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FRAMEWORK OF RELIABILITY-BASED STOCHASTIC MOBILITY MAP FOR NEXT GENERATION NATO REFERENCE MOBILITY MODEL

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ABSTRACT

A framework for generation of reliability-based stochastic off-road mobility maps is developed to support the Next Generation NATO Reference Mobility Model (NG-NRMM) using full stochastic knowledge of terrain properties and modern complex terramechanics modelling and simulation capabilities. The framework is for carrying out uncertainty quantification and reliability assessment for Speed Made Good and GO/NO-GO decisions for the ground vehicle based on the input variability models of the terrain elevation and soil property parameters. To generate the distribution of the slope at given point, realizations of the elevation raster are generated using the normal distribution. For the soil property parameters, such as cohesion, friction and bulk density, the min and max values obtained from geotechnical databases for each of the soil types are used to generate the normal distribution with a 99% confidence value range. In the framework, the ranges of terramechanics input parameters that will cover the regions of interest are first identified. Within these ranges of terramechanics input parameters, a Dynamic Kriging (DKG) surrogate model of the Speed Made Good is generated using NATC Wheeled Vehicle Platform complex terramechanics model runs at the design of experiment points. Finally, inverse reliability analysis using Monte Carlo Simulation is carried out to generate the reliability-based stochastic mobility maps for Speed Made Good and Go/NO-GO decisions. It is found that the deterministic map of the region of interest has probability of only 25% to achieve the indicated speed.

1 INTRODUCTION

For efficient coalition mission planning of NATO forces under different terrain scenarios and for selection of capable vehicles, reliability-based stochastic off-road mobility maps needs to be developed using full stochastic knowledge of terrain properties and modern terramechanics modelling and simulation (M&S) capabilities. In the traditional NATO Reference Mobility Model (NRMM), only the nominal deterministic values of variables involved in the terrain properties and terramechanics simulation models are considered in generation of off-road mobility maps. The developed deterministic mobility maps would not be reliable and thus cannot be used effectively in mission planning of NATO forces under different terrain scenarios and for selection of capable next generation of combat vehicles. Thus, it is desirable to develop reliability-based stochastic mobility maps that can provide with desirable reliability levels in determining mobility of military vehicles across various terrains. The objective of this study is to develop a framework for a stochastic approach for vehicle mobility prediction over large regions and demonstrate generation of reliability-based stochastic mobility maps, such as Speed Made Good and GO/NO-GO associated with target reliabilities. This framework is aimed to be part of a suite of Next Generation NATO Reference Mobility Model (NG-NRMM) tools. Key variables of off-road conditions include those related to terrain elevation and soil property data and their variabilities as shown in Fig. 1 [1]. The ground vehicle parameters and their variabilities could also be addressed for a full stochastics treatment, but were not considered in this study.

The current NRMM output is given in terms of a deterministic mobility map [2, 3]. This map shows the means of cross-country speed between two points in a given region for a given vehicle. As recommended by Refs. 4 and 5, a stochastic analysis should be carried out in terms of probability densities and reliabilities. However, previous attempts to convert NRMM from a deterministic framework to a stochastic one have failed in the origin of uncertainties. No formal mathematical reasoning about the uncertainty types that need to be introduced in the simulations was given in Refs. [4, 5, 6]. Also, the current NRMM does not support autonomous mobility (this issue was pointed out in Ref. [7]). While this capability is highly desirable in the NG-NRMM because current and future defense forces include autonomous systems, it was not considered in this study.

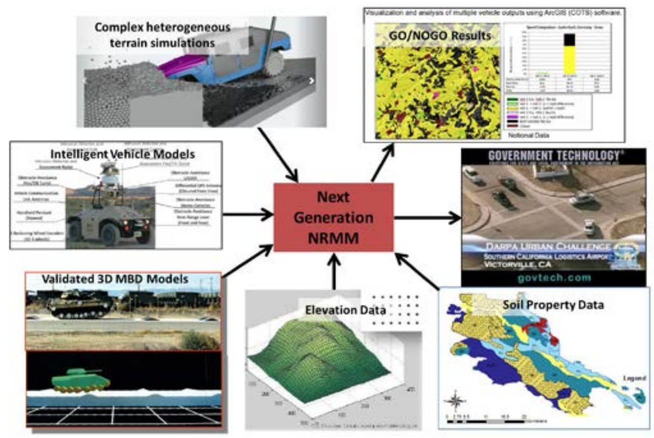

Figure 1. NG-NRMM Mobility Map Generation – Courtesy of [McCullough, et al., 2016]

The stochastic approach for mobility predictions over large regions should be integrated into NG-NRMM, where both the terrain profile and vehicle-terrain interaction play a key role. The following recommendations are made in Ref. [8].

- Any extension of NRMM in terms of stochastic mobility prediction should allow for consideration of uncertainty in elevation as well as in soil physical properties. This is addressed in this study.
- Computation time constitutes a key factor that must be considered in the development of the new NRMM. In this sense, any new proposal

should focus on efficient algorithms. This is addressed in this study.

