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Sensitivity of inland decay of North Atlantic tropical cyclones to soil parameters

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Abstract Using the HURDAT best track analysis of track and intensity of tropical cyclones that made landfall over the continental United States during the satellite era (1980–2005), we analyze the role of land surface variables on the cyclone decay process. The land surface variables considered in the present study included soil parameters (soil heat capacity and its surrogate soil bulk density), roughness, topography and local gradients of topography. The sensitivity analysis was carried out using a data-adaptive genetic algorithm approach that automatically selects the most suitable variables by fitting optimum empirical functions that estimates cyclone intensity decay in terms of given observed variables. Analysis indicates that soil bulk density (soil heat capacity) has a dominant influence on cyclone decay process. The decayed inland cyclone intensities were found to be positively correlated with the cube of the soil bulk density (heat capacity). The impact of the changes in soil bulk density (heat capacity) on the decayed cyclone intensity is higher for higher intensity cyclones. Since soil bulk density is closely related to the soil heat capacity and inversely proportional to the thermal diffusivity, the observed relationship can also be viewed as the influence of cooling rate of the land surface, as well as the transfer of heat and moisture underneath a land-falling storm. The optimized prediction function obtained by statistical model processes in the present study that predicts inland intensity changes during 6-h interval showed high fitness index and small errors. The performance of the prediction function was tested on inland tracks of eighteen hurricanes and tropical storms that made landfall over the United States between 2001 and 2010. The mean error of intensity prediction for these cyclones varied from 1.3 to

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15.8 knots (0.67–8.12 m s^{-1}). Results from the data-driven analysis thus indicate that soil heat flux feedback should be an important consideration for the inland decay of tropical cyclones. Experiments were also undertaken using Weather Research Forecasting (WRF) Advanced Research Version (ARW ver 3.3) to assess the sensitivity of the soil parameters (roughness, heat capacity and bulk density) on the post-landfall structure of select storms. The model was run with 1-km grid spacing, limited area single domain with boundary conditions from the North American Regional Reanalysis. Of different experiments, only the surface roughness change and soil bulk density (heat capacity) change experiments showed some sensitivity to the intensity change. The WRF results thus have a low sensitivity to the land parameters (with only the roughness length showing some impact). This calls for reassessing the land surface response on post-landfall characteristics with more detailed land surface representation within the mesoscale and hurricane modeling systems.

Keywords Tropical cyclone · Land-falling cyclones · Hurricane intensity · Land surface feedback · Soil heat flux · Inland decay

1 Introduction

Cyclones rely on continuous supply of heat and moisture from the surface (in most cases, the ocean surface) for their maintenance and intensification. Warm tropical ocean water enables transfer of heat and moisture to the colder atmosphere aloft. Emanuel (1986) showed a strong relationship between sea surface temperature and the atmosphere and noted that the cyclones would not dissipate if energy fluxes from the surface to the atmosphere are maintained. Over the warm tropical oceans, the convergence of low-level winds toward the center of the cyclone leads to the transfer of energy toward cyclone eye walls resulting in deep convection. This deep convection in turn leads to the condensation and release of enormous amounts of latent heat in the upper atmosphere, resulting in warming of the eye, lowering of central pressure, increase in low-level winds and a further increase in low-level energy transport toward the center (Emanuel 1991).

Over the ocean surface, the above positive feedback loop is limited mainly by cooling of the sea surface and frictional dissipation of energy due to strong winds. Tropical systems weaken rapidly after landfall due to the lack of surface moisture fluxes (Kaplan and DeMaria 1995; Emanuel 2000). Heterogeneities in the landscape features (e.g., in soil moisture, surface roughness, albedo, vegetated land cover) can create mesoscale boundaries that can impact regional circulation, convection and precipitation (Pielke 2001; Pielke and Niyogi 2011). Recent modeling work by Emanuel et al. (2008) over Australia and Chang et al. (2009) over India suggests that the antecedent land surface conditions can alter the post-landfall storm structure because of the heat and moisture source provided from the wet, warm landmasses. Suppression of potential evaporation and associated reduction in the surface temperature is believed to be the main mechanism for the decay of tropical cyclones after landfall (Tuleya 1994).

1.1 Inland decay models

Several models have been proposed to predict the weakening of the cyclone energy and structure after its landfall. Kaplan and DeMaria (1995, referred as KM-95 here onwards) developed a simple empirical model to predict the post-landfall maximum 1-min sustained winds (MSW). The KM-95 model uses the predictors such as initial MSW (just prior to the landfall), distance traveled inland, time duration after landfall and the angle of cyclone track with the land boundary at the time of landfall. These statistical models have been found to be useful predictors across different geographical domains. For example, refined versions of the KM-95 model were developed for storms making landfall in the New England region by Kaplan and DeMaria (2001) and over the narrow landmasses (i.e., islands smaller than the size of a typical storm such as Puerto Rico, Jamaica and western Cuba) by DeMaria et al. (2006). Vickery and Twisdale (1995) developed another model in which the cyclones decay as an exponential function of time. Bhowmik et al. (2005) identified decay coefficients for the Indian Ocean cyclones. Vickery (2005) introduced a concept of "filling rate" to formulate the storm decay process in terms of initial intensity, storm size and translation speed of the storm at the time of landfall. Recently, Colette et al. (2010) used a number of simulated synthetic storms using a mesoscale model to define the optimum shape of the decay process as a function of time and additional predictors such as the fractional area of storm over both ocean and rough terrain a few hours after storm makes landfall. These decay models are simple but useful tools for predicting the time duration for which a cyclone is potentially hazardous post-landfall and also for the estimation of the inland damage.

