRAM), Sustainable Range Awareness (SRA), and geographic information systems (GIS).

RTLA programs are focused on training support and training land management, and may be used to support National Environmental Policy Act (NEPA) and other compliance and planning efforts related to Army transformation, restationing, and realignment. Current policies allow installation-level land managers and range operations staffs to determine how they can best collect and use resource data to support foundational, long-term, and site-specific land management decisions such as training area allocation, training area use, and land rehabilitation effectiveness. Analyzing the impact of military training on soil erosion is part of the RTLA program. Over the past decade a great deal of effort has been given to collecting data and modeling soil erosion from track vehicle activity. However, there is currently no method capable of predicting the initiation point of soil erosion and locating potential gully sites.

The most common methods implemented by range managers to locate gullies on military lands are air and ground surveys. Both are costly and labor-intensive activities that require frequent

repetition as gullies tend to form dynamically as a result of interactions between the intensity and location of maneuvers, intense rainfall events, moisture content of soils, vegetation type and health, and topographic relief. Gullies not only contribute to soil erosion and water quality problems, but are a cause of injury to soldiers and damage to equipment, especially during nighttime maneuvers.

Determining the overland flowpath of surface water runoff is a key process in erosion modeling because concentration of overland flow is a primary cause of soil erosion, and generally the initiation point of gullies. The efficiency of best management practices (BMP) for preventing or minimizing NPS pollution, such as vegetated buffer systems, is significantly affected by overland flow conditions. However, the ability to classify varying flow regimes, from sheet flow to concentrated flow, is problematic because it is difficult to quantify the energy content of runoff water.

The kinematic wave theory has proven to be a useful tool for assessing the process of overland flow at varying flow regimes and, based on this theory, the relationship $nL/S^{0.5}$ has been used to categorize hydrological flow regimes into sheet flow or concentrated flow, where n is Manning's surface roughness coefficient for overland flow, L is the length of overland flow (feet), and S is the slope. In this project, this relationship is reconfigured and operationalized in a GIS as a multilayer raster calculation using classified landuse/landcover (LULC) and digital elevation model (DEM) data, with calculated values summed in a weighted accumulation as simulated runoff travels along a flow path, thereby indirectly incorporating flow length back into the computation. The relationship between actual gully locations and accumulated *nLS+* values are then compared to develop a predictive model and prediction map.

The *nLS+* model is designed as a series of four sub-models for users who wish to predict the current location of gullies or forecast the formation of new gullies in response to a training event. Data sets required for gully prediction include LULC and DEM inputs. From these data layers, the Manning's *n*, slope, profile curvature, and other required intermediate data products are computed. In forecast mode, input data include a filled DEM and Manning's *n* grid (output from the model in prediction mode) and a form of vehicle tracking data from global positioning system (GPS) devices that includes, at minimum, vehicle coordinates and velocity. Model LULC and DEM inputs can be obtained from nationally available geographic datasets such as the National Landcover Database (NLCD) and National Elevation Dataset (NED) to minimize data acquisition and preparation times.

1.2 OBJECTIVES OF THE DEMONSTRATION

Three quantitative performance objectives were identified for this project (Table 1). The first was to identify the critical threshold for accumulated *nLS+* values for each study installation. For this first objective, the *nLS+* model was calibrated and validated independently for each study installation and the threshold for accumulated *nLS+* values corresponding best to known gully locations calculated. The second quantitative performance objective determined whether a single critical threshold for accumulated *nLS+* values was adequate for each installation study site. This objective assessed whether a single common critical threshold for accumulated *nLS+* values was valid for all installations or whether the individual installation threshold values were statistically different (i.e., place-specific). The third, and final, quantitative performance objective used the

nLS+ model in a predictive mode to forecast areas where gullies are likely to form in response to future military training events. Here, the *nLS+* model can be operated after a training exercise and new areas of gully erosion predicted by using vehicle tracking data and corresponding estimates of vegetation damage and rut depth to modify the installation DEM and LULC layers. The ability to predict future erosion potential with the *nLS+* model offers several significant advantages to military installations including:

1) The ability to assess training land impacts from scheduled training exercises given current environmental conditions.
2) Providing a consistent and scientific basis to estimate LRAM costs to repair and prevent gully erosion on current, future, or rental training lands.
3) The ability to estimate and compare environmental impacts due to training events associated with installation realignment or mission change.

An additional set of qualitative performance objectives were also assessed (Table 1). Accomplishment of the first is dependent on the outcome of the second quantitative objective and, should installation-specific critical *nLS+* thresholds be required for satisfactory model predictive accuracy, will explore appropriate geographic regions where critical *nLS+* thresholds might be valid. The second qualitative and final overall performance objective is the development and deployment of a downloadable GIS tool that ITAM personnel can use to run the *nLS+* model themselves.

1.3 REGULATORY DRIVERS

Since the passage of the NEPA in 1969 and the publication of U.S. Army Regulation 200-2 (Department of Army, 1988), the military has been required to minimize or avoid both short and long-term environmental impacts caused by military training. Because there is a limited amount of available land for military training, it is in the Army's best interest to protect these areas to fulfill their mission requirements for realistic training and testing. Additionally, the Clean Water Act (1972) and the Clean Water Act Amendments of 1987 require control of NPS pollution.

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2.0 TECHNOLOGY/METHODOLOGY DESCRIPTION

Demonstration technology and methodology is described in the following section.

2.1 TECHNOLOGY/METHODOLOGY OVERVIEW

Determining the flow path of surface water runoff is a key process in erosion modeling because the concentration of overland flow is a primary cause of soil erosion (Abrahams and Atkinson, 1993, Bennett et al., 2000). The efficiency of BMPs, such as vegetated buffer systems for minimizing or preventing NPS pollution, is significantly affected by overland flow conditions (Abrahams and Atkinson, 1993; Abraham et al., 1999). However, the ability to classify varying flow regimes, from sheet flow to concentrated flow, is problematic due to the difficulty of quantifying the energy content of runoff water (Meyer et al., 1999).

Many researchers have shown that the kinematic wave theory is a useful tool for assessing the process of overland flow at varying flow regimes (Laguna and Giraldez, 1993; Wong and Chen, 1999; Singh, 2001). Based on this theory, McCuen and Spiess (1995) showed that the relationship of $nL/S^{0.5}$ effectively categorized hydrological flow regimes into sheet flow or concentrated flow (Figure 1), where n is Manning's coefficient for overland flow, L is the length of overland flow (feet), and S is the slope. In this project, the equation presented by McCuen and Spiess (1995) is inverted and the flow length variable omitted ($S^{0.5}/n$). Inversion allows the smoother surfaces with lower Manning's *n* coefficients (*i.e.*, potential for more soil erosion) to yield higher computed values than rougher surfaces (higher Manning's *n* coefficients) and is important for determining 'maximum value' thresholds for potential gully erosion

This enhanced *nLS* equation (abbreviated from here on as *nLS+*) is operationalized in a GIS as a multilayer raster calculation using classified LULC data and DEMs. Slope is calculated from a DEM using a 3 x 3 cell neighborhood and the average maximum technique (Burrough and McDonnell 1988). Classified LULC dataset provide the relevant Level I or Level II landcover types (Anderson et al., 1976) on a cell-by-cell basis for an entire study area. This nominal data is reclassified into quantitative estimates of Manning's *n* by using a look-up table of coefficient values. Profile curvature is also calculated on a cell-by-cell basis based on a fourth-order polynomial derived from a 3 x 3 window of DEM elevation values (Zeverbergen and Thorne, 1987).

The computed *nLS+* output grid represents a unitless estimate of surface runoff water energy as it flows downslope. These individual cell-based energy estimates, linked by the direction of overland flow, can then be summed in the fashion of a weighted flow accumulation grid. To accomplish this, the D8 (eight direction flow algorithm) algorithm (O'Callaghan and Mark, 1984) is used to create a flow direction grid that estimates the direction of water flow from cell-to-cell (i.e., "upstream" to "downstream") using slope and aspect information from a DEM input. Individual cell values computed from slope, Manning's *n* coefficients, and profile curvature are then summed to generate a weighted flow accumulation grid where each output cell is populated with a value equal to the summed energy of cells flowing into it from the "upstream" direction. The relationship between actual gully locations and accumulated energy are then compared to develop a predictive model.

2.2 ADVANTAGES AND LIMITATIONS OF THE METHODOLOGY

Currently, locating gullies is a time-consuming and potentially dangerous task if conducted on the ground and very expensive if completed via air survey. Application of the user-friendly tools demonstrated in this project allows land managers to reduce the size of, and prioritize, search area by focusing attention on sites most likely to develop gullies in accordance with the biophysical characteristics of the training area. Because of the model's flexible GIS format, additional spatial data layers such as troop movements/vehicle tracks can be easily added to enhance the model performance and usability. The tangible dollar value is time saved in locating gullies. The unknown savings comes in reduction of injuries to soldiers and repairs to damaged equipment. The *nLS+* modeling approach can also assist with siting BMPs designed to reduce soil erosion, helping installations meet current, and future, sediment TMDLs for streams leaving federal lands.

The ability to predict future erosion potential with the *nLS+* model offers several significant advantages to military installations including:

1) The ability to assess training land impacts from scheduled training exercises given current environmental conditions.
2) Providing a consistent and scientific basis to estimate LRAM costs to repair and prevent gully erosion on current, future, or rental training lands.
3) The ability to estimate and compare environmental impacts due to training events associated with installation realignment or mission change.

Financial considerations can be expanded from analyzing the expected expense of only one exercise to predicting annual and/or re-occurring costs by simulating multiple training exercises. Other federal and state environmental and natural resource agencies may find the *nLS+* model useful for assessing impacts caused by specific land management decisions such as identifying lands for the Conservation Reserve Program (CRP) and gully erosion risks associated with forest clear cut, road building, and off-road all-terrain vehicle (ATV) operations.

The *nLS+* model was developed using, and for, the ArcGIS 10.0 (Environment System Research Institute [ESRI], Redlands, CA) suite of GIS software applications that are routinely utilized across U.S. Department of Defense (DoD) agencies and installations. Because of this, the model itself can be delivered in a variety of forms, including as an ArcToolbox "tool," a Python script, or as an ArcGIS ModelBuilder graphic model.