- It is desirable from a stochastics perspective to base vehicle-terrain interaction on the Bekker-Wong model [9, 10], as these models are compatible with numerous multi-body dynamic simulation codes. The Bekker-Wong model is usually used for simple terramechanics models. As we used a complex terramechanics model for vehicle-terrain interaction, the Bekker-Wong model is not used in this study.

The propagation of variability involves calculating propagation of variabilities from elevation and soil property measurements into to mobility, such as Speed Made Good and GO/NO-GO, using terramechanics simulation models for generation of reliability-based stochastic mobility map, across the given geographic area. In this paper, we describe a framework that is developed for a stochastic approach for vehicle mobility prediction over a region of interest [11]. In this framework, an input model of the terrain is created using geostatistical methods. The performance of a vehicle is then evaluated while considering the terrain profile and the vehicle-terrain interaction. In order to account for terrain property variability, Monte Carlo simulations are performed, leading to a statistical analysis.

2 INPUT ELEVATION AND SOIL PROPERTY DATA INCLUDING VARIABILITY

This section describes different types of uncertainties and input distribution models for terrain elevation and soil property and their variabilities.

2.1 Irreducible and Reducible Uncertainties in NG-NRMM

In developing reliability-based stochastic mobility maps, it is necessary to use right types of input uncertainties as they will affect the reliability-based stochastic mobility map results. There are two types of uncertainties: irreducible uncertainty (variability) and reducible uncertainty (imperfection). Irreducible uncertainty refers to the inherent variability of data such as in terrain elevation and soil property variables. It is often expressed through statistical metrics such as variance, standard deviation, and interquartile ranges that reflect the variability of the data. The variability cannot be reduced, but it can be better characterized (i.e., better distribution model). Reducible uncertainty refers to imperfections in mechanical simulation models or input distribution models. The term imperfection in mechanical simulation models is biasness of the terramechanics simulation model. The term imperfection in input distribution models is the uncertainty caused by the inability to correctly predict the input distribution and its parameters from limited data – it does not refer to variability. Reducible uncertainty can be either qualitative or quantitative and can be eliminated or reduced with better simulation model and more data.

Based on these definitions, the irreducible and irreducible uncertainties in NG-NRMM are as followings.

- ➢ Irreducible uncertainty:
  - ✓ Terrain property variables (e.g., elevation, soil composition, bulk density, temperature, moisture content, etc.), including known measurement errors.
  - ✓ Terramechanics input parameters (e.g., slope, soil cohesive strength, soil friction coefficient, bulk density, etc.).
- ➢ Reducible uncertainty:
  - ✓ Input distribution models obtained using limited number of terrain data.
  - ✓ The terramechanics simulation models are abstractions of the physical system (*i.e.*, vehicle) and it is possible that these models may not depict the actual physical event correctly. Uncertainty about the model's structure, i.e. uncertainty about the cause-and effect relationships, is often very

difficult to quantify. If so, it should be treated as reducible uncertainty.

- ✓ Another situation is, when generating response surfaces using design of experiment (DOE) samples, if the response surface includes error, then we have reducible uncertainty. Thus, the Kriging variance (estimation error) should not be treated as irreducible uncertainty but as reducible uncertainty.

When evaluating reliability, only irreducible uncertainty (i.e., variability) should be considered as the input since the reliability is not a function of reducible uncertainty. If uncertainty exists due to (1) lack of information in input terrain data for input distribution modeling, (2) terramechanics simulation models do not depict the actual physical event correctly, or (3) Kriging surrogate model variances are not ignorable, then attempts should be made to reduce imperfections in mechanical simulation models and/or input distribution models instead of using these reducible uncertainties as input variabilities. To deal with reducible uncertainty, a confidence measure needs to be developed to have confidence in the reliability-based stochastic mobility map. In addition, existence of reducible uncertainty calls for employment of validation and verification (V&V) procedure to ensure the effectiveness of the terramechanics models. In this study, only terrain property variabilities are considered for development of the reliability-based stochastic mobility map.

2.2 Input Distribution Model

Terrain elevation data are usually obtained using remote sensory techniques (i.e. radar technology, imagery methods, etc.). Those techniques lead to uncertainty in terrain data values as well as the spatial position of data points. Thus, any elevation model of the terrain includes uncertainty. Digital Elevation Models (DEMs) produced by the US Geological Survey agency are a good example of this issue. Spatial variability of physical terrain properties (e.g. soil bulk density, cohesion, internal friction angle, etc.) also leads to uncertainty in vehicle-terrain interaction models. In addition, measurement methods of the soil properties are uncertain in nature. Specifically, this framework involves methods for using ArcGIS/ENVI data [12] and complex terramechanics model, to generate reliability-based stochastic mobility prediction maps. It is noted that the developed framework in this study should allow continuous future improvements, which can be repeated when (1) the input distribution models are refined with better data and (2) the terramechanics models used are revised, improved or changed as long as the terramechanics models accept the same input format from the ArcGIS/ENVI database [12] and generate appropriate speed outputs.