It can be hypothesized that the skill of the inland decay models can be enhanced by considering land surface feedbacks into the formulation. There are several significant yet unresolved issues regarding the role of land surface processes on the decay of land-falling cyclones. Some examples are the channeling effects of topographic features e.g., mountains and hills on cyclone winds, effects of surface roughness and pre-existing soil wetness on eye wall break down during the initial few hours of landfall, the impact of inland land cover characteristics and from the modeling perspective, the need for the degree of land surface complexity in representing the pre- and post-landfall evolution of the storm characteristics.

Tuleya (1994) performed a series of numerical experiment and noted that even when the land evaporation rates were prescribed as the potential evaporation rates, the cyclone decayed rapidly. His study further concluded that the thermal property of the land surface (i.e., the combined effect of soil heat capacity and conductivity) can have a dramatic impact on the post-landfall evolution of the cyclone. Soil heat capacity and conductivity are the key factors that determine the temperature of the surface beneath the storm and the variation of temperature due to radiation and evaporation. Yet, an observational or data-driven analysis has not been reported on this issue of the role of soil properties on the post-landfall storm evolution and is the basis of this study.

1.2 Study objective and outline

In this study, we focus on assessing the sensitivity of quasi-static land parameters like soil conductivity and soil density on the post-landfall decay of tropical cyclones over the Atlantic basin. The study is based on the best track analysis of North Atlantic cyclones from HURDAT (Hurricane Dataset) during satellite era (1980–2005) and observed soil parameters over the continental United States. The sensitivity analysis was carried out statistically using a data-adaptive genetic algorithm (GA) approach. The GA-based empirical models for the post-landfall cyclone winds are formed by automated selection of the most appropriate predictors from a given set of variables. The nature of the dependency of decayed winds on each predictor was studied by analyzing the statistical dependencies obtained as output from the data-adaptive algorithms. The details regarding the data and methods are presented in the following section. Study results are analyzed in Sect. 3, and verification studies are presented in Sect. 4. The results from the statistical analysis are also used to test the ability of the Weather Research Forecast (WRF–ARW) model to simulate post-landfall feedbacks. This is also briefly discussed using a case study-based approach in Sect. 4. It is to be noted that the objective of the present work is not to develop a post-landfall decay model for storm intensity but to assess to what extent land surface parameters affect the storm intensity after landfall.

2 Data and methodology

2.1 The genetic algorithms

Genetic algorithms (GA) and its subset Genetic Programming are examples of machine learning. Studies such as Szpiro (1997) have shown the robustness of machine learning approaches such as GA to forecast the behavior of chaotic dynamical system. Alvarez et al. (2000) adopted GA technique for modeling real physical systems such as the prediction of space–time variability of the sea surface temperatures (SSTs) in the Alboran Sea. Kishtawal et al. (2003) developed a GA-based technique to predict the summer rainfall over India. More recently, Niyogi et al. (2010) applied GA approach to map and analyze the rainfall trends over the Indian monsoon region. Building off these studies, we have chosen to use GA to assess the parametric sensitivity of soil parameters to post-landfall cyclone intensity change. This is because (1) GA can detect solutions for a highly complex and non-linear process involving large number of parameters and (2) GA can automatically build an optimum set of predictors from a given pool of available input variables without a priori assumptions.

Accordingly, a genetic algorithm is programmed to approximate the equation, in symbolic form, that best describes the relationship between independent and dependent parameters. For a given training data set, a population of possible solutions is generated randomly and each solution is tested against a fitness function. Solutions that score best on the fitness function can "breed" (i.e., get higher weight in modifying the fits and would be considered equivalent of cloning, mutating or recombining the future data fits) creating the population for the next generation. This process continues until predetermined number of generations has been evolved. At that point, the solution with the best score on the fitness function in the final generation would be determined the best solution.

Thus, the solution seeks to identify a smooth mapping function $P(.)$ that explains the relationship between a desired variable "x" and a set of dependent variables $[a, b, c, d, e, \ldots]$, such that

$$x = P[a, b, c, d, e, \ldots] \tag{1}$$

First, for an amplitude function x, a set of candidate equations for $P(.)$ is randomly generated. An equation is stored as a set of characters that define the independent variables, a, b, c, d, e,… etc. in Eq. 1, and four elementary arithmetic operators ($+$, $-$, $\times$, and/). A criterion that measures how well the equation strings perform on a training set of the data is its fitness to the data, defined as sum of the squared differences between data and independent parameter derived from the equation string. The strongest individuals (equations with best fits) are then selected to exchange parts of the character strings between them (reproduction and crossover) while individuals (variable functional forms) less fitted to the data are discarded. Finally, a small percentage of the equation strings' most basic elements, single operators and variables are mutated (modified) at random. The process is repeated a large number of times to improve the fitness of the evolving population of equations. The fitness strength of the best scoring equation is defined as:

$$R^2 = 1 - \left[\Delta^2 / \sum (x_o - \langle x_o \rangle^2\right] \tag{2}$$

where $\Delta^2 = \sum (x_c - x_o)^2$, x_c is parameter value estimated by the best scoring equation, x_o is the corresponding "true" value and $\langle x_o \rangle$ is the mean of the "true" values of x.