An interesting part of this demonstration includes development of an ArcGIS Server application to deliver *nLS+* modeling capability to a large number of users over networks through a single shared system. This prototype delivery method facilitates the technology transfer process by centralizing model development and maintenance, simplifying model use, facilitating access to required input datasets, and eliminating the need to physically distribute executable files and updates.

3.0 PERFORMANCE OBJECTIVES

The performance objectives outlined in Table 1 represent the means and metrics by which the successful demonstration of this project will be made. A total of five performance objectives are described, including the objective, the metric(s) associated with each objective, a list of the basic data required to realize the metric(s), the specific criteria by which the successful completion of each objective may be evaluated, and a summary of the results.

Table 1. Project performance objectives and results summary.

Performance Objective	Metric	Data Requirements	Success Criteria	Results
Quantitative Objectives				
1. Identify the critical threshold for accumulated *nLS+* values for each study installation.	Correspondence between the installation specific critical threshold value and gully locations.	• Installation DEMs. • Installation landcover maps. • Manning's surface roughness coefficients (*n*) for installation landcover types. • Ground truth dataset of actual gully locations.	• > 80% of gully locations correctly identified for each installation using the installation specific critical threshold. • The valid precision of the prediction is dependent on the spatial resolution of the DEM with predictions considered correct if located within a one cell resolution buffer distance of actual gully sites.	• Distances at which 80% correct criterion was reached using NED DEM inputs: Fort Benning: 20 m Fort Hood: 30 m Fort Riley: 30 m Kahuku Range: 20 m Keamuku: 10 m • Distances at which 80% criterion was reached using LIDAR DEM inputs: Fort Hood: 9 m Fort Riley: 6 m Keamuku: >12 m
2. Determine whether a single critical threshold for accumulated *nLS+* values is adequate for all study installations.	Correspondence between a single critical threshold value and gully locations.	• Computed accumulated *nLS+* values for each known gully location for all study installations.	• Between installation variation of critical threshold values and gully locations is less than the within installation variation.	• ANOVA indicated significantly different *nLS+* values among installations when using NED DEM inputs. • Kruskal-Wallis Chi-squared analysis indicated significantly different *nLS+* values among installations when using LIDAR DEM inputs.

ANOVA = analysis of variance
LIDAR = light detection and ranging
m = meter

Table 1. Project performance objectives and results summary (continued).

Performance Objective	Metric	Data Requirements	Success Criteria	Results
Quantitative Objectives (continued)				
3. Forecast areas where gullies are likely to form in response to future military training events at Pohakuloa Training Area (PTA).	Correspondence between actual or suspected gullies and the most appropriate critical threshold value identified for the installation.	• All data from quantitative objective #1. • Vehicle paths (from tracking data or training simulations). • Vehicle-specific estimates of soil and vegetation damage. • Evidence of post-maneuver gully activity.	• Success criteria from quantitative objective #1.	• Using actual vehicle tracking data from maneuvers at Keamuku Parcel, and modified NED DEM and LULC inputs, the *nLS+* model forecasted an additional 3 ha of erosion activity.
Qualitative Objectives				
4. Propose geographic regions within which installation specific critical thresholds for accumulated *nLS+* values are valid.	Between installation variation of critical threshold values and gully locations is greater than the within installation variation.	• Results from ANOVA • Peer-reviewed ecoregion system (e.g., USEPA Level II/III ecoregions).	Place installations into regions of similar critical thresholds for accumulated *nLS* values according to the logic and methods used to develop generally accepted ecological regions.	Ecoregion framework showed to be inappropriate for assigning threshold values; potential use of Euclidean distance allocation and interpolation for assigning values illustrated.
5. Develop and disseminate a downloadable and easy-to-use GIS-based modeling tool with documentation.	Ability of an ITAM GIS technician to obtain and operate the model.	Feedback from ITAM GIS technicians on ability to find model on the SRA website, its usability, and the value of documentation.	An ITAM GIS technician can download the model, acquire necessary data, and generate results within four hours.	GIS model developed with significant feedback from ITAM personnel; results can be generated within four hours.

ha = hectares
PTA = Pohakuloa Training Area
SRA = Sustainable Range Awareness
USEPA = U.S. Environmental Protection Agency

4.0 SITE DESCRIPTION

Several criteria were used to identify military installations that would make ideal study sites for calibrating and validating the *nLS+* model. First consideration was given to the location of the installation, and its associated biological and physical characteristics. From the perspective of military operations, candidate sites that were important, or "mission critical," installations supporting high levels of training activities, especially vehicle-based training, were preferred. Also important to site selection was the anticipated level of support that this project would receive by installation environmental managers.

Though a total of seven sites were identified for this demonstration, only five sites opted to participate after the project was approved and funded: Schofield Barracks, PTA, Fort Hood, Fort Benning, and Fort Riley. Despite initial interest, Fort Irwin and Camp Lejeune cited several reasons for lack of participation, including limited (and frequently changing) personnel, limited time available to facilitate work given other demands, and lack of long-term benefit.

4.1 SITE LOCATION AND HISTORY

The initial group of study sites selected (Figure 1) included critical military training installations within the DoD (e.g., Fort Hood, Fort Irwin) that were also home to military land managers with confirmed interest in this project and those with a history of working with researchers (e.g., PTA, Fort Benning). These installations were also experiencing new management challenges due to mission changes and the fielding of new equipment, which placed increased pressure on training lands (e.g., PTA, Schofield Barracks). In addition, Marine Corps Base Camp Lejeune was selected to complement the six Army reservations.

Figure 1. Map of installations initially selected for field validation of the *nLS+* model.

4.2 SITE CHARACTERISTICS

The selected sites included a diverse set of landscapes and biophysical characteristics. For example, landcover spans the range from hot desert to tropical rainforest, soils from lava flows to sand, and landforms from mountains to coastal wetlands. Table 2 summarizes a general set of descriptive features and phenomena. The dominant landcover listed for each installation allows one to deduce approximate surface roughness conditions; the rainfall-runoff erosivity factor (or R factor) to better appreciate the erosive power of rainfall that occurs locally (i.e., high values indicate more potential for water-based soil erosion; and runoff potential, as determined by the U.S. Department of Agriculture (USDA) Natural Resource Conservation Service (NRCS) soil hydrologic group, which characterizes soil water infiltration capabilities. Note that the listed runoff potential for Fort Irwin of "low" or "high" reflects the frequency of sandy soils and impermeable rock surfaces throughout the installation.

Table 2. Abbreviated comparison of biophysical and climatic characteristics for selected demonstration sites.

Installation	Ecoregion[(1)]	Dominant Landcover[(2)]	Annual Avg Precip (mm) [(3)]	R Factor[(4)]	Runoff Potential[(5)]
Camp Lejeune	Middle Atlantic Coastal Plain	Evergreen Forest	1373.4	389	Low
Fort Benning	Southeastern Plains	Deciduous Forest	1233.6	377	Low to Intermediate
Fort Riley (original validation site)	Flint Hills	Grassland	826.5	188	High
Fort Hood	Edwards Plateau	Grassland	825.1	243	High
Fort Irwin	Mojave Basin and Range	Bare Land, Shrub/Scrub	110.1	14.5	Low or High
PTA	Tropical High Shrublands/Dry Forest	Bare Land, Shrub/Scrub	539.3	65.2	High
Schofield Barracks	Tropical Moist Forest	Shrub/Scrub, Evergreen Forest	1263.7	288	High

(1) Identification based upon USEPA Level 3 Ecoregions or World Wildlife Fund (WWF) Terrestrial Ecoregion designations.
(2) Calculated from data from the NLCD 2001.
(3) Data obtained from weather.com (http://www.weather.com).
(4) Rainfall-Runoff Erosivity Factor (R) determined using data from the USDA Revised Universal Soil Loss Equation 2 Climate Database (Version 1.26.6.4).
(5) Assessment based upon the Soil Hydrologic Group of the dominant soil or soils as described in the USDA NRCS Generalized Soil Map of the United States.
mm = millimeters

It is important to note that while Schofield Barracks and PTA are two of the selected study sites, validation activities were conducted only on subsets of the installations. At Schofield Barracks, installation ITAM staff were primarily concerned with soil erosion within the Kahuku Range. At PTA, the newly acquired Keamuku Parcel (formerly privately owned cattle grazing land) was studied in preparation for the first of many future Stryker training exercises.

5.0 TEST DESIGN

A detailed description of the test design from conception through execution is documented below.

5.1 CONCEPTUAL TEST DESIGN

The data collection, model development, data analysis, accuracy assessment, and technology transfer activities associated with this project took place during three primary project phases:

- Phase 1: Calibration
- Phase 2: Validation
- Phase 3: Training and Technology Transfer

During Phase 1 (Calibration), field visits to each installation site were conducted during the first and second year of funding. During these visits, installation spatial data was inventoried and any unique datasets acquired from local ITAM offices. Also during Phase 1, the need to purchase satellite imagery to classify current LULC type and condition information was assessed. The *nLS+* model was calibrated for each installation and critical *nLS+* threshold values (including measures of central tendency and dispersion) identified. Upon calibration, an erosion potential map for each site was created and shared with installation ITAM staff.

A second series of visits to each installation study site were conducted during Phase 2 (Validation) activities, which were completed during the third and fourth year of funding. Field work focused primarily on acquiring additional gully locations (where and when necessary). Research team personnel began familiarizing installation ITAM personnel with the *nLS+* model background and operation and conducted GIS training with the model. Subsequent to each site visit, the installation *nLS+* model was refined by re-calibration when additional gully observations were recorded and then validated by assessing the calibrated model accuracy. Phase 2 activities also included initial efforts to operate the *nLS+* model in predictive mode at PTA.

During the final year of funding (Phase 3: Training and Transfer), final maps of gully locations, model results, and gully density estimates were shared with installation ITAM staff, along with compact disc (CD)/digital video disc (DVD) copies of completed GIS models, installation data, and results. Final work related to operating the *nLS+* model in predictive mode was also completed.

