Response to Editor Peter Finke
Shepard C., Schaap MG., Pelletier JD., and Rasmussen C.

We thank the editor for his comments and recommendations on the manuscript titled "A probabilistic approach to quantifying soil property change through time integration of mass and energy input." We have responded to and addressed the editor's comments and remarks below and in the revised version of the manuscript.

Response to general remarks:
The model requires the inputs of time and effective energy and mass transfer (EEMT, Rasmussen et al., 2005; Rasmussen and Tabor, 2007; Rasmussen et al., 2011) to predict the probable range of a particular soil physical property at a given location. In this presentation, we focus on clay content as a physical property that reflects pedogenic change. EEMT is clearly rooted in the classical Jenny factorial approach for describing soil forming system, and as such does not describe any particular soil forming process. EEMT is a flux term, and is it not used here to parameterize a mechanistic model of pedogenesis as suggested by the editor. EEMT simply quantifies the energetic contributions from effective precipitation and net primary productivity as quantitative measures of climatic and biological forcing/input to the soil forming system. EEMT quantifies the energy transferred to the soil system that can perform pedogenic work, such as chemical weathering or carbon cycling, or any other soil forming process; it does not describe or quantify any one process, and this is indicated on lines 102-105.

Application of the present approach in the critical zone environment requires no soil information. Here we used an established geomorphically based numerical model that predicts local erosion rates, soil depth and local soil residence time from topography and a maximum rate of soil production (that can be assumed or based on local catchment derived denudation rates) (Pelletier and Rasmussen, 2009). The geomorphic model is mechanistic and process based, describing mass production and transport using established transport "laws". The editor expressed doubt of the ability to predict soil information in the critical zone environment; however, we present clear model results that this approach can be used to predict clay content completely independent of soil data. This is a key piece of soil information to understanding critical zone function and evolution. We further argued that the present approach can greatly inform our understanding of the distributions of soil physical properties and facilitate further hypothesis generation. For example, the present approach did not accurately predict clay stocks at specific locations within the Santa Catalina Mountains-Jemez River Basin granite sub-catchment (Lines 329-339); any number of hypotheses and questions can be formulated and tested as to why the model failed to predict clay stocks at these locations, and the current model formulation can be updated to accommodate these findings. Further, the present results suggest an incomplete understanding of the soil-landscapes within these catchments, which may not have been found by using techniques such as digital soil mapping.

The strength of the current approach lies in the ability of the model to capture all soil forming factors into one relatively simple mathematical apparatus. We make no claims of modeling particular soil forming processes, a fact that we state clearly in lines 145-149 and in lines 151-152. As true of any factorial treatment of soil systems, the model captures either the net effect of all considered soil forming processes or rather the implicit result of soil forming processes, by considering all soil profiles equally. This is the same foundation for any number of digital soil mapping exercises, as typified by the SCORPAN statement of McBratney and others – the model uses factors to predict soil properties and is not a mechanistic model of process. The model only indirectly captures soil forming processes by not restricting the model to any particular spatial or temporal extent or any particular parent material. We disagree with the editor's comment about the delineation of the model domain. By restricting the model domain, either spatially, temporally, or with regards to parent material, entire suites of soil forming processes would not be captured, limiting the applicability of the present approach.

Response to Question 1. Why is the model forced to a bivariate pdf form? Techniques were on the shelf?

A bivariate normal density distribution was used for the present approach because it generally represents the mathematically simplest bivariate distribution and is easily parameterized. However, we did not consider other bivariate density functions, we wanted to demonstrate proof of concept before exploring complexities or refinements to the approach. We have added language to the revised manuscript at lines 131, indicating that we choose to force the data to a bivariate normal structure and that other density functions are available and may provide a better fit to the soil physical property of interest.

Response to Question 2. Question with regards to quantifying soil age and EEMT.

The editor is correct in that the model assumes EEMT is constant over the duration of pedogenesis. Further, we agree with the reviewer that climate throughout the Quaternary has not been constant (Zachos et al., 2001), and that this inconsistency likely has influenced our predicted soil property values. We directly addressed this model limitation in section 4.3, lines 503-514:

"Furthermore, global climate patterns have shifted dramatically over the last 65 Mya (Zachos et al., 2001). The majority of soils observed in the compiled chronosequence database span the Quaternary, including both the Holocene and Pleistocene. The Pleistocene was marked by a number of major glacial-interglacial cycles at approximately 100,000-year intervals (Imbrie et al., 1992; Wallace and Hobbs, 2006), which corresponded with shifting climatic conditions, e.g., for large portions of the northern mid-latitudes glacial periods were generally cooler and wetter, and interglacial periods were warmer and drier (Connin et al., 1998; Petit et al., 1999). Further, the Pleistocene climate shifts likely influenced the rates of weathering and clay production (Hotchkiss et al., 2000). Taking into account the differences in past and modern climate would likely diminish disparities between observed and modeled soil physical properties. Reconstructed global paleo-EEMT values would improve model accuracy, and limit uncertainty in the probabilistic ranges of soil properties for soils older than Holocene age."