2.2 HURDAT data

We analyzed the maximum winds and storm position available from the Hurricane Database (HURDAT) available from the NOAA's National Hurricane Center (NHC http://www.nhc.noaa.gov/pastall.shtml#hurdat). HURDAT data are archived every 6 h (at 0Z, 6Z, 12Z and 18Z) and include reports on storm position and maximum winds from 1851 to 2008[1] (Jarvinen et al. 1984; Landsea et al. 2004). There is a noticeable change in the characteristics of observed and recorded cyclones before and after the advent of satellites (Chang and Guo 2007). We, therefore, consider storms that occurred during the satellite era (1980 onwards) to ensure the uniformity of biases in the observed intensity values in HURDAT data set. The study objective is to assess the impact of surface characteristic on post-landfall decay, and only the storms that made landfall over the continental United States are considered. Additionally, the analysis did not consider the storms that decayed within 6 h of making landfall or the storms that made landfall more than once after re-entering the ocean after first landfall. Besides the land surface effects, extratropical transition is known to significantly impact the cyclone intensity after landfall (Hart and Evans 2000). Therefore, to limit the extratropical interactions and focus on the feedback of land surface processes, we confined the analysis south of 35°N.

2.3 Land surface data

The soil data were obtained from the Oak Ridge National Laboratory—Distributed Active Archive Center (ORNL-DAAC). The "Global Gridded Surfaces of Selected Soil Characteristics (IGBP-DIS)" data available at 5 arc-minute spatial resolution were used (Global Soil Data Task Group 2000). The soil data fields are comprised of seven parameters as follows: total nitrogen, the soil carbon density, soil field capacity, thermal capacity, wilting point, available water capacity profile and bulk density. In this data set, the bulk density provides a good proxy for soil heat capacity, which is more intuitively linked to the surface atmospheric feedbacks in meteorological literature (Fig. 1a, b; also see McNider et al. 2005).

The land-use data were obtained from U.S. Geological Survey (USGS) National Mapping Division's EROS data center and the Land Cover Institute. Default values of seasonally varying roughness lengths were used according to land-use category and time of the observation. Surface topography fields (and their gradients) were obtained from the 2.5 arc-minute gridded topography data for continental United States, prepared by PRISM data group at Oregon State University (Daly et al. 1994). The land-use data were also used as a land–sea mask for delineating the landfall for a given cyclone track in HURDAT data set.

[1] The HURDAT data are routinely updated, and the period 1851–2008 only refers to the data availability corresponding to the time the analysis reported in this paper was initiated.

2.4 Analysis

The mechanisms by which cyclone intensity changes within first 6 h after making landfall are still not well understood (Marks et al. 1998). During this time interval, winds, pressure and cyclone structure undergo dramatic changes due to complex processes like wind shear, land–atmosphere interaction, existence of mesovortices, break down of eye wall and turbulence associated with all the above processes. However, the scope of this study is limited to analysis of the sensitivity of land surface parameters to cyclone decay process. The land surface predictors are soil thermal capacity, soil bulk density, roughness length and terrain height. In addition to land surface parameters, a number of possible predictors like inland distance traveled by cyclone, time since landfall and local time of storm positions were also considered. All these predictors were provided to GA-based program during the "training" period comprising from 1980 to 1996. The GA procedure automatically selected the most appropriate predictors by fitting the best possible empirical model that predicts the decayed cyclone intensity during next 6 h in terms of the chosen predictors. The period from 1997 to 2000 was used for testing the fitness of the model. The performance of the model was then validated for the land-falling cyclones on the independent validation data set comprising from 2001 to 2010. The performance of GA-based model was validated by comparing predicted intensity values with observations as well as with those predicted by KM-95 model, for eighteen major North Atlantic hurricanes and tropical storms during the test period (2001–2010).

2.5 GA implementation

Table 1 shows the list of possible predictors for cyclone intensity decay (represented by maximum sustained wind or MSW) adopted within GA process. Prior studies (e.g., Kaplan and DeMaria 1995; Vickery and Twisdale 1995) have identified that the cyclone intensity decays as an exponential function of time and/or distance. In order to retain the exponential nature of the decay in predictive equations, we used logarithms of MSW (for the predictor as well as the predictand) for fitting the optimized functions through GA process. The resolution of soil parameters was $\sim$4 km, while that of land use, roughness length, topography and topography gradients was $\sim$8 km. The point from where the 6-h prediction of intensity is to be made is termed as "departure point," while the cyclone's position after 6 h is termed as "arrival point." The value of all land surface predictors at any point is computed by taking its average over 100 $\times$ 100 km around that point.

Table 1 List of possible predictors considered for prediction of intensity decay over land during 6-h time

No.	Definition	Sampling type
1	Initial intensity	None
2	Distance traveled during next 6 h (km)	None
3	Time since landfall (h)	None
4	Roughness length (defined by land-use type)	Mean of 100 km $\times$ 100 km
5	Terrain height (m)	Maximum of 100 km $\times$ 100 km
6	Local gradient of terrain height (m)	Maximum of 100 km $\times$ 100 km
7	Soil heat capacity	Mean of 100 km $\times$ 100 km
8	Soil bulk density	Mean of 100 km $\times$ 100 km

Experiments were carried out by defining the land surface predictors and intensities at the "departure points" and decay intensities at the "arrival points." Thus, there were several sets of dependent and independent variables that were used for building the functional relationships between storm intensity and land parameters using GA approach. One set consisted of the following parameters:

$$\text{Data set} = \{\log(V_{\mathrm{d}}), \log(V_{\mathrm{o}}), D_6, D_{\mathrm{L}}, T_{\mathrm{L}}, S_{\mathrm{c}}, S_{\mathrm{d}}, z, h, \Delta h, \mathrm{LT}\} \tag{3}$$

where V_{d} the decay intensity at the "arrival point" is the dependent variable, V_{o} is the intensity at "departure point," D_6 is distance covered during 6-h period between "departure" and "arrival" points, D_{L} and T_{L} are, respectively, the inland distance and time since landfall, S_{c}, S_{d}, z, h, Δh and LT, respectively, denote soil thermal capacity, soil bulk density, roughness length, mean terrain height, terrain height gradient and local time at the "departure points." Terrain height gradient is the maximum value of bidirectional gradient of terrain height within 100×100 km area surrounding a location. Even though several predictors were considered, GA process selects only the most suitable parameters for final solution.