While the terrain elevation data can come from various sources and take on various formats, in our study, the elevation data is provided in a raster format. Common resolutions for the elevation data is 30-m and 90-m. The variability information for the elevation data is required to take into account the uncertainty of the elevation data measurement. This variability information should ideally come in the form of a plus-minus tolerance with an associated confidence interval with, e.g., ±12 m with 90% confidence. This can then be used to construct a normal (i.e., Gaussian) distribution that represents the variability of the elevation measurements. For the prototype demonstration presented in this study, the Monterey, California, data is used. The elevation data for this location was provided by the Shuttle Radar Topography Mission (SRTM) database [13]. The website for SRTM provides the variability information and states that for the 30x30 m data the accuracy is ±16 m with accuracy being at the 90% confidence level. Figure 2 shows how the elevation variability information is used to construct a distribution for the elevation for cell of the raster.

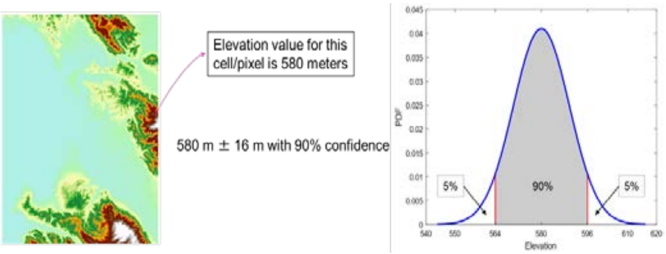

Figure 2. Elevation Variability and Distribution

The slope is calculated by ArcGIS using the elevation raster. Thus, to obtain the variability of the slope, the variability of the elevation is needed so it can be propagated through the slope calculation. A simple toolbox was created in ArcGIS that calculates the slope using the elevation raster as shown in Fig. 3. The toolbox loops over all the elevation rasters provided in a directory and calculates the slope for each raster. To generate the distribution of the slope at given point, realizations of the elevation raster have to be generated using the normal distribution. Once the elevation raster realizations are generated, the slope realizations can be generated using the toolbox in ArcGIS. This then provides the variability of the slope.

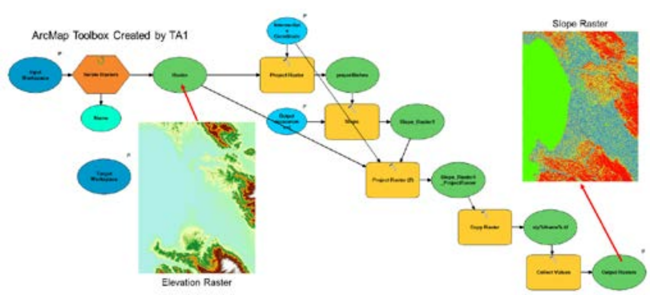

Figure 3. ArcGIS Slope Calculation Toolbox

Currently there is very little information available on the variability of the soil properties. The only information found was from Geotechnical Parameters site [14]. This site provided two tables, one soil cohesion values and the other friction angle values. These two tables provided minimal variabilities, which are all that currently available. For some of the soil types, the min and max values of the soil property were provided. For some other soil types, a specific values were provided without min and max values. Using the min and max values, the distribution type was assumed to be a normal distribution with a 99% confidence on the min and max value range. Using these two assumptions, the distributions for the soil parameters for each of the different soil types were constructed. For the soil types that did not have min and max values provided, an assumption was made on the min and max values based on the specific value and other soil types that were similar. It is acknowledged that this may not be accurate, but was the best information available at the time. For the peat soil type, the Geotechnical Parameters site [14] did not provide a range or a specific value. For peat, Ref. [15] provided min and max values for the cohesion of undistributed and reconstituted peat. Since there was no other variability information provided, these min and max values were used with the same assumptions as the other soil types to construct the distribution.

For the bulk density, a USDA SSURGO Web Soil Survey database [16] containing bulk density measurements was available. There were a few measurements available for each soil type in the database, which were not enough data for fitting a distribution. Therefore, these measurements were used to determine the min and max values of the bulk density for the different soil types. These min and max values were used with the same assumptions to construction the distribution for the bulk density for different soil types. With all of these soil variability information gathered, each soil type has its own distribution for each of the soil properties, cohesion, friction, and bulk density. Figure 4 shows a representative of this variability information: for a given soil classification, there is a distribution for the cohesion, friction, and bulk density. It is acknowledged that more data on the soil properties are required in order to construct accurate distributions for each soil type and parameter.

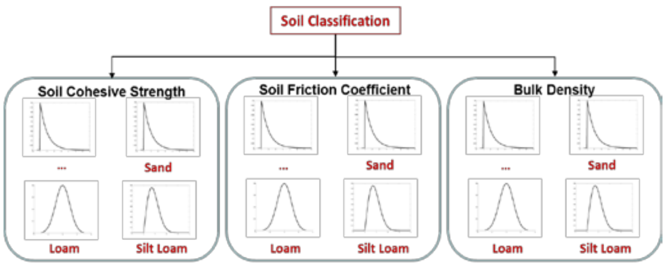

Figure 4. Variability of Soil Properties

3. ADVANCED KRIGING FOR SURROGATE MODELLING

The previous NG-NRMM uncertainty treatment effort [11] used simple Kriging (i.e., ordinary Kriging) to fit elevation data via the ArcGIS Geostatistical extension. This was used to generate a sample of random elevation realizations. They have generated a mobility map accounting for two sources of uncertainty, namely measurement errors (RMSE of a digital elevation model) and interpolation error (Kriging method). However, as described in Section 2.1, the interpolation error is reducible uncertainty and should not be included in generation of stochastic mobility prediction. The slopes from each realization were used to make a stochastic mobility prediction. This was overlaid with a soil type map and all points with silty soil were declared off limits. The resulting GO/NO-GO maps were used for an optimal route planning demonstration using ArcGIS functions.