5.2 BASELINE CHARACTERIZATION AND PREPARATION

For each installation, *nLS+* models were developed using nationally available datasets. Initial gully data layers were constructed using high resolution photography when available. During the initial installation visits, any relevant locally available data, such as improved LIDAR derived DEM products and local gully information was obtained. If gully information was not available, project personnel worked with the installation land management office to gain access the training areas and conduct limited field surveys of gully locations.

Gullies were characterized based on their topographic position, width, depth, and length at the current gully head location. Gully location was determined using a GPS unit and each site was documented with digital photography. Where possible, gullies were characterized by width, depth, and length. This descriptive information was helpful when used during the model validation stage to document local differences in the meaning of the term "gully." Wherever possible, gully data collection in the field conformed with the gully definition presented in Section 3.

5.3 DESIGN AND LAYOUT OF TECHNOLOGY AND METHODOLOGY COMPONENTS

Figure 2 shows the general framework of the *nLS+* model, which is designed as a series of four sub-models for users who wish to predict the current location of gullies or forecast the formation of new gullies in response to a training event. Data sets required for gully prediction include LULC and DEM inputs. From these data layers, the Manning's *n*, slope, profile curvature and other required intermediate data products are computed. In forecast mode, input data include a filled DEM and Manning's *n* grid (output from the model in prediction mode) and a form of vehicle tracking data from GPS devices that includes, at minimum, vehicle coordinates and velocity.

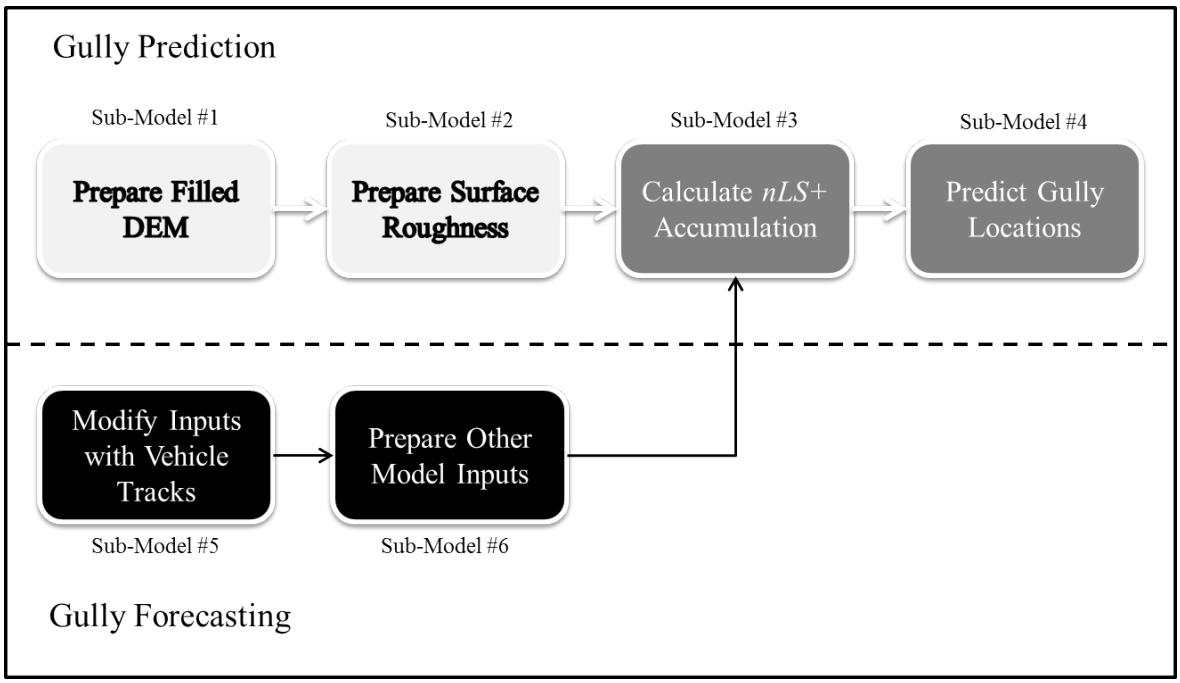

Figure 2. General schematic of the *nLS+* model for gully prediction and forecasting.

5.4 FIELD TESTING

After the initial *nLS+* model was run, a point file of gully head locations, acquired in the field or digitized from digital orthophotography, was overlaid with model results to extract the accumulated *nLS+* value at each gully location. The model was calibrated using approximately 30% of the known gully locations and validated with the remaining data points. During calibration, actual gully locations were relocated ("snapped") to the highest flow accumulation

grid value within a 1 cell distance from the recorded GPS location to account for error in the DEM. A series of descriptive statistics were then generated from the accumulated *nLS+* values to best characterize the critical threshold where overland sheet flow is expected to transition to concentrated flow.

Once the model was calibrated and the critical threshold range for the installation determined, the model was validated using the remaining 70% of actual gully locations. The prediction of where sheet flow transitions to concentrated flow and, therefore where gullies are most likely to be found, was developed via a structured query language (SQL) query for the calibration threshold value range within the accumulated *nLS+* value layer generated by the *nLS+* model. Actual gully locations that fall within a one cell buffer distance of those meeting the SQL query conditions were assessed as an accurate prediction.

A series of sensitivity analyses were conducted to better understand the relative importance of two model inputs (slope and Manning's *n* coefficient), and any associated data error/uncertainty, on model output and the resulting correlation with accumulated *nLS+* values and gully locations.

The key factors affecting computed *nLS+* values are Manning's surface roughness coefficient (*n*) and slope (*S*). Results indicated that slope was the dominant control on model output, and that the *nLS+* model is very sensitive to slope especially at low values. When assessing model sensitivity to Manning's *n*, the model showed little sensitivity to spatial distribution of LULC types. The *nLS+* model was shown to be both highly sensitive to, and suffer most from, DEM error.

5.5 SAMPLING PROTOCOL: OPERATING THE *nLS+* MODEL IN PREDICTIVE MODE

Key to operating the *nLS+* model in predictive mode at PTA (Performance Objective #4) was the ability to obtain vehicle track data (via GPS tracking data or training simulations) and use the track location and characteristics to modify existing installation DEMs and LULC maps. After making appropriate modifications to these input datasets, the *nLS+* model was re-run after a training event and field data collected to determine whether the model successfully forecasted new areas of actual (or suspected) gully activity.

Three Stryker vehicles from a reconnaissance platoon of the 2nd Brigade of the 25th Infantry Division were tracked during an off-road proofing mission on the Keamuku Parcel at PTA using GPS-based tracking systems to determine vehicle movement patterns and estimate soil loss impacts (Howard et al., 2011). Track data recorded by GPS units onboard the three vehicles were obtained from Dr. Paul Ayers (personal communications). The data was received as a text file with geographic coordinate information acquired at approximately one second intervals. Each GPS record also included key attributes such as vehicle velocity (VEL) and course over ground (COG) along with a detailed date/time stamp identifying when the position record was acquired.

Rut depth was calculated as a function of vehicle turning radius. To do so required first the calculation of vehicle turning radii from the original GPS track file. Estimates of vehicle turning radii for each recorded location were based on five consecutive position fixes and using the five-

point method outlined in Engineering Research and Development Center (ERDC)/ Construction Engineering Research Laboratory (CERL) Technical Report 00-43 (Ayers et al., 2000).

Following the turning radius, impact severity, and rut depth calculations, vehicle track files were imported into a GIS and combined into a single file of all GPS position records. These points, and their corresponding attributes, were then converted into two gridded track files representing the calculated values for impact severity (IS) and rut depth (RD), respectively, at the same spatial resolution of the DEM used to describe installation terrain. During this point to raster conversion, the maximum value for IS and RD were retained if more than one GPS point would be located within the same grid cell. The IS grid was used to scale the original Manning's *n* surface roughness coefficients downward to reflect changes in vegetation condition. The resulting scaled Manning's *n* and RD grids were then re-incorporated back into the original Manning's *n* grid and DEM for the Keamuku Parcel to serve as new inputs for the *nLS+* model that more accurately reflected post-maneuver landscape conditions.

5.6 SAMPLING RESULTS

A total of 389 gully locations were used in *nLS+* model calibration and validation (Table 3). Most gully locations were provided by installation ITAM staff; however a significant proportion (17-100%) were generated by project personnel during field visits and through heads-up digitizing of high-resolution aerial photographs. Digital files of gully locations are available in GIS format (i.e., shapefiles) and are packaged with the *nLS+* model tools.

Table 3. Summary of gully data acquired from installations and generated for *nLS+* model calibration and validation.

Installation	Total Gully Locations	Installation Provided (%)	Project Generated (%)
Fort Benning	65	53 (82%)	12 (18%)
Fort Hood	192	159 (83%)	33 (17%)
Fort Riley	49	18 (37%)	31 (63%)
Kahuku Range	47	36 (77%)	11 (23%)
Keamuku Parcel	36	0 (0%)	36 (100%)

6.0 PERFORMANCE ASSESSMENT

The following section provides a summary of all data analysis conducted in the assessment of the performance objectives.

6.1 OBJECTIVE #1: IDENTIFY THE CRITICAL THRESHOLD FOR ACCUMULATED *nLS+* VALUES FOR EACH STUDY INSTALLATION

Data on the location of gullies at selected installations were obtained from ITAM staff and/or collected during site visits. Gullies for each installation were assessed and "cleaned" using GIS procedures to minimize impact of DEM and field location error and multiple statistical tests. Gullies excluded during each step of analysis are detailed below (Tables 4 and 5).

Table 4. Number of gullies excluded from further analysis for each installation (and total) after primary, secondary, and tertiary data pre-processing when using NED DEMs as model input.

Installation	No. of Gullies Excluded from Analysis			Total Gullies Excluded	Original No. of Gullies	No. of Remaining Gullies (%)
	Primary	*Secondary*	*Tertiary*			
Fort Benning	10	5	2	17	65	48 (74%)
Fort Hood	2	23	1	26	192	166 (86%)
Fort Riley	3	5	0	8	49	41 (84%)
Kahuku Range	10	4	0	14	47	33 (70%)
Keamuku Parcel	0	6	0	6	36	30 (83%)
All Installations	25	43	3	71	389	318 (82%)

Table 5. Number of gullies excluded from further analysis for each installation (and total) after primary, secondary, and tertiary data pre-processing when using LIDAR DEMs as model input.