For the 1980–2005 period, a total of 360 sets were available from HURDAT database for which both initial and 6-h future positions of cyclones lay over the land surface. For the training period (1980–1996), nearly 200 such sets were available.

The GA process was initialized with 300 random solutions. Each empirical equation was allowed to hold maximum of 16 terms, which included independent variables, coefficients and arithmetic operators. Probability of mutation was set at 0.1. The GA process normally converges to the optimum solution within 2,000 iterations, and in the present study, we terminated the processes after 10,000 iterations. The outcome of GA process is the empirical equation with numerical values of fitness to training and test data sets.

It is to be noted that all independent as well as dependent variables are analysis fields or blended observations and contain noise of random and unknown magnitudes. Also, the relationship between cyclone decay process and land surface parameters is expected to vary with the prevailing atmospheric conditions like the presence of continental trough and magnitude of wind shear. Due to these uncertainties, a change in GA parameters or the length of training data set might result in a change in the form of empirical model obtained at the end of GA process. Analysis of the ensemble of sufficiently large number of simulations is one of the methods to overcome the uncertainty to some extent. To ascertain the most optimum predictors for the cyclone decay process, we perturbed various GA control parameters (e.g., size of initial random population of functions, length of equation and size of training data set) randomly by maximum variation of 20%. One hundred such simulations were performed by GA, and 100 different empirical functions were obtained.

3 Results

3.1 Models and significant parameters

The analysis of GA equations revealed that initial MSW (maximum sustained winds) was selected by all resulting functions as predictor. The identification of MSW is intuitive and consistent with different intensity models (e.g., KM-95). Interestingly, in addition to MSW, the soil bulk density was also selected as a potential predictor maximum a number of times (70%). About 54% functions contained both soil bulk density and soil thermal capacity.

22% solutions contained local gradients of topography, while roughness length and topography appeared in less than 10% of the solutions. Interestingly, the inland distance covered during the 6-h period was not identified by GA models in its list of predictors, despite a large variation in the speed of cyclones over the land surface.

Table 2 shows four best equations fitted by GA process. The most optimum model was selected on the basis of best fitness score using both training as well as the test data sets. The form of the equation for the intensity during next 6-h decay was of the form:

$$\ln(V_{\mathrm{d}}) = \ln(V_{\mathrm{o}}) + S_{\mathrm{d}}^{3}/(25.5/(3.39 - \ln(V_{\mathrm{o}}))) \tag{4}$$

where V_{o} is the initial intensity, V_{d} is the decayed intensity after 6-h time and S_{d} is the soil bulk density (kg/m^3). Both V_{o} and V_{d} in the above equation are measured in km/h (a factor of 0.5395 needs to be multiplied for conversion to standard units of knots). As stated earlier, the exponential nature of inland decay is implicitly accounted for by forming the equation in logarithm form. After developing Eq. 4, we computed the residual errors (observed minus predicted intensities) using only training data. We then fitted, using GA with same configuration as used earlier, the residual errors in terms of predictors other than soil parameters, already considered by Eq. 4. The best GA solution showed dependency of residual errors on "topography gradients" and led to an equation for "topography corrected decayed intensities" as:

$$\ln(V_{\mathrm{d}})^{\mathrm{corrected}} = \ln(V_{\mathrm{d}}) - \ln(V_{\mathrm{d}})/(1988.2/(\Delta h + 1.0) + 197.2) \tag{5}$$

where uncorrected $\ln(V_{\mathrm{d}})$ on the right-hand side of Eq. 5 is provided by Eq. 4 and Δh is the local maxima in the 1° neighborhood of bidirectional gradient of topography computed using 2.5 arc-minute gridded topography data.

3.2 Discussions

It is interesting to note that the best empirical model shows the dependency largely on the initial intensity and soil properties, while topography gradients add minor corrective value to the predictions. Note that within the soil data set, the soil thermal bulk density is highly

Table 2 Four best equations fitted by GA model for decayed intensities (rank 1 indicates the best equation)

Rank	GA-fitted equation (without residual correction) d = Inland distance after landfall (km)/500 T_{g} = log(mean terrain gradient) + 1.0 S_{d} = Soil bulk density S_{c} = Soil heat capacity	Fitness score (training data)	Fitness score (test data)	MAE (training data) kt	MAE (test data) kt
1	$\ln(V_{\mathrm{d}}) = \ln(V_{\mathrm{o}}) + S_{\mathrm{d}}^{3}/(25.5/(3.39 - \ln(V_{\mathrm{o}}))$	0.89	0.91	2.51	2.40
2	$\ln(V_{\mathrm{d}}) = \ln(V_{\mathrm{o}}) - S_{\mathrm{d}}*S_{\mathrm{c}}*T_{\mathrm{g}}/(38.26/(\ln(V_{\mathrm{o}}) - 3.37))$	0.88	0.84	2.54	2.62
3	$\ln(V_{\mathrm{d}}) = \ln(V_{\mathrm{o}}) - S_{\mathrm{d}}/(d + (8.06/(\ln(V_{\mathrm{o}}) - 3.29)))$	0.86	0.85	2.59	2.60
4	$\ln(V_{\mathrm{d}}) = \ln(V_{\mathrm{o}}) + S_{\mathrm{d}}*S_{\mathrm{d}}/((-51.18/T_{\mathrm{g}})/((\ln(V_{\mathrm{o}}) + (116.01/(d - 35.59))))$	0.85	0.84	2.59	2.62

correlated ($r^2 = 0.9999$) with the soil thermal capacity, and therefore, the soil bulk density is truly representative of soil heat capacity and vice versa. This dependence of soil bulk density and heat capacity is expected and can be explained as follows (PSC Suresh Rao, Purdue University, personal communication, 2011). Soils are heterogeneous mixtures of minerals (sand-quartz, silt and clays) and organic matter. The heat capacity and density of such a mixture will depend on weighted average of the component properties.