In conventional universal Kriging, the responses at design of experiment (DOE) points $\mathbf{x}_i$, $i = 1,\ldots, n$, are represented by

$$\mathbf{y} = \mathbf{F}\boldsymbol{\beta} + \mathbf{Z}, \qquad \mathbf{F} = [\, f_k(\mathbf{x}_i),\ k = 1,\ldots, K,\ i = 1,\ldots, n\,]_{n\times K}$$

where $\boldsymbol{\beta}_{K\times 1}$ is regression coefficients, $f_k(\mathbf{x}_i)$ are polynomial basis functions, and $\mathbf{Z}_{n\times 1} = \left[Z(\mathbf{x}_1),\ldots, Z(\mathbf{x}_n)\right]^T$ are realizations of Gaussian random process $Z(\mathbf{x})$ with zero mean and covariance $Cov\left(Z(\mathbf{x}_i), Z(\mathbf{x}_j)\right) = \sigma^2 R(\boldsymbol{\theta}, \mathbf{x}_i, \mathbf{x}_j)$. Here $R(\boldsymbol{\theta}, \mathbf{x}_i, \mathbf{x}_j)$ is the correlation function of the stochastic process, σ^2 is the process variance and $\boldsymbol{\theta}$ is the process correlation parameter vector.

For the objective of this study, the features identified from literatures that are desirable to be included in the advanced Kriging method to deal with the non-stationary and non-Gaussian geostatistical data are as listed below:

- The first one is a subregion-based Kriging model to deal with the common issue of non-stationary variogram models [11, 17, 18, 19, 20], since the variogram can be considered stationary within the smaller subregion. In addition, the subregion method will allow parallel processing in generation of the Kriging models and thus achieve faster computational time. Furthermore, this will yield smaller dimension of the correlation matrices that need to be inverted.
- The second method to deal with non-stationary issue is using the universal Kriging with higher order polynomials [17, 21] instead of the ordinary Kriging (simple Kriging) that uses 0^{th} order polynomial for the trend function. Combined with the subregion-based Kriging model, up to the second order polynomial would be sufficient for the trend function. However, using one second order polynomial as the default trend function for all subregions would not provide the best accurate results. Thus, a method to select the best polynomial order of the trend function for each subregion is desirable for accurate Kriging model.
- Kriging produces an interpolation function based on a covariance (i.e., variogram) model

derived from the data rather than an a priori model of the interpolating function. For this, the Gaussian correlation model is widely used. To improve accuracy for the non-stationary and non-Gaussian data, a standard approach is finding some non-linear transformation that enables the use of Gaussian models [18]. However, as the models grow more complex, for example by introducing non-stationary covariance functions; spatially varying measurement errors; or covariates for the mean, the effects of the transformation methods become less transparent and more stale [22]. In these situations, one would like to use latent non-Gaussian models without resorting to transformations. Or seven correlation functions (exponential, general exponential, Gaussian, linear, spherical, cubic, spline) could be used to model the covariance. Like the trend function, the best correlation function needs to be selected for each subregion depending on the data in the subregion.

- A method for selection of a combination from three trend functions and seven correlation functions for each subregion to yield the best accuracy of the Kriging model would be desirable.
- Need to find the global optimal correlation parameters **θ** of the covariance function that maximizes the likelihood function based on all observations. It is desirable that the method provides the global optimal correlation parameter **θ**.
- Desirable to have a sub-sampling method for reduced-order representation of the DEM points for Kriging model that minimizes the Kriging variance (and thus reduce uncertainty). Also, the sub-sampling method would help in reducing the computational time as well as inverting the correlation matrix in Kriging model by avoiding close data points (i.e., singularity) when inverting.

In this study, the Dynamic Kriging (DKG) method developed by RAMDO Solutions is used as the advanced Kriging for terrain modelling. The uniqueness of the DKG method include:

- Select best trend function from 0^{th}, 1^{st}, and 2^{nd} order polynomials using cross validation (CV) error.
- Select best correlation function $R(\boldsymbol{\theta}, \mathbf{x}_i, \mathbf{x}_j)$ from 7 candidates using maximum likelihood estimation (MLE).
- Automatically select best DKG model from $7\times3 = 21$ different options for surrogate models.
- Search global optimal correlation parameter **θ** using MLE and the Global Pattern Search (GPS) algorithm [23].
- Adaptive sequential DOE point to minimize the variance of the Kriging results in between DOE sample points.

The DKG method [20, 24, 25] is identified as one of the most accurate surrogate modeling methods in Ref. [26].