Further, we discussed a possible model correction in which paleo-EEMT values could be calculated and used to provide better estimates of TPE. However, in order to calculate an accurate accounting of paleo-EEMT values would require datasets of about past mean monthly air temperature, mean monthly precipitation and monthly net primary productivity (Rasmussen et al., 2005, 2011; Rasmussen and Tabor, 2007) for the entire duration of pedogenesis.

Unfortunately, few, if any, locations on the planet have spatially explicit paleoclimatic records with all the necessary data requirements to perform this calculation, although paleoclimate predictions are improving, e.g. the recent CIMP4 general circulation model application to predict global LGM climates, which represents an ongoing opportunity to incorporate such data into pedogenic models. As such, we made the simplifying assumption that the current climate can be used to represent of climates that many of the included soils evolved under. This is true of any factorial approach and representation of soil data that includes soils older than the Holocene. Any representation of soil properties relative to mean annual temperature or precipitation or any plot of soil property change vs time invariably includes past climate variation influence of soil property evolution. We clearly stated and recognized this in the text.

Defining soil age is a challenge in many landscapes as the editor suggests; however, there are simple techniques that can be used to estimate soil age without the need for expensive cosmogenic radionuclide dating. The age of geomorphic landforms can be estimated by using the cross-sectional shape of gully cuts or scarp-like surfaces and hillslopes and a known hillslope diffusivity value (Bucknam and Anderson, 1979; Hsu and Pelletier, 2004; Pelletier et al., 2006; Pelletier and Cline, 2007). Estimating geomorphic landform age requires only the use of either a digital elevation model (DEM), or profiles of scarp elevation, both of which are easily and inexpensively attained. Further, relative age dating is widely used in chronosequence studies and provides general estimates and constraints of soil-geomorphic surface ages (Schaetzl and Anderson, 2005). With regards to upland catchments, catchment averaged denudation rates can be estimated from cosmogenic radionuclides (CRN) using a smaller number of samples than would be necessary for quantifying full CRN depth profiles (Granger et al., 1996). Using a geomorphically based model of soil depth, spatially explicit soil ages can be calculated was discussed in lines 220-224. As such, we do not agree with the editor the target variables are more easily determined than soil age; for any chronosequence study, soil age would have to be determined regardless of the target variables of interest, assuming soil age is too expensive or indeterminable is not an appropriate or accurate critique of the presented model.

Response to Question 3. Removal of buried horizons.

Buried horizons were removed from the dataset, as we assumed that these buried horizons were not reflective of the relationship between the modern climate and the subaerial soil horizons. We decided to remove buried horizons, as the subaerial soil horizons likely are more correlated with the current climate, as compared to the buried horizons. Eolian horizons were removed from soils described in McFadden et al. (1986), because these horizons are likely significantly younger than the basaltic flow dates that were used to represent the soil age; however, based on the reviewer's suggestion we have removed these soils from the current dataset and updated lines 194 to reflect this change. Only buried horizon have been removed from the dataset presented in the revised manuscript.

Response to Question 4. Non-linear or transient soil formation.

We specifically addressed non-linear soil formation and internal or intrinsic feedbacks driving soil development in section 4.3, lines 490-502:

“Internal or intrinsic feedbacks and thresholds within the soil system drive pedogenic development without changes in the external state factors (Muhs, 1984; Chadwick and Chorover, 2001). For example, greater chemical weathering and clay production due to increased water residence time caused by argillic horizon development is the result of an internal feedback that is independent of the external climatic and biological system (Schaetzl and Anderson, 2005). These thresholds can operate as progressive or regressive processes, driving soil formation forward or hindering further development (Johnson and Watson-Stegner, 1987; Phillips, 1993). Internal soil development feedbacks were not explicitly considered in the present model formulation. The presence of these internal feedbacks may partially explain error within the model predictions. Changes in EEMT would not explain all observed differences in soil properties over the age of the soil. However, if these feedbacks were operating in the included soils, the influence of intrinsic thresholds was implicitly captured within the probability distributions, partially accounting for the role of internal soil development feedbacks on soil formation.”

The model does capture all soil forming processes implicitly, in that no one process is explicit expressed or quantified. Further, we agree with the reviewer that the model does produce a prediction of soil physical properties based on the net effect of these soil forming processes. We have edited lines 149-153 by removing the word “implicitly”.

Response to Question 5. Human impacts on soil formation.

We did not address human impacts within the current manuscript or even discuss anthropogenically driven changes in land use or climate. Here we demonstrate the use of a probabilistic model for quantifying the distribution of soil properties we observe currently on the Earth’s surface that has arisen during the Quaternary. Furthermore, the energetic contributions from human impacts and dust influx can and have been incorporated within the EEMT apparatus (Rasmussen et al., 2011). The energetic inputs from dust or fertilizer additions, for example, are generally orders of magnitude smaller than the energetic inputs from solar radiation, precipitation, or primary productivity into the soil system. The energetic inputs to the soil from other direct human activities such as the compression of soil due to farming equipment or the increased erosion due to construction or plowing (Rasmussen et al., 2011). We have added language to indicate the adaptability of the EEMT model for differing soil environments at lines 212-215 in the revised manuscript. In specific systems, both dust inputs and human impacts may be significant, however, the vast majority of the soils included in the presented dataset are not directly impacted by human activities or modern dust influx. As the model is probabilistic in nature, the model can simply predict a probable range of target soil physical properties, the domain is generally unconfined. As stated above, human and dust inputs to the soil system can be incorporated into EEMT allowing the inclusion of these soils within the model. Furthermore, the application of the model in this manuscript was to predict clay content, this is a soil property that does not readily change over human time-scales – but rather reflects geologic time scale pedogenic change.