Installation	No. of Gullies Excluded from Analysis			Total Gullies Excluded	Original No. of Gullies	Remaining Gullies (%)
	Primary	*Secondary*	*Tertiary*			
Fort Riley LIDAR	7	7	2	16	49	33 (67%)
Fort Hood (LIDAR)	0	12	1	13	192	179 (93%)
Keamuku Parcel (LIDAR)	5	4	3	12	36	24 (67%)
All Installations	12	23	6	41	277	236 (85%)

Gullies remaining after data pre-processing were divided into calibration and validation datasets with 30% of the total number of gullies (or a minimum of 10) used for model calibration and the remainder for validation. Installation gullies in the calibration dataset were randomly selected from the complete set by first generating a spatially random point layer in a GIS, whose distribution was constrained by the installation boundary, then choosing gullies closest to each randomly-place point. Installation-level critical thresholds for accumulated *nLS+* values were then calculated as the installation mean plus and minus one-half of the standard deviation (SD) (Table 6).

Table 6. Critical threshold values from calibration gully datasets for accumulated *nLS+* values.

Threshold values for gully prediction represented by the interval defined by the lower- and upper-bounds.

Installation	Accumulated nLS+ Values (Log Transformed)				Contributing Area (m^2)*	
	Mean	*SD*	*Lower Bound#*	*Upper Bound@*	*Minimum*	*Maximum*
Fort Benning	0.37	0.50	0.12	0.62	132	417
Fort Hood	0.02	0.87	-0.42	0.46	38	288
Fort Riley	0.59	0.86	0.16	1.02	145	1,047
Kahuku Range	0.60	0.80	0.20	1.00	158	1,000
Keamuku Parcel	0.56	0.81	0.165	0.97	146	933
Fort Riley – L	1.11	1.38	0.42	1.80	24	568
Fort Hood – L	2.39	1.15	1.24	2.97	156	8,399
Keamuku – L	4.14	0.32	3.98	4.30	85,949	179,574

Lower bound calculated as mean – (0.5 * SD)
@ Upper bound calculated as mean + (0.5 * SD)
* Estimates backcalculated from log-transformed accumulated *nLS+* values and DEM resolution

When considering all installations and only model runs using NED DEM inputs, 131 of 222 total validation gullies (59%) were predicted within 10 meters of their correct location. This percentage correct value increases to 79% and 89% for distances within 20 and 30 m, respectively. Mean distance to correct location ranged from a low of 4.93 m at Keamuku Parcel to a high of 18.46 m at Fort Hood. Percentage correct predictions (<= 10 m) for individual installations ranged from a high of 85% for Keamuku Parcel and a low of 50% for Fort Benning (Table 7). The total range in distances varied from a low of 20 m at Keamuku Parcel to a high of 95.52 m at Fort Hood. Predictions for only one installation, Keamuku Parcel, met the success criteria of having more than 80% of gully locations correctly identified using installation-specific accumulated *nLS+* thresholds within the required distance precision. If the precision condition is loosened to a distance window of two times DEM cell resolution, model success is also achieved at Fort Benning and Kahuku Range. All installations reached the minimum 80% prediction accuracy level at three times DEM cell resolution.

Table 7. Distance (in meters) summary statistics and prediction accuracy for *nLS+* model results at each installation using validation gully datasets and NED DEM inputs.

Installation	Distance Summary Statistics (m)					*Correct Predictions – No. (%)			
	Min	*Mean*	*SD*	*Max*	*Range*	*<=10m*	*<=20m*	*<=30m*	*<=40m*
Fort Benning	0	11.79	10.58	45.89	45.89	17 (50%)	30 (**88%**)	32 (94%)	33 (97%)
Fort Hood	0	14.73	18.46	95.52	95.52	68 (59%)	86 (74%)	99 (**85%**)	106 (91%)
Fort Riley	0	13.25	15.19	51.48	51.48	17 (59%)	19 (66%)	24 (**83%**)	28 (97%)
Kahuku Range	0	10.65	11.46	45.28	45.28	12 (52%)	20 (**86%**)	22 (96%)	23 (100%)
Keamuku Parcel	0	4.93	5.68	20.00	20.00	17 (**85%**)	20 (100%)	20 (100%)	20 (100%)
All Installations						131 (59%)	175 (79%)	197 (**89%**)	210 (95%)

* Numbers and percentages are cumulative by distance.

The total hectares of land identified as potential gully erosion sites ranged from a low of 496 (Kahuku Range) to a high of 17,051 (Fort Hood), with the total installation area susceptible to predicted gully erosion falling between 2% (Fort Hood) and 21% (Keamuku Parcel) (Table 8).

The predicted cell output from the *nLS+* model, along with the related gully density surface, can be used as a tool to focus field surveys for gully monitoring, reducing the need to conduct detailed fieldwork for extensive portions of an installation. This same information may also be used in planning military exercises to limit, where possible, training in gully-prone areas and to promote solider safety by showing where gully hazards are mostly likely to be encountered.

Table 8. Comparison of predicted gully to total installation areas based on model runs using NED DEM inputs.

Installation	Total No. Cells (ha)	Predicted No. Cells (ha)	Predicted Gully Area (% of Total Installation)	#Reduction in Monitoring Area (ha)
Fort Benning	7,360,670 (73,608)	715,289 (7,153)	10%	66,455
Fort Hood	8,851,863 (88,519)	1,686,203 (16,862)	19%	71,657
Fort Riley	4,114,075 (41,141)	476,945 (4,769)	12%	36,372
*Kahuku Range	382,803 (3,828)	49,618 (496)	13%	3,332
*Keamuku Parcel	931,294 (9,313)	193,772 (1,938)	21%	7,375

* Values for these sites are a subset of their respective installations.
# Area where gully field surveys can be minimized.

For the three installations with available LIDAR-derived DEMs, 98 of 163 total validation gullies (60%) were predicted within 3 m of their correct location. This percentage correct value increases to 75% and 82% for distances within 6 and 9 m, respectively. Mean distance to correct location ranged from a low of 1.64 m at Fort Riley to a high of just over 100 m at Keamuku Parcel. Percentage correct predictions (<= 3 m) for individual installations ranged from a high of 75% for Fort Riley and a low of 36% for Keamuku Parcel (Table 9). The total range in distances varied from a low of 10.61 m at Fort Riley to a high of over 300 m at Keamuku Parcel. No installations met the success criteria of having more than 80% of gully locations correctly identified using installation-specific accumulated *nLS+* thresholds within the required distance precision. If the precision condition is loosened to a distance of 3 times DEM cell resolution, model success is achieved at Fort Riley and Fort Hood.

Table 9. Distance (in meters) summary statistics and prediction accuracy for *nLS+* model results at each installation using validation gully datasets and LIDAR-derived DEMs.

Installation	Distance Summary Statistics (m)					*Correct Predictions – No. (%)			
	Min	*Mean*	*SD*	*Max*	*Range*	*<=3m*	*<=6m*	*<=9m*	*<=12m*
Fort Riley	0	1.64	3.13	10.61	10.61	18 (75%)	21 (**88%**)	21 (88%)	23 (100%)
Fort Hood	0	3.19	4.97	29.55	29.55	75 (60%)	97 (78%)	107 (**86%**)	112 (90%)
Keamuku Parcel (Priority 1 Area)	0	100.32	101.66	303.71	303.71	5 (36%)	5 (36%)	5 (36%)	5 (36%)
All Installations						98 (60%)	123 (76%)	133 (**82%**)	140 (86%)

* Numbers and percentages are cumulative by distance.

The total hectares of land identified as potential gully erosion sites ranged from a low of 1 (Keamuku Parcel) to a high of 1,241 (Fort Hood), with the total installation area susceptible to predicted gully erosion ranging from approximately 1-2% (Table 10). Use of the higher spatial resolution DEMs result in substantially lower areas of predicted gully erosion as compared to similar estimates made using NED data and may prove useful in further limiting the extent of fieldwork needed for ground-based gully surveys.

Table 10. Comparison of predicted gully to total installation areas based on model runs using LIDAR-derived DEM inputs.

Installation	Total No. Cells (ha)	Predicted No. Cells (ha)	Predicted Gully Area (% of Total Installation)	#Reduction in Monitoring Area (ha)
Fort Riley	45,712,015 (41,141)	990,763 (892)	2%	40,249
@Fort Hood	219,720,338 (87,888)	3,103,310 (1,241)	1%	86,647
Keamuku Parcel	3,516,359 (3,165)	13,254 (12)	< 1%	3,153

@ The spatial resolution of the Fort Hood DEM was 4 m x 4 m.
* Values for this site is a subset of its respective installation.
# Area where gully field surveys can be minimized.

Assessment of both *nLS+* model performance was also evaluated by using a contingency table, or classification error matrix (Story and Congalton, 1986; Lillesand and Kiefer, 1994). In classification error matrices, ground truth data consists of gully locations recorded in the field using GPS receivers or digitized from high resolution digital orthophotography using standard aerial photo interpretation techniques (Arnold, 1997). Predicted gully locations are those where the *nLS+* model predicts the presence of a gully. In a GIS, the number of pixels corresponding to locations of predicted, and actual, gully locations are summed and entered into the corresponding column and row in the error matrix. Similarly, the number of cells where no actual or predicted gullies were found is also summed and their values placed in the matrix. Simple calculations are them performed to determine model accuracies and errors.

The classification error matrices for model results using NED and LIDAR DEM inputs are presented in Tables 11 and 12, respectively. For this assessment, actual gullies that were within four times the distance criterion established by quantitative performance objective #1 were considered correct predictions. Model accuracies, specifically producer's accuracy for both the gully and non-gully class, as well as overall accuracy for predictions using both DEM types were very high. The principle issue with model results is in the significant overprediction of gully locations, resulting in commission errors for the gully class of 100% (rounding).