The training data consisted of 200 data sets, where the decayed intensities ranged from 11 to 86 kt. The mean absolute error (MAE) of Eq. 5 was 2.55 kt for the training data set and 2.40 kt for the validation data set comprising of 155 data points. The function showed high degree of fitness for training ($r^2 = 0.893$) and validation ($r^2 = 0.916$) data sets (Fig. 2).

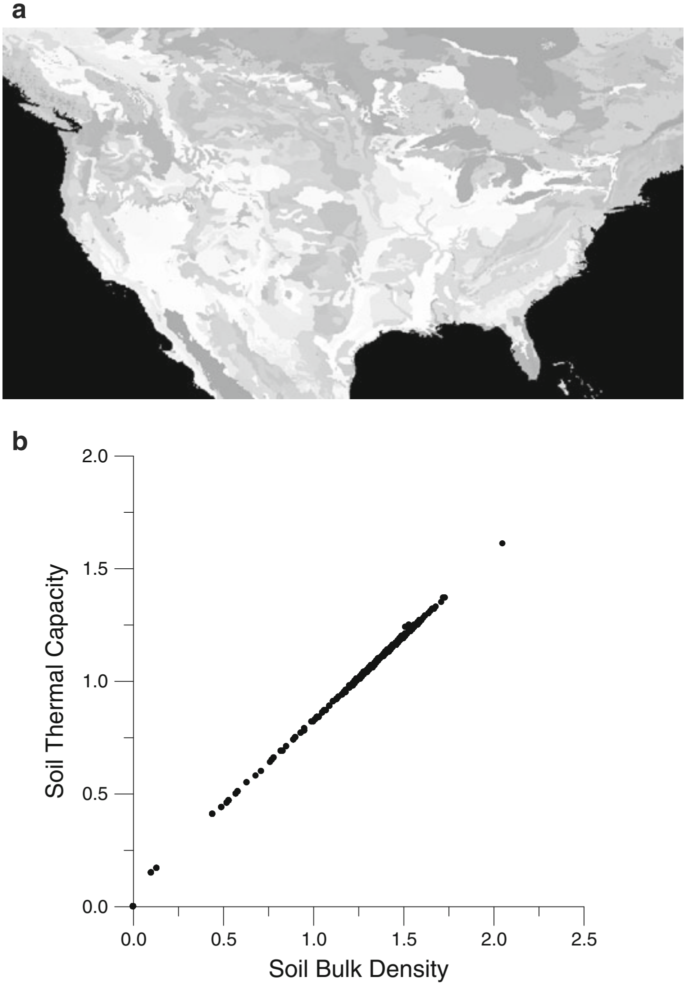
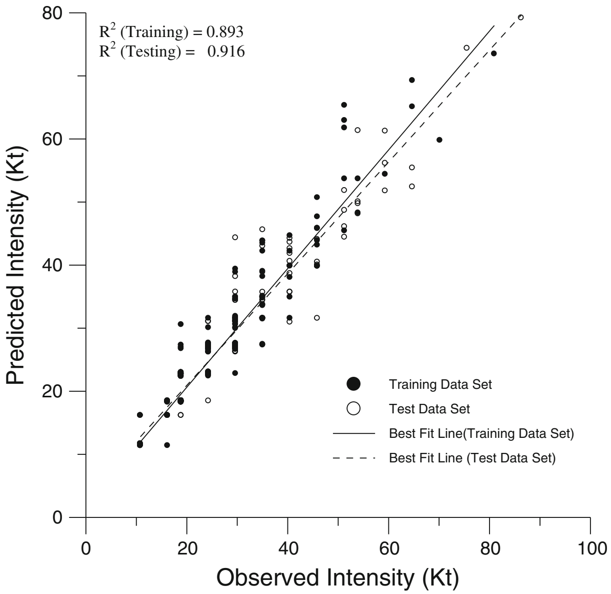


Fig. 1 (**a**) The variation of soil bulk density over the continental United States. *Brighter shades* indicate higher values. Due to high correlation between soil bulk density and soil heat capacity (**b**), similar variations can be expected for soil heat capacity

The dependency of decayed intensity on initial intensity is obvious and has been used extensively in earlier decay models (Kaplan and DeMaria 1995; Vickery and Twisdale 1995). It is, therefore, interesting to analyze the sensitivity of cyclone decay process on the soil parameters, e.g., the bulk density (heat capacity) that appears in the most optimum function determined by GA process. Over the spatial domain considered in the present study, the soil density varied from 1.09 to 1.72. Figure 3 shows the decayed intensities after 6-h time for varying values of initial intensities. It is interesting to note that the impact of soil bulk density should be considered as a surrogate for heat capacity and resulting ground heat flux changes and leads to an increase in the intensity of cyclones. For Category-5 hurricanes, a 30% change in soil density can cause more than 20% change in the decay in the intensity. The role of soil parameters in cyclone decay processes thus appears to be significant and worth considering in development of future assessments for improved prediction of cyclone decay over the land surfaces.