4. PROPAGATION OF UNCERTAINTY FOR RELIABILITY ASSESSMENT OF MOBILITY

For the objective of this study, the capability that needs to be developed is uncertainty quantification (UQ) and reliability assessment for Speed Made Good and GO/NO-GO decisions based on the input distribution models of the terrain elevation and soil property parameters. For this, the DKG surrogate model of the vehicle Speed Made Good with respect to four parameters (slope, bulk density, soil adhesive strength and soil friction coefficient) needs to be generated using the complex terramechanics model (i.e., the vehicle) runs at the DOE points as shown in Fig. 5. Using the DKG surrogate model of the Speed Made Good; input distribution models of the four parameters; and the ArcGIS/ENVI data of the region of interest; the inverse reliability analysis is carried out to obtain reliability-based stochastic mobility map for Speed Made Good and GO/NO-GO decision.

The developed framework for propagation of uncertainty is as following (refer to Fig. 5).

Step 1. Identify Ranges of Terramechanics Input Parameters That Will Cover the Regions of Interest:

Use the ranges (lower and upper bounds) of four terramechanics input parameters over the regions of interest to construct 4-D Dynamic Kriging (DKG) surrogate model of the Speed Made Good using the complex terramechanics model.

Step 2. Design of Experiment (DOE) Samples of Speed Made Good for DKG:

a. Generate initial DOE points within the lower and upper bounds of four parameters using a modified Transformations Gibbs Sampling (TGS) algorithm.
b. Evaluate Speed Made Good (i.e., steady-state speed) at the selected DOE points by running the complex terramechanics model on the Army DSRC High Performance Computing (HPC) systems (parallel runs).
c. Add additional multiple DOE points using an adaptive sequential DOE sampling method at locations where the DKG surrogate model has largest amounts of the Kriging (DKG) variances.
d. The sequential sampling process is iterative and continues until the accuracy tolerance of the convergence MSE of the DKG surrogate model is achieved.

Step 3. DKG Surrogate Model of Speed Made Good:

Generate the DKG surrogate of the Speed Made Good as a function of the four terramechanics parameters. Steps 2 and 3 are the most compute intensive process. However, the surrogate model can be reused for other regions of interest to generate reliability-based stochastic mobility map, which is the map for the same terramechanics model (i.e., the same vehicle).

Step 4. Input Distribution Models

Obtain input distribution models of the four terramechanics parameters (slope, soil cohesive strength, soil friction coefficient and bulk density) for the region of interest as described in Section 2.2.

Step 5. Inverse Reliability Analysis of Speed Made Good:

Carry out inverse reliability analysis to predict the Speed Made Good for reliability-based stochastic mobility map of the region of interest. A number of Monte Carlo Simulation (MCS) samples at each location of the pixels to generate reliability-based stochastic mobility map. Using the DKG surrogate of the Speed Made Good previously generated, this process can be carried out efficiently. This will allow quicker generation of the stochastic mobility map. If necessary, then repeat Steps 4 and 5 to generate new stochastic mobility map for another region of interest.

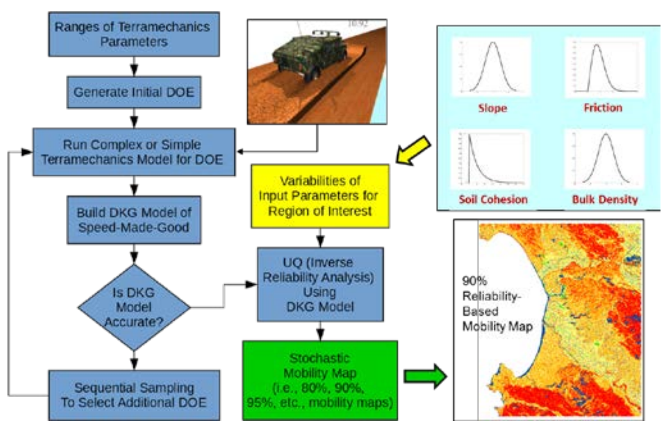

Figure 5. Generation of Reliability-Based Stochastic Mobility Map

The simulation-based uncertainty quantification of the mobility map is accurate assuming: (1) accurate input distribution models, (2) accurate terramechanics simulation models and (3) accurate surrogate model. However, in reality, as we have seen in this study, only limited numbers of input data for terramechanics parameters are available for modelling input distributions. Thus, the estimated input distribution models are uncertain. Also, the terramechanics simulation model could possibly be biased due to assumptions and idealizations used in the modelling process. In addition, the surrogate model could be inaccurate. For validation of the Speed Made Good prediction, only a limited number of physical vehicle driving test data can be obtained in practical applications. As a result, target output distributions for the vehicle speed, against which the terramechanics simulation model can be validated are uncertain and the corresponding reliability become uncertain as well. To assess conservative reliability of the vehicle speed properly under these reducible uncertainties due to limited numbers of both input and output test data and a biased terramechanics simulation model, a confidence-based reliability assessment method [27] would be desirable to be developed in the future.

5. PROTOTYPE DEMONSTRATION

This section presents the prototype demonstration of generation of the reliability-based stochastic mobility maps. For the prototype demonstration, Monterey, California is selected as the region of interest. For the complex terramechanics model, NATC Wheeled Vehicle Platform shown in Fig. 6 is used. The complex terramechanics model was developed by Advanced Science and Automation Corporation [28, 29].