Table 11. Classification error matrix consisting of data from all installations and based on results from *nLS+* model runs using NED DEM inputs.

		Model Predictions					
		Gully	**Non-Gully**	**Row Total**	**Producer Accuracy**	**Omission Error**	**Total Accuracy**
Ground Truth Data	**Gully**	210	12	222	95%	5%	
	Non-Gully	3,121,617	18,518,866	21,640,483	86%	14%	
	Column Total	3,121,827	18,518,878	21,640,705			
User Accuracy		0%	100%				
Commission Error		100%	0%				86%

Table 12. Classification error matrix consisting of data from Fort Riley, Fort Hood, and Keamuku Parcel and based on results from *nLS+* model runs using LIDAR DEM inputs.

		Model Predictions					
		Gully	**Non-Gully**	**Row Total**	**Producer Accuracy**	**Omission Error**	**Total Accuracy**
Ground Truth Data	**Gully**	140	22	162	86%	14%	
	Non-Gully	4,107,187	264,841,363	268,948,550	98%	2%	
	Column Total	4,107,327	264,841,385	268,948,712			
User Accuracy		0%	100%				
Commission Error		100%	0%				98%

6.2 OBJECTIVE #2: DETERMINE WHETHER A SINGLE CRITICAL THRESHOLD FOR ACCUMULATED *nLS+* VALUES IS ADEQUATE FOR ALL STUDY INSTALLATIONS

The second performance objective seeks to determine whether a single critical threshold for accumulated *nLS+* values is adequate for all study installations. Thresholds for each installation were identified as explained in the previous section and log-transformed values of accumulated *nLS+* values for all gullies, combining the calibration and validation datasets, were used in this statistical analysis.

A one-way ANOVA test was used to compare mean differences in log-transformed accumulated *nLS+* values for gullies from each installation. One-way ANOVA tests are appropriate when there is only one independent variable (i.e., the accumulated *nLS+* value) and if three key assumptions are met: (1) the gully populations from which the sample locations were obtained should be normally (or near normally) distributed; (2) sample independence; and (3) sample populations must be equal. Several statistical tests were used to insure assumptions were met including Bartlett's test for homogeneity of variance (Snedecor and Cochran, 1989) and Tukey's honestly significant difference (HSD).

Defining a single critical threshold for log-transformed accumulated *nLS+* values was not appropriate given the installations studied using NED DEM inputs (Table 13; Figure 3). Values calculated for two installations – Fort Hood and Keamuku Parcel – contributed most to this difference. While Fort Hood was significantly different in all pairwise comparisons except for Fort Benning, Keamuku Parcel differed from all but Kahuku Range and Fort Riley.

Table 13. Results from the post-hoc Tukey HSD test based on data from NED DEM model runs.

Installations in bold have significant differences in mean accumulated *nLS+* values based on a 95% confidence coefficient.

Installation Pairs	Difference in Means	Lower Limit	Upper Limit	p-Value (Adjusted)
FHT-FBG	-0.24250561	-0.62664950	0.1416383	0.4157654
FRK-FBG	0.46071399	-0.03776190	0.9591899	0.0854122
KAH-FBG	0.41199004	-0.11807191	0.9420520	0.2089164
KEA-FBG	**0.75092499**	**0.20538353**	**1.2964665**	**0.0017699**
FRK-FHT	**0.70321960**	**0.29442900**	**0.29442900**	**0.0000350**
KAH-FHT	**0.65449565**	**0.20773261**	**1.1012587**	**0.0006942**
KEA-FHT	**0.99343060**	**0.52840692**	**1.4584543**	**0.0000001**
KAH-FRK	-0.04872396	-0.59691088	0.4994630	0.9992158
KEA-FRK	0.29021100	-0.27295747	0.8533795	0.6191600
KEA-KAH	0.33893496	-0.25237390	0.9302438	0.5160636

FHT = Fort Hood; FBG = Fort Benning; KAH = Kahuku Range (Schofield Barracks); KEA = Keamuku Range (Pohakuloa Training Area); FRK = Fort Riley

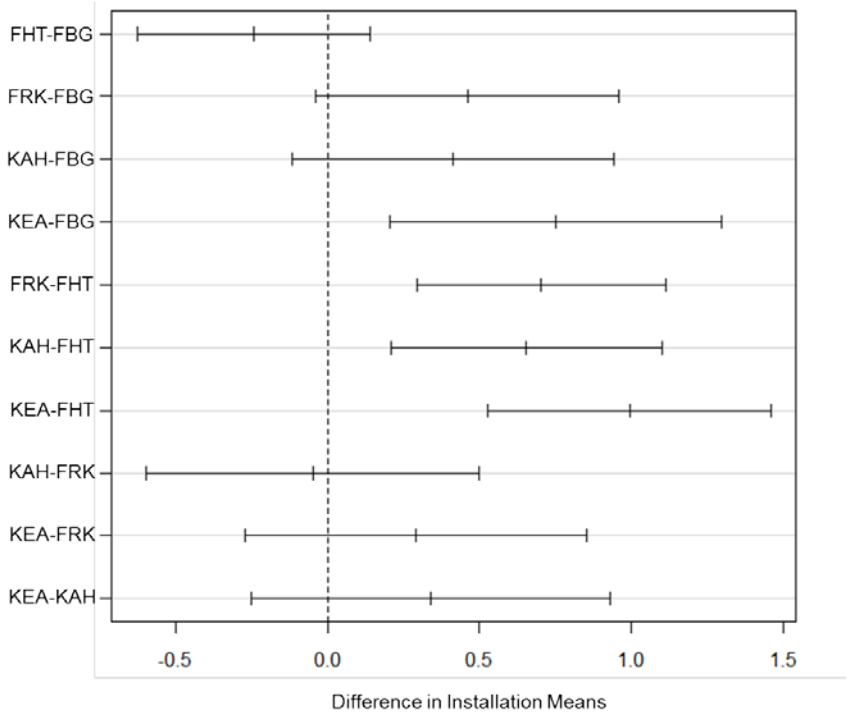

Figure 3. Graphical results from the post-hoc Tukey HSD test based on data presented in Table 17.

Intervals that do not contain a zero value (dashed vertical line) indicate a significant difference exists between installation mean accumulated *nLS+* values.

6.3 OBJECTIVE #3: FORECAST AREAS WHERE GULLIES ARE LIKELY TO FORM IN RESPONSE TO FUTURE MILITARY TRAINING EVENTS AT FORT RILEY AND POHAKULOA TRAINING AREA (KEAMUKU PARCEL)

The third, and final, quantitative performance objective used the *nLS+* model to predict where gullies were likely to form in response to a military training event. For this objective, the location of vehicle tracks was used to modify the original installation DEM and LULC layers (and associated Manning's *n* coefficient) based on information regarding the velocity of a traveling military vehicle, the radius of track curves, and estimated soil moisture conditions (e.g., wet versus dry). Past research by investigators from the University of Tennessee and ERDC-CERL that quantified vehicle track impacts in terms of RD and vegetation damage was used to modify the original DEM and LULC datasets. Though actual vehicle track widths will almost always be less than the spatial resolution of DEM and LULC datasets used as model input, vehicle-induced changes to the landscape were applied to any pixel through which a track passed, regardless of that pixel's dimension. Because the erosion potential model, and its resulting gully predictions, are based on a raster, or grid format, it is not necessary to account for sub-pixel impacts or processes. All that is necessary to know is (1) that a vehicle passed through a cell and (2) the estimated reduction in elevation (i.e., RD) and change in surface roughness (i.e., vegetation removal) caused by that passage.

Three Stryker vehicles from a reconnaissance platoon of the 2nd Brigade of the 25th Infantry Divison were tracked during an off-road proofing mission on the Keamuku parcel using GPS-based tracking systems to determine vehicle movement patterns and estimate soil loss impacts (Howard et al., 2011). Track data recorded by GPS units onboard the three Stryker vehicles were obtain from Dr. Paul Ayers (pers. comm.). The data was received as a text file with geographic coordinate information acquired at approximately one second intervals. Each GPS record also included key attributes such as vehicle VEL and COG along with a detailed date/time stamp identifying when the position record was acquired.

Using previous research conducted by Ayers et al., (2000), Li et al., (2007), and Liu et al., (2009), the impact severity, turning radius, and RD calculations for the maneuver exercise were calculated. These points, and their corresponding attributes were then converted into two gridded track files representing the calculated values for IS and RD, respectively, at the same spatial resolution of the DEM used to describe installation terrain. During this point to raster conversion, the maximum value for IS and RD were retained if more than one GPS point would be located within the same grid cell. The IS and RD grids were then used to modify the original Manning's *n* and DEM layers for the installation using conditional statements embedded within a raster calculation to create new inputs for the *nLS+* model.

As reported by Howard et al., (2011), most of the vehicle movement during proofing maneuvers occurred on roads. A total of over 27 kilometers (km) of off-road travel was recorded with a vehicle average of 9.1 km at an average speed of 3.69 meters per second (m/sec). For all of the vehicles, 1251 m^2 of vegetation was removed per vehicle during the proofing maneuver.

A summary of the computed data for IS and RD used to modify the *nLS+* model inputs in shown in Table 14. Figure 4 illustrates the resulting IS and RD values for Stryker vehicle PTA19 for a portion of its off-road track.

Table 14. Summary of computed data for IS and RD used to modify *nLS+* model inputs and predict new gully erosion areas after the Stryker proofing maneuver conducted at Keamuku Parcel (PTA), Hawaii.