It is indeed worthwhile to explore the possible mechanism by which soil properties might affect the intensity of tropical storms over the land surfaces. The rapid decay of tropical cyclones over the land surfaces is primarily due to reduction in evaporation caused by the reduction in surface land temperature near the storm core (Tuleya 1994). On the other hand, some land-falling storms have been reported to re-intensify while passing over regions of heterogeneous wetness and hot sandy surfaces (e.g., Kehoe et al. 2010). Emanuel et al. (2008) hypothesized that the re-intensification of these storms is made possible by large vertical heat fluxes from deep layers of very hot sandy surfaces that has been wetted by the first rains of the approaching systems, which significantly increase the thermal diffusivity of the sandy surfaces. In case of normal, decaying inland storms, it can be argued that higher (lower) thermal diffusivity of soil can result in higher (lower) amounts of heat (and moisture in case of wetting by storm rain) transfer from subsoil surfaces to the atmosphere and can thus lead to reduced (enhanced) rate of decay. Our decay Eq. 4 shows a strong dependency of inland intensity on soil bulk density, which is highly correlated with soil thermal capacity (Fig. 2b). Thus, Fig. 3 shows a rapid decrease

Fig. 2 A comparison of observed and predicted decayed intensity of cyclones using the most optimized relationship denoted by Eq. 4 for Training data set (*solid circles*) and Test data set (*open circles*)



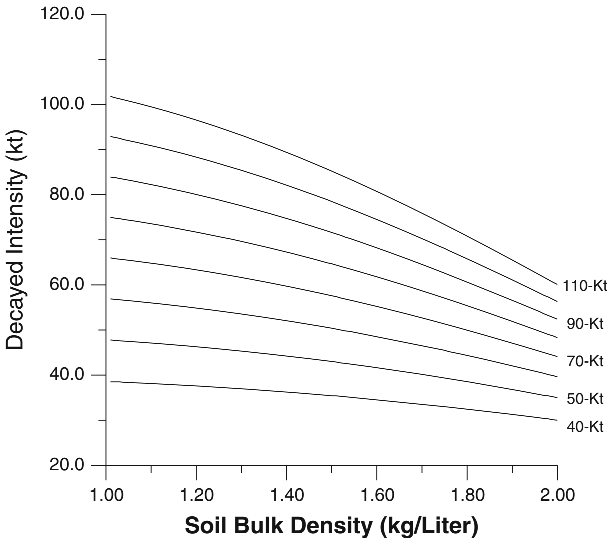


Fig. 3 Sensitivity of predicted decayed intensity for variation in soil density for different values of initial intensity, shown at the end of each curve

in decayed intensity for a storm with initial maximum sustained wind of 80 kt with increasing soil bulk density (heat capacity) during 6-h period over a flat terrain, as predicted by Eq. 4. Since soil bulk density can be considered a proxy of soil thermal capacity and is inversely proportional to the soil thermal diffusivity if thermal conductivity is assumed constant, the variations depicted in Fig. 3 denote the reduction in storm intensity decay rates with higher thermal diffusivity. There is an enhancement of thermal diffusivity with the wetting of soil due to initial rains from storm (Al Nakshabandi and Kohnke 1965; Emanuel et al. 2008). Note that this again relates to the codependence of soil bulk density and heat capacity, as availability of water can modify the effective density, mineralogy, organic matter content and hence the heat capacity. This enhanced thermal diffusivity may be expected to maintain the heat/moisture transfer from land to atmosphere and thus reduce the decay rates. The nature of Eq. 4 can be a possible representation of the above mechanism.

3.3 Does the soil-based decay model have a predictive skill?

We applied GA-derived decay model with explicit soil characteristic consideration for the prediction of inland cyclone intensity for eighteen hurricanes and tropical storms that made landfall over the continental United States. Although the decay function denoted by Eq. 5 is valid for 6-h decay, we used only the first observation of inland intensity from HURDAT data, and remaining intensities were predicted using the intensities predicted for the previous segments as input initial intensities. We also computed the decay of these storms using the prediction model reported by KM-95.

Table 3 shows the results of the predicted decayed intensities for these cases from the present model and the KM-95 model. The evolution of predicted decayed intensities and their comparison with observed intensity changes for four cases is shown in Fig. 4. The mean absolute errors for 18 test cases for 6-, 12-, 18- and 24-h prediction were 6.3, 7.3, 6.6 and 6.8 kt, respectively. It is to be noted that even if the 6-h prediction error of best-fit equation was $\sim$2.5 kt, it is the propagation of initial errors (just at the time of landfall) that

Table 3 Mean absolute error (MAE) of predicted decayed inland intensities for major Atlantic hurricanes and tropical storms (2001–2010)

Cyclone number	Name	Date of landfall	MAE (KM-95) (kt)	MAE (present method) (kt)
1	Barry	06-Aug-2001	6.8	6.4
2	Isidore	26-Sept-2002	8.9	5.2
3	Bill	30-June-2003	7.2	3.9
4	Lili	03-Oct-2003	7.0	4.4
5	Frances	05-Sept-2004	6.2	3.8
6	Jeanne	26-Sept-2004	17.0	15.8
7	Arlene	11-June-2005	4.9	1.9
8	Cindy	06-July-2005	5.3	3.5
9	Dennis	10-July-2005	3.0	2.5
10	Katrina	29-Aug-2005	8.0	2.7
11	Rita	24-Sept-2005	4.9	1.3
12	Alberto	13-June-2006	9.0	7.7
13	Humberto	13-Sep-2007	**6.6**	11.8
14	Gustav	01-Sept-2008	7.9	7.8
15	Ike	13-Sept-2008	**7.1**	8.0
16	Edouard	05-Aug-2008	**5.5**	7.9
17	Alex	01-July-2010	9.9	6.4
18	Hermine	07-Sept-2010	9.3	7.8
Mean of 18 samples			7.5	6.3

MAE are mean for entire inland tracks regardless of the prediction lead time. KM-95 errors are denoted in boldface if they are smaller than the errors from present model

led to errors exceeding 6 kt. The errors for inland intensity predictions remain almost stable with time. For example, the MAE for 42- and 48-h predictions was found to be 6.1 and 6.4 kt. Relatively, larger errors of prediction in case of some cyclones (e.g., Jeanne, Humberto and Ike) are mostly contributed by the errors in the first step of prediction, which then propagated to subsequent steps.