Figure 7 shows the concept of how the variability of terrain and soil properties are used with a UQ tool [30] together with the terramechanics simulation model to generate the reliability-based stochastic mobility maps. The deterministic soil type data is provided as a GeoTIFF as shown in Fig. 7. The provided soil type is assumed to be correct, i.e., no variability in the soil type (e.g., sand, clay, etc.) is assumed. Variability in the soil comes from the variability in the soil parameters (bulk density, soil adhesive strength and soil friction coefficient).

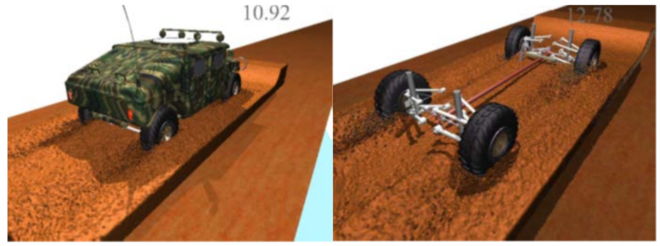

Figure 6. Complex Terramechanics Model of NATC Wheeled Vehicle Platform

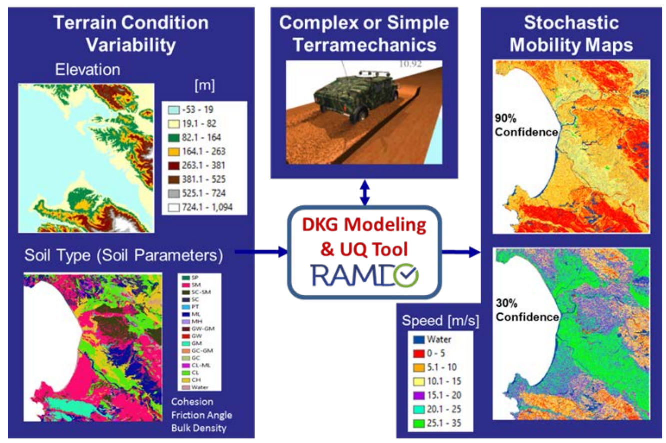

Figure 7. Propagation of Variability to Generate Reliability-Based Stochastic Mobility Maps

RAMDO [30] is used to create the DKG model of the complex terramechanics simulation model (i.e., the vehicle) of the NATC Wheeled Vehicle Platform. To create the DKG model 32 DOE points were created for the four-dimensional problem. The four variables used were slope, cohesion, friction angle, and bulk density of the soil. The 32 complex terramechanics simulation models were created. The 32 runs were carried out using 32 cores for each job and running all 32 jobs in parallel. Each run took between 5-7 days to complete. The response of interest from the simulation was the speed made good. Once the DKG model is created, it is used together with the UQ tool for the variability propagation by carrying out inverse reliability analysis to predict the Speed Made Good for reliability-based stochastic mobility map of the region of interest. For the inverse reliability analysis, we need more than 1,000 of Monte Carlo Simulation (MCS) samples at each location of $3{,}601^2 = 12{,}967{,}201$ pixels for Monterey, California to generate reliability-based stochastic mobility map. However, using the DKG surrogate of the Speed Made Good previously generated, this process can be carried out efficiently. This will allow quicker generation of the stochastic mobility map without requiring to use HPC. Using the UQ tool the distribution of the Speed Made Good at cell of the raster is obtained as shown in Fig. 8. These distributions can then be used to create the reliability-based stochastic mobility maps as shown in Fig. 8. The 90% Speed Made Good map means that there is 90% probability that the maximum obtainable speed is greater than or equal to the value shown on the map as shown in Fig. 8. If speed is mission critical, e.g., delivering supplies urgently needed, then using a higher probability map would be desirable. If speed is not mission critical then using a lower probability map could be acceptable.

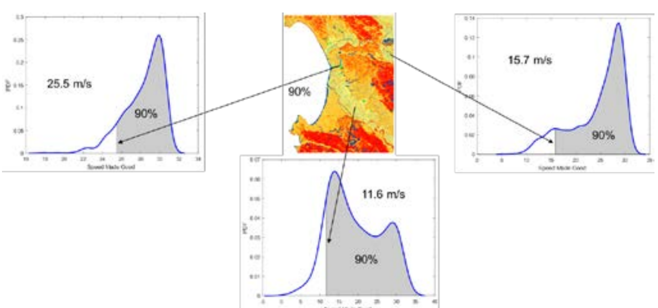

Figure 8. Distribution of Speed Made Good for each Cell of Raster

The propagation of the variability of the terrain and soil properties was successfully demonstrated in creating the reliability-based stochastic mobility maps shown in Fig. 9 for Monterey, California. If variability is not taken into consideration when generating the Speed Made Good maps, then a deterministic map is generated as shown in the last figure in Fig. 9. It is seen that the deterministic map appears to be somewhere between the 20% and 30% reliability maps, meaning the deterministic map only has probability of approximately 25% to achieve the indicated speed just from visual comparison. This demonstrates the need for taking into account the variability so that accurate Speed Made Good maps can be generated and have a given reliability or confidence attached to them, in order to provide more information to the decision maker.