Vehicle	No. GPS Points	IS Score (%)			RD (cm)		
		1st Quart	*Median*	*3rd Quart*	*1st Quart*	*Median*	*3rd Quart*
PTA 08	1672	10.15	22.46	53.32	0.03	0.17	0.93
PTA 17	2972	13.62	42.37	52.44	0.07	0.24	0.85
PTA 19	2518	11.42	39.86	54.22	0.04	0.17	0.70

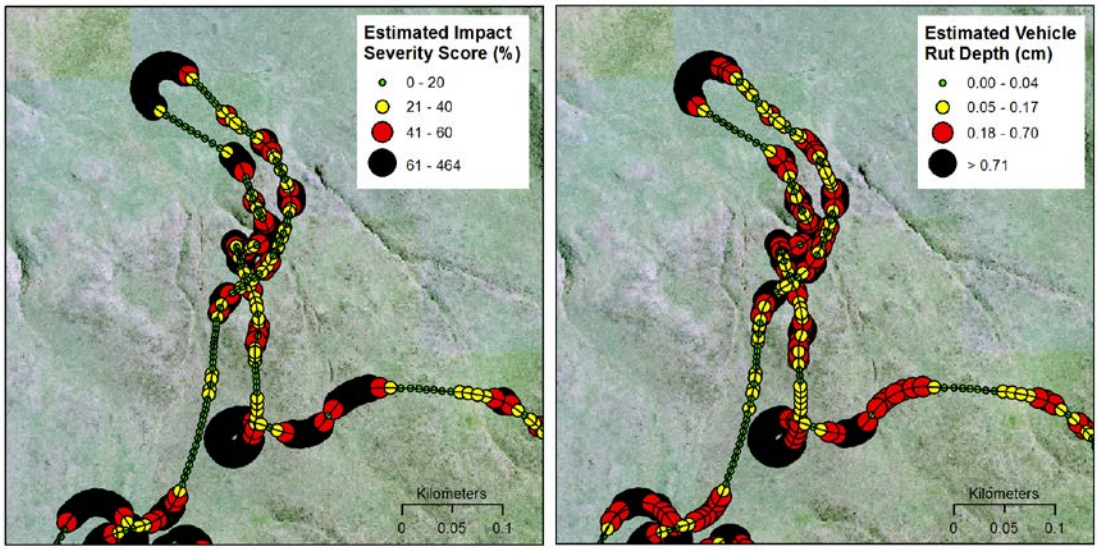

Figure 4. Estimated IS and RD values for Stryker vehicle PTA19 for a portion of its off-road track during proofing maneuvers conducted at Keamuku Parcel (PTA), Hawaii.

The *nLS+* model was re-run for Keamuku Parcel using the modified DEM and Manning's *n* grids to reflect post-maneuver landscape conditions. The previously computed accumulated *nLS+* threshold value for Keamuku Parcel, 0.155 to 0.965, was used again to determine if new areas of erosive potential would be generated and visible after applying estimated landscape impacts from GPS-derived vehicle tracks. This "re-analysis" of model results showed an additional 326 cells that were candidate sites for gully erosion (Figure 5). Given the 10 m spatial resolution of the Keamuku DEM used, this translates into an additional 3.26 ha of new land area that may be subject to active erosion or approximately 0.12 ha per off-road kilometer travelled by the maneuvering Strykers.

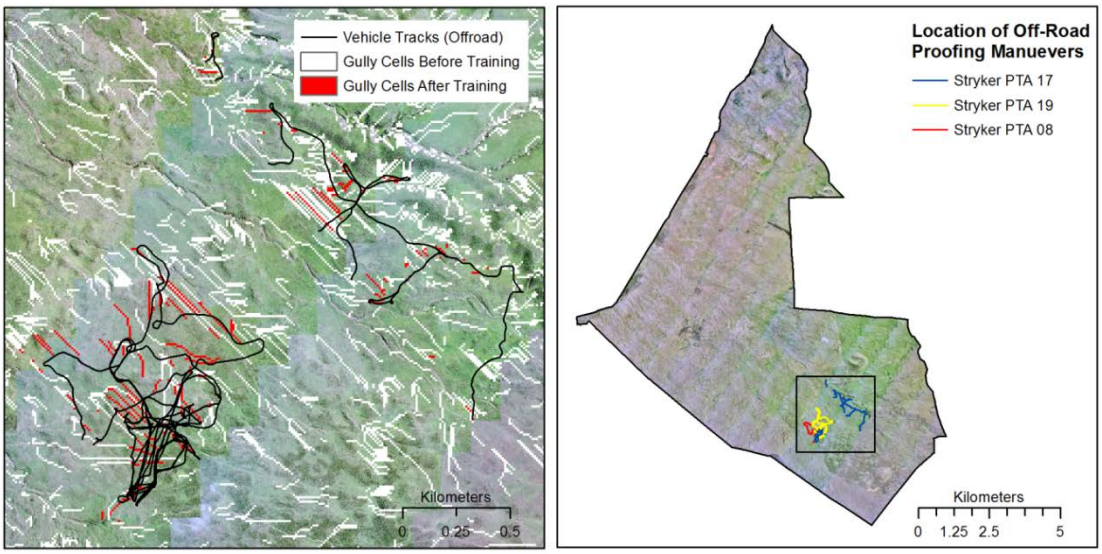

Figure 5. Predicted future gully erosion sites (left) from Stryker proofing maneuvers conducted on the Keamuku Parcel (PTA), Hawaii (right).

As of this report, predicted new erosion sites had not been re-visited in the field to assess erosion status. However, Howard et al., (2011) noted that significant vegetation recovery and regrowth took place one month after the proofing maneuver and that over 90% of the damaged vegetation had recovered after 15 months of the initial impact. This rapid vegetation recovery rate will help limit post-maneuver erosion unless precipitation events take place soon after maneuvers.

6.4 OBJECTIVE #4: PROPOSE GEOGRAPHIC REGIONS WITHIN WHICH INSTALLATION-SPECIFIC CRITICAL THRESHOLDS FOR ACCUMULATED *nLS*+ VALUES ARE VALID

Results from Performance Objective #2 showed that a single critical threshold for accumulated *nLS*+ values was not valid for all study installations. Instead, the critical thresholds calculated in this study have location-specific significance. Because of this, the fourth performance objective sought to use of ecoregion boundaries (e.g., USEPA Level II/III) as a framework to make installation-specific critical thresholds more applicable off-site.

As an initial check on the feasibility of using ecoregion boundaries as a means to translate individual installation results into a spatially continuous estimate of critical *nLS*+ thresholds, general environmental conditions at each site were assessed using the Jaccard distance (J_δ), or dissimilarity index (Jaccard, 1902; Jaccard, 1912). Variables selected for Jaccard analysis included soil hydrologic groups, landcover types, and slope > 10% for each installation. The large distance values reported by the Jaccard's test suggested that using common biogeophysical properties (e.g., ecoregions) as the means to make installation critical *nLS*+ values, as computed here, more spatially explicit would not be successful (Table 15).

Table 15. Values for Jaccard's distance (J_δ) for all study installations, including Fort Irwin and Camp Lejeune.

Values range between 0-1, with higher values indicating more differences between sites.

	Fort Hood	Fort Benning	Fort Riley	Fort Irwin	Camp Lejeune	Kahuku Range
Fort Benning	0.625					
Fort Riley	0.333	0.714				
Fort Irwin	0.625	0.750	0.714			
Camp Lejeune	0.750	0.500	0.857	0.714		
Kahuku Range	0.500	0.778	0.750	0.429	0.750	
Keamuku Parcel	0.667	0.778	0.750	0.429	0.750	0.500

Given that ecoregionalization of critical *nLS+* threshold values do not hold promise at this time, two different techniques were applied to help visualize how these thresholds might be applied in a more spatially continuous manner. First, a Euclidean allocation calculation was run in a GIS that identified for each location in the lower 48 United States the nearest "source" or installation (note that USEPA Ecoregions are not available for Hawaii). The allocation function generates a gridded output with unique values corresponding to a specific source that was summarized using zonal statistics with USEPA Level III ecoregion boundaries (USEPA, 2013) as the unique zones. Each Level III ecoregion was then assigned to an installation based on the majority value present within each boundary (Figure 6).

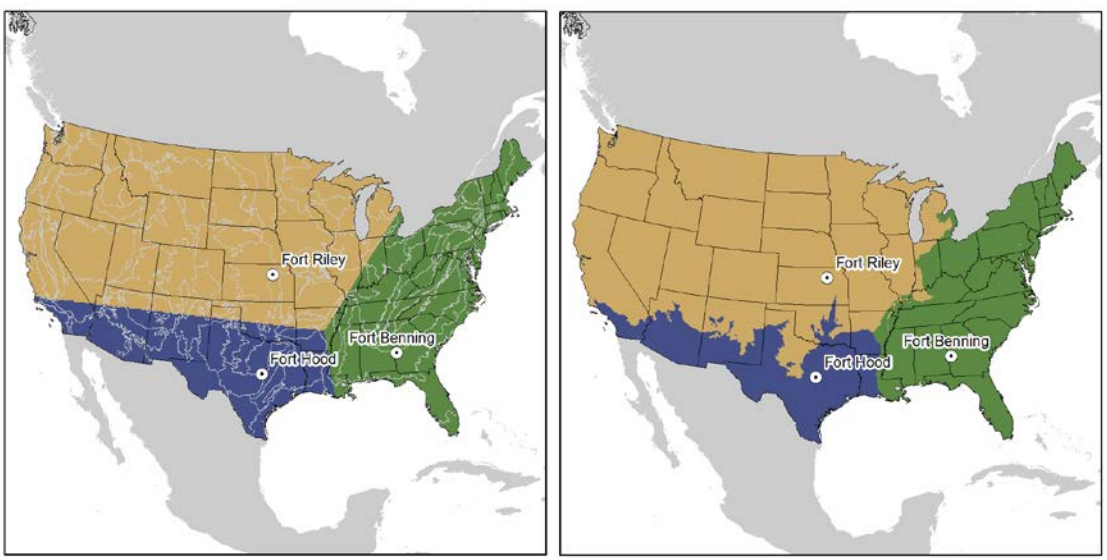

Figure 6. Ecoregion assignment of installation critical *nLS+* thresholds based on Euclidean allocation criteria.

Majority values from the initial allocation grid (left) are used to assign each ecoregion to a unique installation (right).

The second approach used to create a more spatially continuous view of the installation critical *nLS+* thresholds involved spatial interpolation. A thin-plate spline radial basis functions (RBF) was selected as the interpolation method (Figure 7). Though an exact interpolator, RBFs will

predict values above, and below, the measured maximum and minimum values in the dataset. Though mean prediction error for this interpolation was low (0.006), the root-mean-square error was high (0.621) given the paucity of data points used in the interpolation.