As mentioned earlier, the prediction of cyclone decay during first 6–12 h of landfall is known to be a complex process, and its complete analysis is beyond the scope of the present study. However, the results indicate that the soil feedback can be an important modulator of the post-landfall intensity change and deserves further investigation.

Using numerical simulations of land-falling storms, Tuleya (1994) concluded that surface roughness and albedo do not significantly affect land-falling storm intensity if the surface temperatures remain artificially high for potentially wet conditions. Reduced heat capacity and conductivity of soil were considered to be the prime factors responsible for diminished evaporation and minimization of equivalent potential temperature just above the land surface, a situation opposite to what is expected over the ocean surface. Model analyses reported by Chang et al. (2009) also suggest that warm, wet soils can lead to potential for increased post-landfall intensity. Our sensitivity analysis also indicates that the soil bulk density, and therefore soil heat capacity, plays an important role in storm decay processes. Tuleya (1994) also noticed that due to cloud canopy the net downward radiation is reduced during the day time and enhances during the night time, thus resulting

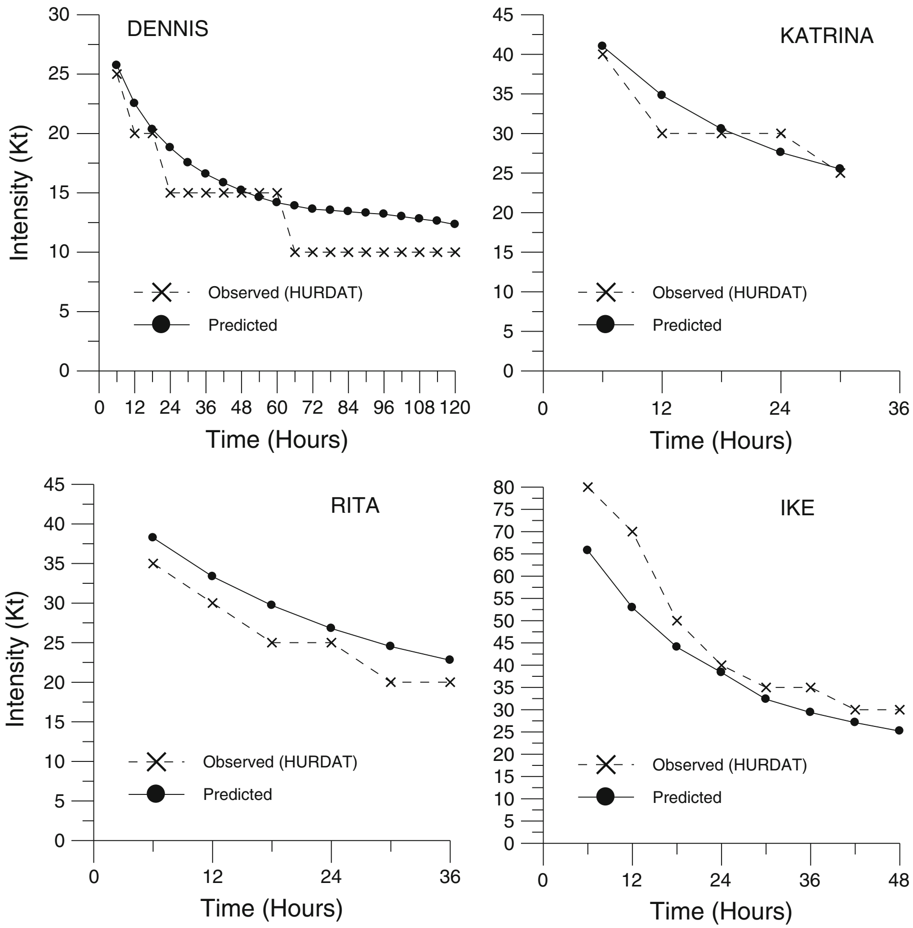


Fig. 4 Prediction of intensity change for four major North Atlantic hurricanes using Eq. 4

in a large size of land surface "cool-pool" during the day time. Our analysis did not find compelling evidence in favor of this diurnal pattern and could be an artifact of the limited size of the sample under study.