It is interesting to note that these reliability-based stochastic mobility maps are like "FEMA Flood Map." For example, the 100-year flood map is referred to as the 1% annual exceedance probability of flood, since it is a flood that has a 1% chance of being equaled or exceeded in any single year (*i.e.*, 99% reliability).

The same DKG model of the terramechanics simulation model (i.e., the vehicle) in Fig. 7 is used for the variability propagation by carrying out inverse reliability analysis to predict the GO/NO-GO region. The UQ tool that is used to obtain reliability-based Speed Made Good at cell of the raster shown in Fig. 8 is used to create the reliability-based GO/NO-GO maps for Monterey, California as shown in Fig. 10. For GO/NO-GO maps, the cut-off speed used is 5 miles/hour. In this map, the green color means GO, the red color means NO-GO and the blue color means water. Thus, the green color in 90% GO/NO-GO map means that there is 90% probability that the vehicle can move with at least 5 miles/hour speed. Note that for up to 40% reliability, the NO-GO region does not seem to be significantly showing. However, starting at 50% reliability, the NO-GO region is beginning to show up clearly.

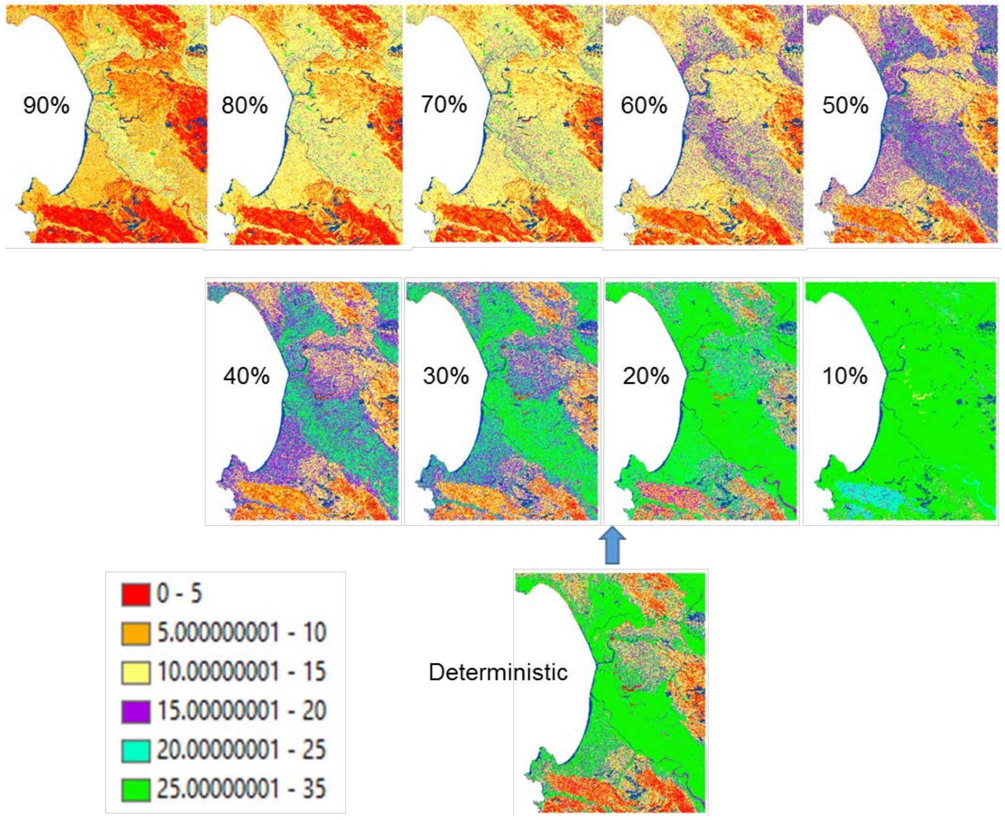

Figure 9. Reliability-Based Stochastic & Deterministic Speed Made Good Mobility Maps