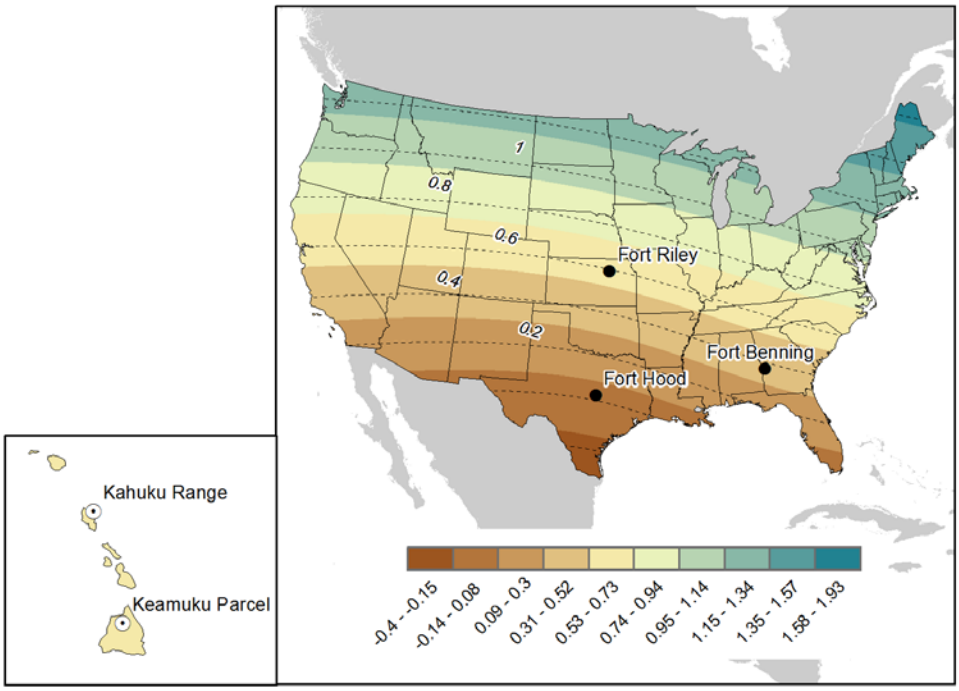

Figure 7. Preliminary spatially distributed estimate of critical *nLS+* threshold values based on the interpolation of installation results using a thin-plate spline radial basis function technique.

6.5 OBJECTIVE #5: DEVELOP AND DISSEMINATE A DOWNLOADABLE AND EASY-TO-USE GIS-BASED MODELING TOOL WITH DOCUMENTATION

The *nLS+* model was developed with the ArcGIS 10.0 (ESRI, Redlands, CA) suite of GIS software applications that are routinely utilized across DoD agencies and installations. Because of this, the model itself can be delivered in a variety of forms, including as an ArcToolbox "tool," a Python script, or as a ModelBuilder graphic model. For this project, the model was packaged as a "toolbox" with multiple sequenced tools than can be downloaded and used on a local computer workstation running ArcGIS version 10.0 or above (Figure 8). The toolbox and associated modeling tools also included an integrated help system to explain the underlying processes, data requirements, and recommendations for default settings or values as they apply to execution of the model.

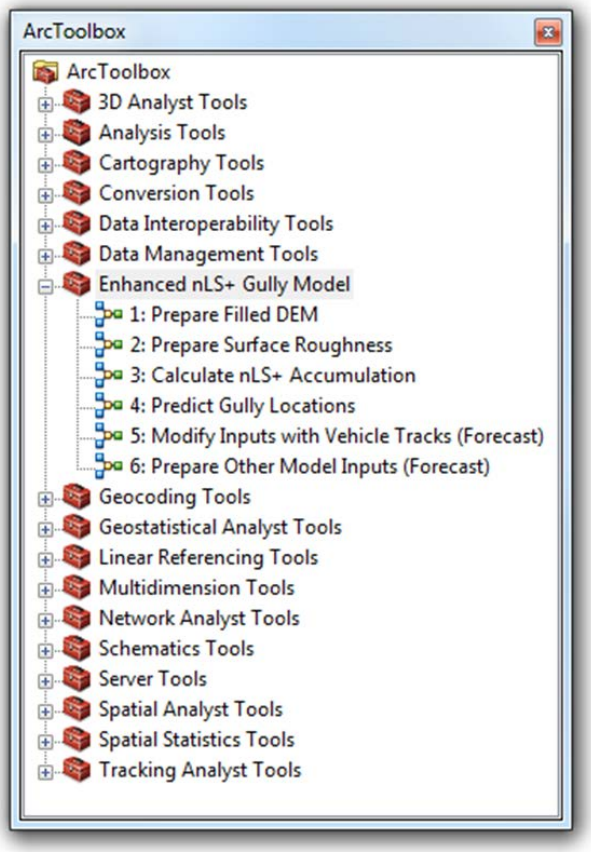

Figure 8. Screen capture image of the model toolbox and component sub-models in the ArcToolbox application of ESRI's ArcGIS 10.0 GIS program.

The final model – Rapid Soil Erosion Assessment Toolbox – is comprised of six total sub-models labeled within the toolbox by number and title. Users run the model and arrive at final results by executing each sub-model in numeric sequence from #1 (Prepare Filled DEM) to #4 (Predict Gully Locations). Sub-models #5-6 can be used to forecast future gully locations by modifying the installation DEM and Manning's *n* grid with GPS-derived vehicle tracks.

Feedback from installation ITAM GIS technicians helped shape the final form of the modeling tool as a sequence of smaller and quicker performing sub-models rather than one large model. Comments and questions generated during site visits were also invaluable in creating the integrated help system to guide users through the geoprocessing procedures.

Current ESRI and open-source GIS technology supports development and deployment of GIS web services and GIS server applications that minimizes and, in some cases eliminates, the need for users/installations to operate proprietary software as long as Internet access is available. Central management of modeling tools benefits end users by rendering much of the analytical complexity transparent while ensuring they adhere to best practices and techniques defined by GIS professionals. To demonstrate some of these benefits, a limited ArcGIS Server application was developed that delivers *nLS+* geoprocessing for a single installation (Fort Riley) to users over a network via the following uniform resource locator (URL):

http://services.geog.ksu.edu/ESCTP. This application will be maintained at this URL for approximately one year following the conclusion of this project.

This prototype delivery method facilitates the technology transfer process by simplifying model use, facilitating access to required input datasets, and eliminating the need to physically distribute executable files and updates. This approach also offers the potential for greater efficiency as models and data developed once can be used by the entire organization. Alternatively, end users can utilize Web services based on ArcGIS Server on their own desktop systems and infuse their own data or supplement new applications with existing models and data. By delivering an effective and user friendly GIS server application in this project, the potential for using server applications as an integrative analysis platform with other biological, hydrological, and engineering models within the DoD enterprise is demonstrated.

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7.0 COST ASSESSMENT

This section provides cost information for implementation of the model at a site.

7.1 COST MODEL

No significant cost element is introduced with implementation and operation of the *nLS+* model (Table 16). The requisite software is already available to all DoD agencies through a separate software site license agreement. The model will also operate with nationally-available, and free, input data. However, model results may be superior if using higher spatial resolution DEM and LULC inputs. Time to operate the model is minimal, though installation ITAM personnel should dedicate some time to field assessment and refinement of critical threshold values. Finally, the GIS model tool, itself, may require revision to operate within future updates to the current GIS software version.

Table 16. Cost model for Enhance *nLS+* model.

Cost Element	Data Tracked during Demonstration	Estimated Costs
GIS software acqusition	No unique data tracked	Covered by DoD license agreement with ESRI
Model data acquisition	No unique data tracked	Nothing – nationally available and free datasets
Operation costs	• Time to operate model • Computer specifications	< 2 man-hours
Model operation	• Refine model critical thresholds to improve site performance.	160 man-hours dedicated to field assessment and model updates.
Model maintenance	• Update/revise model to reflect new GIS software versions	10 man-hours

7.2 COST DRIVERS

The U.S. Army ITAM program is charged with managing its training lands to achieve the objectives outlined in Army Regulations 250-4 and 350-19. ITAM, itself, is composed of four sub-programs, including RTLA, LRAM, SRA, and TRI. Each of these sub-programs fills specific roles in ensuring military commanders have suitable training lands at their disposal. A key term used in these guiding regulations is “sustainable use,” which helps installation ITAM offices develop an overall philosophy for training land management, as well as identifying specific methods and approaches for conduct of the RTLA, LRAM, SRA, and TRI elements.

Over the last several years the DoD has significantly reduced funding for the ITAM program and is considering eliminating the RTLA program, which is responsible for monitoring natural resources within training lands and identifying when and where problems might prevent training land use by military units, due to a perceived lack of value. This is largely due to the lack of guidance on how to balance the often conflicting demands of current training needs and land management for a sustainable future as well as the limited automated and/or low-cost monitoring tools in place to support training land assessments that facilitate proactive land rehabilitation efforts. Current monitoring practices in place to assist military commanders with maximizing the availability and use of training lands are essentially done on an “ad hoc” basis without the benefit

of a consistent set of landscape metrics being examined or uniform methods for interpreting and reporting the results of environmental assessments. Such a decentralized approach prevents (1) consistent descriptions of the condition of military training lands at the installation and national scales, and (2) the ability to implement early and proactive land rehabilitation efforts and to fund those rehabilitation and maintenance efforts in an effective and efficient manner.

By developing land assessment and management tools, such as the rapid erosion assessment tool, that can take advantage of automated data acquisition and analysis using scripts and GIS models, installations can shift available land management funds toward rehabilitation and mitigation of training lands.