3.4 WRF simulations

We sought to assess whether the soil sensitivity noted in the data-driven GA approach is also found within the Weather Research Forecast (WRF) model simulations. Experiments were conducted using Advanced Research WRF ver 3.3 (ARW). The model setup consisted of single domain with 1-km horizontal resolution and 35 vertical layers, with the initial and boundary conditions prescribed using the North America Regional Reanalysis (NARR) available at 32-km resolution spatially and every 3 h temporally. The physics options chosen include the following: (a) WRF single-moment (WSM) 6-class microphysics scheme (Hong and Lim 2006) with explicit graupel, ice and snow and is suitable for high-resolution model study, (b) Noah land surface model with prognostic soil moisture

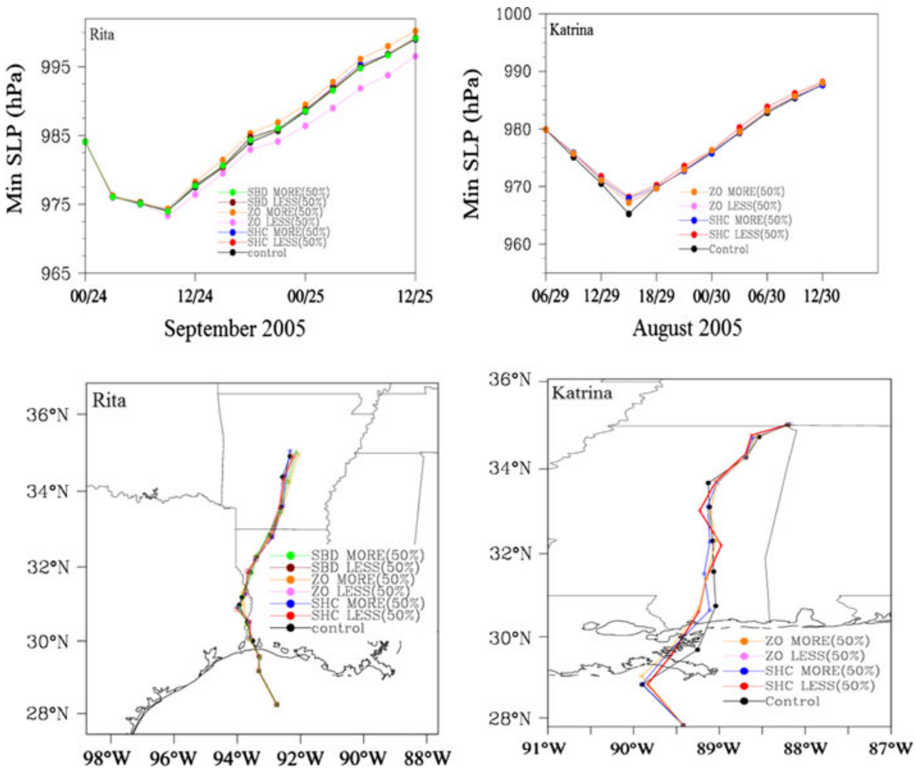


Fig. 5 Example of track and intensity sensitivity to soil bulk density (SBD), soil heat capacity (SHC) and roughness (ZO) changes for Hurricane Rita and Katrina

and soil temperature, (c) Yonsei University scheme (YSU) Planetary Boundary Layer (PBL) physics, which is non-local-K scheme with explicit entrainment layer in unstable mixed layer and (d) Rapid Radiative Transfer Model (RRTM) for longwave radiation based on Mlawer et al. (1997) and shortwave radiation following Dudhia (1989). A number of model experiments were conducted in which the surface characteristics were altered by ±50% of the control value, and the resulting impact on the model track and intensity was analyzed.[2]

Overall, the model results showed limited impact but the experiments with the changes in soil heat capacity, soil bulk density and roughness length showed some modest sensitivity. Results for hurricane Katrina and Rita are shown in Fig. 5 as an example for model simulations conducted from 0000 UTC 29 to 1200 UTC 30 August 2005 and 0000 UTC 24 to 1200 UTC 25 September 2005, respectively. These time windows were chosen to begin approximately 6 h before landfall and approximately 12 h past the storm weakening to a tropical storm classification for both cases. This resulted in a 30-h simulation for Katrina and a 36-h simulation for Rita respectfully. Interestingly, the model shows a limited sensitivity to either the track or intensity of the storm changes, as compared to the

[2] The surface variables were altered using the following methods: (a) the soil bulk density variable involved changing the GAMMD constant in the module_sf_noahlsm.F module, (b) the soil hat capacity was changed with the CSOIL_DATA variable in the GENPARM.TBL table, (c) the soil roughness length was altered through the Z0MIN and Z0MAX values in the VEGPARM.TBL table.

observational analysis. Consistent with Tuleya (1994), the most significant impact on intensity was due to roughness change, followed by a second-order effect of heat capacity change. This mismatch between the observed and the modeled sensitivity highlights the need for improving the land feedbacks within the mesoscale modeling framework to realistically assess the post-landfall transition and intensity prediction.

4 Conclusions

Using the track and intensity observations of tropical cyclones that made landfall over the continental United States during the satellite era (1980-2005), we analyzed the role of land surface variables on the cyclone decay process. A number of potential land surface variables were considered in the present study, which included soil parameters, roughness scales, topography and local gradients of topography. The sensitivity analysis was carried out using a data-adaptive genetic algorithm (GA) approach, which automatically selects the most suitable variable from a given list, by fitting optimum empirical functions that predict decayed cyclone intensity in terms of given variables. We restricted the size of resulting empirical functions in GA process to avoid the over-fitting of data by these functions and also to obtain the most simplistic functions. A number of simulations indicate that soil bulk density (which is directly related to soil heat capacity in the soil data set available to use) influences cyclone decay process in a significant manner. The impact of the changes in soil bulk density (heat capacity) on the cyclone decay intensity is higher for higher intensity cyclones. The most optimized prediction function obtained by GA process in the present study that predicts inland intensity changes during 6-h interval showed high fitness index and small errors ($\sim$2.5 kt). The performance of the prediction function was tested on entire inland tracks of 18 major cyclones that made landfall over the United States. The mean error of intensity prediction for these hurricanes varied from 1.84 to 6.87 kt. Numerical experiments with the WRF modeling system show that the coupled models currently have a limited ability to reproduce the land surface sensitivity and additional assessment is critically needed with more detailed analysis to address this issue of land surface feedback on post-landfall intensity change further.

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