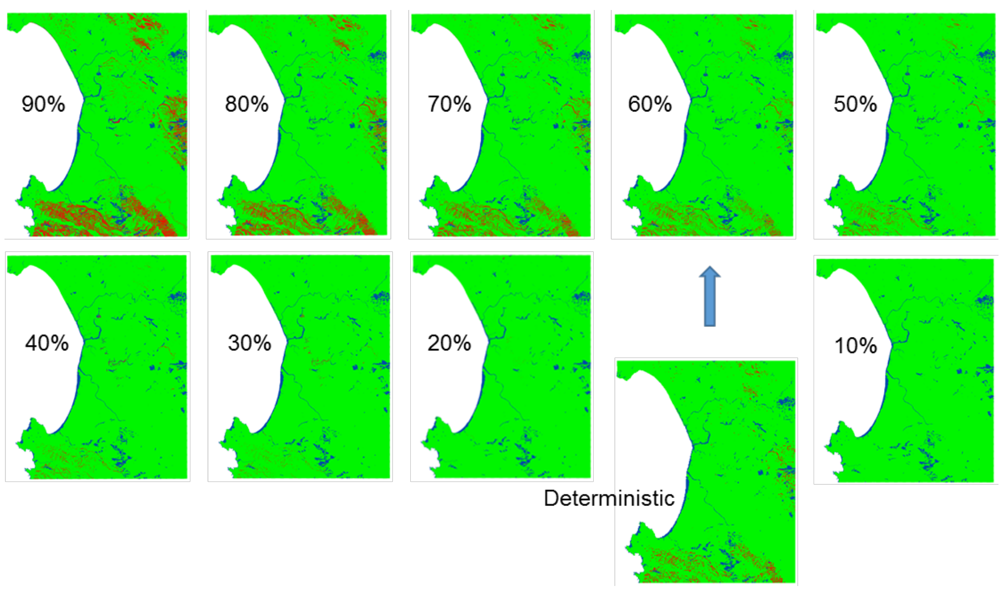

Figure 10: Reliability-Based GO/NO-GO Decision Maps

6. GAPS AND PATH FORWARD

This section breaks down the gaps that need to be filled for continuous future improvement of the framework for a stochastic approach for vehicle mobility prediction over large regions and generation of accurate reliability-based stochastic mobility maps for Speed Made Good and GO/NO-GO decision.

6.1. Raster Data

For the area of interest all the raster data should be the same size. This is because the uncertainty propagation is done cell-by-cell in the raster. Converting the data to the same raster size may introduce additional approximations or errors. A standard method for how to handle this should be developed in the future.

6.2 Terramechanics Simulation Model

There are several features needed for the terramechanics simulation model to be robust and fully automated for effective and seamless development of DKG surrogate models and integration with UQ Tools for a non-terramechanics expert to be able to use it. First, the model should have an auto steering capability to keep the vehicle on the track during the simulation. It is very much desirable that the model input be the raw soil parameter data as variabilities of these raw soil parameter data will be used for input distributions for the reliability-based stochastic mobility map. The terramechanics simulation model should take these raw soil parameter data values and convert them to the input values needed/used in the terramechanics simulation. A time step determination and adjustment capability should be available so that models will run successfully and need to be rerun with a different time step if they fail due to an incorrect time step. An automatic result extraction capability is needed so that the responses can be easily extracted. Currently it is carried out by a manual process of looking at the history file and averaging the time history results. A method to automatically determine if steady-state speed has been reached is needed. This is so that terramechanics simulations do not continue to run if steady-state is reached.

6.3 Soil Parameter Data

As mentioned throughout the paper, there is little to no soil parameter data available and little to no variability information on the soil parameters. This data is required for each soil type in order to generate accurate reliability-based stochastic mobility maps. The most ideal data would be data on the raw soil parameters for the area of interest. If this is not possible, then a general database for different soil types should be put together so that it can be used for a given area of interest. This may result in some inaccuracies as the variability and parameter values for a given soil type might be different from the actual properties in the area of interest; however, this could probably be the best obtainable result.

7. SUMMARY AND CONCLUSION

A framework for propagation of the variability of the terrain and soil properties was successfully demonstrated in creating the reliability-based stochastic off-road mobility maps for Speed Made Good and GO/NO-GO decisions to support the NG-NRMM using full stochastic knowledge of terrain properties and modern terramechanics modelling and simulation capabilities. To generate the distribution of the slope at given point, realizations of the elevation raster are generated using the normal distribution.

For the soil property parameters, such as cohesion, friction and bulk density, the min and max values obtained from geotechnical databases for each of the soil types are used to generate the normal distribution with a 99% confidence value range. In the framework, the ranges of terramechanics input parameters (i.e., slope, cohesion, friction and bulk density) that will cover the regions of interest are first identified. Within these ranges of terramechanics input parameters, a

Dynamic Kriging (DKG) surrogate model of the Speed Made Good is generated using a complex terramechanics model runs at the design of experiment points. This is the most compute intensive process in the framework that may require HPC.

Once the DKG surrogate model is generated for the selected ground vehicle, then inverse reliability analysis using Monte Carlo Simulation can be carried out to generate the reliability-based stochastic Speed Made Good and GO/NO-GO maps of the region of interest. Using the generated DKG surrogate of the Speed Made Good, this process can be carried out efficiently. This will allow quicker generation of the stochastic mobility map without requiring to use HPC. For a prototype demonstration of the developed framework, Monterey, California is selected as the region of interest. For the complex terramechanics model, NATC Wheeled Vehicle Platform is used. It is found that the deterministic map appears to have probability of approximately only 25% to achieve the indicated speed. This demonstrates the need for taking into account the variability so that accurate Speed Made Good maps can be generated and have a given reliability or confidence associated with them, in order to provide reliable information to the decision maker.

The variability information of the terrain and soil parameters was discussed and it was found that currently there is a gap in the available information for the soil parameters. It was also noted how there is little to no variability information available for the soil properties and that more information is required in order to generate accurate reliability-based stochastic mobility maps. This is one of the bigger gaps that needs to be addressed near future. There are additional gaps with the raster data and terramechanics simulation model that were discussed as well.

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