7.3 COST ANALYSIS AND COMPARISON

It is difficult to compare the cost of implementing the rapid erosion assessment tool with current military land management practices for identifying gully sites because the amount currently spent is typically dictated by the funding available rather than installation need. Prior to this project, all installations located gullies using extensive, on-the-ground land surveys. For installations with significant vegetation, such as the tallgrass prairie on Fort Riley, gully locations were often difficult to see requiring personnel to traverse the entire landscape at close intervals to locate gully/erosion problems. A complete survey of Fort Riley would take 4 to 6 months and require 600-1000 hours of labor. Because of the dynamic nature of training area damage and erosion potential, these surveys were needed on a relatively continuous basis. Using the rapid erosion assessment tool to identify locations susceptible to extensive erosion and gully formation, the area requiring detailed ground surveys is reduced on average by more than 15% when using the nationally available data sets (10 m DEM) and 1% when using high resolution LIDAR data. This significantly reduces the amount of time required in locating gullies and allows installations to become more proactive in preventing future gully formation. Additionally by reducing the cost of locating gullies, installations can invest more funds into fixing current gullies, and more importantly, preventing new gullies.

Use of current digital geospatial data characterizing topography and LULC will benefit model operation by yielding improved gully predictions, both in terms of numbers and locations. Given frequent disturbances to military lands caused by training activities, the need to update data holdings is even more important. The cost of purchasing LIDAR-based digital elevation data ranges between $4.38 to $8.75 per hectare depending on the total imaged area (Renslow et al., 2000). Estimates for the development of current LULC maps from multispectral satellite imagery begin at approximately $38.61 per square km, excluding imagery costs (Moskal and Styers, 2010). While multispectral imagery from the LANDSAT platforms can be acquired free of charge from the U.S. Geological Survey, most installations will benefit more from imagery acquired by one of the privately-owned high-resolution satellite systems such as Quickbird, IKONOS, and GeoEye. Military installations should be able to coordinate with the U.S. Army Corps of Engineers or National Geospatial Intelligence Agency (NGA) to obtain such imagery without additional cost through current government contracts. Estimated costs for data acquisition for each of the study installations is presented in Table 17.

Table 17. Cost estimate to purchase LIDAR DEMs and to develop current LULC maps for study installations.

Estimates assume a base cost for LIDAR acquisition of $5.00 per hectare and $40 per square km for LULC development.

Installation	Area (ha)	Area (km^2)	Estimated LIDAR Cost	Estimated LULC Cost	Total Cost
Fort Benning	73,608	736.08	$ 368,040	$ 29,443	$ 393,221
Fort Hood	88,519	885.19	$ 442,595	$ 35,408	$ 472,877
Fort Riley	41,141	411.41	$ 205,705	$ 16,456	$ 219,779
Kahuku Range	3,828	38.28	$ 19,140	$ 1,531	$ 20,450
Keamuku Parcel	9,313	93.13	$ 46,565	$ 3,725	$ 49,751

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8.0 IMPLEMENTATION ISSUES

Military commanders and DoD resource managers face the difficult challenge of maximizing accessibility to ranges and training lands to meet mission requirements while ensuring their sustainable use for future operational demands. Little guidance exists on how to balance these often conflicting demands and few automated and/or low-cost monitoring tools are in place to support training land assessments that facilitate the prioritization of rehabilitation work.

Current monitoring practices that might be in place to assist military commanders with maximizing the availability and use of training lands are essentially done on an "ad hoc" basis without the benefit of a consistent set of landscape metrics being examined or uniform methods for interpreting and reporting the results of environmental assessments. Such a decentralized approach prevents (1) consistent descriptions of the condition of military training lands at the installation and national scales, and (2) the ability to implement early and proactive land rehabilitation projects and to efficiently budget for future work needs.

The results of this project were largely positive, despite not meeting the success criteria for each performance objective. Future users should be aware that the operational definition of a "gully" and the positional accuracy of mapped gully locations greatly influences the threshold accumulated *nLS+* values, and other basic measures such as flow accumulation and contributing area, used to characterize and predict gully locations. Assuming future users at the installations studied target gully locations consistent with the definition presented in this report, no evidence was found that would dictate the need to re-calibrate the model prior to implementation. However, users at other installations would be wise to invest some time in model calibration and validation prior to using the *nLS+* model on an operational basis. Another issue that remains with interpreting model results is the large rate of false positive gully predictions. Despite the strong tendency for the *nLS+* model to overpredict gullies, the area identified as being a potential gully site is significantly lower than the total installation area. This benefits the planning and execution of field monitoring activities by focusing time and attention on the limited geographic extent likely to pose a gully hazard.

Use of the *nLS+* model in "forecasting" mode illustrated how data from recent activities can be used to predict where gullies might develop in the future. Though vehicle tracking data is neither routinely collected by installations nor often made available to natural resources staffs for use, the technology and procedures for geolocating each military vehicle at fine spatial and temporal scales exists and will likely become "standard operating procedure" in the future. However, use of vehicle tracking data to modify *nLS+* model inputs illustrates how installations might approach simulating the impact of other landuse changes on training lands, such as road construction, addition of hardened vehicle pads supporting firing exercises, and the placement of agricultural leases. Any planned development that would change installation topography or landcover, and its resulting impact on gully erosion, can be assessed with the model.

Although this project included a comparison of *nLS+* model results using DEMs of varying spatial resolutions, the impact of spatial (or temporal) scale on the generation of model inputs was not assessed. Direct comparison of model output with different resolution DEMs show comparable results with respect to the spatial precision of gully predictions and modest

improvements in classification accuracy. Perhaps more important than resolution is the "currentness" of model inputs and how well digital representations of topography and LULC reflect actual ground conditions.

Methods for using LIDAR data to generate estimates of Manning's *n* have been published (e.g., Smith et al., 2004). The scientific consensus is that LIDAR holds promise in this effort, but additional research is needed to document appropriate data procedures, scales of analysis, and improvements over traditional and field-derived estimates. Much of the work accomplished to date focuses on extracting the Chow's theoretical roughness in feet (*k*) from data derived from the difference of LIDAR-derived digital terrain (DTM) and digital surface models (DSM) (Chow, 1973; Smith et al., 2004). While an interesting approach, this resulting measure of vegetation canopy depth and architecture may be a better estimator of rainfall interception than true surface roughness. It should also be noted, that each of the three installations in this study with LIDAR DEMs purchased only "bare earth" DEM products from contractors. Including multiple return data may be useful – for a variety of applications – but would result in greater acquisition and data handling costs.

Should the *nLS*+ model find widespread use across installations, it is important that an organization be identified to maintain the model and make any updates and/or revisions necessitated by future GIS software versions. As with any GIS-based model for which installation use is expected, the *nLS*+ model is an ideal candidate to be delivered to end-users as a web-based geoprocessing service made available, and maintained, by a central environmental organization.

Results from Performance Objective #4 showed that using ecoregion boundaries to recommend operational critical thresholds for accumulated *nLS*+ values at other installations would not be appropriate. Instead, two approaches – Euclidean distance allocation and interpolation – were used to provide rough estimates of thresholds as an alternative to the ecoregion framework. It is important to note that these values have not been validated for other installations and that they should only be used with caution and in cases where installations are unable to perform their own *nLS*+ model calibration and validation. Should the model itself be maintained by a central organization, this organization could also assume responsibility for model calibration and validation if provided with a spatially and temporally accurate dataset of gully locations for partnering installations.

Along with providing for online geoprocessing capabilities, all data products required by the *nLS*+ model, and other environmental/sustainability indicators, could be stored in a geospatially-enabled relational database to facilitate access to current data by both installations and centralized management/support organizations. Storing data in the geospatially enabled relational database supports distributed viewing and editing by land managers and their staff, as well as distribution via mapping and geoprocessing web services. An example of this capability is the "Military Training Lands Map Viewer" web application, and its underlying SQL Server geodatabase, hosted by Kansas State University (http://services.geog.ksu.edu/frk_rtla) that provides a shared and real-time decision support tool for Fort Riley land managers.

The *nLS+* model represents one tool that is now available to military land managers to promote sustainability by demonstrating the data types, analytical methods, visualization tools, and information delivery mechanisms that could become routine across installations for assessing training land condition and trends. One installation – Fort Riley – already takes advantage of the model to assess erosion potential and help planning for field surveys. For maximum benefit, this single tool needs to be complemented with others that form a coordinated suite of environmental/sustainability indicators for key monitoring themes that can be collected, assessed, and synthesized to help identify when, and where, sustainable use of training lands is not being achieved.

8.1 DEFINITIONS AND DATA HANDLING

During the course of this project, it was clear that among ITAM personnel there was no consensus definition for the term "gully." When asked to visit gullies during initial site visits, ITAM staff drove to erosional features varying in size from ephemeral rills to large ravines. Contributing to this inconsistency might be the varying definitions for, and meanings behind, the terms "gully" and "gap" presented in military literature.

Related to this definition concern, is the varied ways in which installation land managers and GIS technicians measure and record gully information. Datasets ranged in quality from gullies represented digitally as line features spanning all, or most, of the length of the gully and including complete descriptive attributes such as depth, width, and date surveyed to completely undocumented point datasets. In no case did digital gully datasets also include Federal Geographic Data Committee (FGDC)-compliant metadata

The by-product of this inconsistent definition and lack of required practices and procedures for recording gullies are datasets that they varied significantly in spatial, temporal, and attribute quality. Clearly these characteristics can greatly influence the corresponding accumulated *nLS+* values calculated for an individual gully. Despite care in data processing, some of the variation in model results reported in this study could be attributed to a lack of common definitions and procedures across installations. The gully definition presented in this report, informed both the agricultural sciences and military mobility restrictions, might be considered for official adoption. So, too, should a set of required minimum attributes to be recorded for each gully instance including depth, width, and date of survey.

8.2 INSTALLATION ITAM STAFFING

Most of this project was conducted during an extremely volatile period for installation ITAM staffs. Frequent changes in ITAM personnel, including ITAM directors, and significant reductions in the number of GIS staff members was a near universal issue at each installation participating in this effort. While certainly a factor in the execution of this project, continued staffing issues for any installation office interested in better understanding the spatial and temporal dynamics of gully formation will discourage widespread adoption and use of model-based natural resource management tools. Prerequisites for successful implementation include technical staff with training in GIS as well as administrative leaders who see value in the approach and can effectively use model output to improve land rehabilitation efforts.

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