Response to Question 6. Regards to use of energetic models.

Energetic approaches to quantifying soil physical properties and soil formation are able to deal with differing mixtures of the soil forming factors. The soil state factor model has the potential to be expanded beyond the classical five soil forming factors to include influences from site-specific soil forming factors such as the addition of fertilizer to soils or increased erosion due to human activity (Jenny, 1941, 1961). All energetic pedogenic models are derived from the soil state factor model (Minasny et al., 2008), and as such have the potential to be expanded to accommodate additional soil forming factors. Energetic approaches account for the potential fluxes of matter and energy into the soil system that are associated with the soil forming factors, relating the energetics of the fluxes into the soil system to soil physical properties and structures (Volobuyev, 1964; Runge, 1973; Smeck et al., 1983; Rasmussen et al., 2005, 2011; Rasmussen and Tabor, 2007). The energetic input from fertilizer can be easily quantified and included with the model scheme for EEMT when appropriate, however, the energetic additions to the soil from fertilizer are orders of magnitude smaller when compared to the energetic additions of soil radiation, effective precipitation, and net primary productivity (Rasmussen et al., 2011).

The impact of anthropogenic climate change on soil physical properties can be incorporated into the EEMT model space. EEMT can be updated to include the impacts of increased atmospheric CO_2 on the fluxes of matter and to the soil system. Local changes in air temperature, precipitation, evapotranspiration, and net primary productivity due to increased atmospheric CO_2 are quantifiable, and can be easily incorporated into the EEMT model. Further, EEMT can be calculated on a range of temporal scales from near-real time through the use of eddy flux tower and meteorological flux measurements to annually (Rasmussen et al., 2015). With EEMT values updated to include the impacts of anthropogenic climate change, the presented model structure is capable of incorporating these influences on soil formation. As such, we disagree with the reviewer that energetic-based pedogenic models are not capable of handling changing earth surface conditions, and can be updated to accommodate human influences on the climate and landscapes.

Response to specific remarks

Response to remarks on Lines 94-97, interchangeability of P_x and L_o:

The soil state factor model developed by Jenny (S=f(cl,o,r,p,t)) was later formulated by Jenny as $S=f(P_x,L_o,t)$, recognizing that climate and biology are generally flux inputs into the soil system and relief and parent material are site factors. P_x influences pedogenesis and soil evolution over the lifetime of the soil and may be time dependent, whereas L_o generally represents the initial state of the soil forming system and is not time dependent (Jenny, 1961). Interchanging the influence of P_x and L_o is not possible. Relief or topography can vary over time, and in certain formulations of the soil state factor model may be considered time dependent, however, the chronosequence data used to parameterize the present approach are sited on low sloping surfaces, and changes in topography were minimized. Furthermore, as described by Jenny, and approximately 70 decades of soil science, the soil state factors do not describe soil forming processes, the state factors only describe the soil forming environment, i.e. climate is not a soil forming process, but a description of the conditions under which certain soil properties are observed and soil processes operate.

Response to remarks on Lines 182-183: Depth weighted percent clay calculation and bulk density values

We used depth weighted average percent clay in the prediction of clay stocks to account for the greater influence of thicker soil horizons on the account of clay stocks. By calculating a depth weighted average we are accounting for the distribution clay with depth, and summarizing those values into one value. Our model was trained on depth weighted average clay percentages from the chronosequence database; consequently, we also used depth weighted average clay values for predicting clay on a mass per area basis. We agree with the editor, bulk density is not constant throughout a profile, unfortunately, bulk density is difficult to measure, or is often not measured in the field. Further, bulk density data are not commonly reported within the soil science literature or in the available chronosequence literature. Without the necessary data, we chose to assume a constant value of 1500 kg m^{-3} for all soil profiles used in the calculation of predicted mass per area clay. If bulk density data were available, those data could be easily included in the prediction of mass per area, and likely the presented probabilistic-energetic would likely better predict clay stocks.

Response to remarks on Lines 238-240: Assumption of 1500 kg m^{-3} bulk density and use of RF% for calculating clay stocks.

Bulk density is not a commonly measured soil variable as it is often difficult to obtain measurements for bulk density from soil profiles, and values for bulk density are highly method dependent; there was low reporting of bulk density estimate in the available chronosequence literature. Due to a lack of measured values, a constant value was chosen for all profiles; if bulk density measurements are available than the measured values should be used in the predictions of clay stocks. Further, RF% data were used in the predicted clay stocks, as (1-RF%) in Eq. 9 describes the volume or fraction of the soil profile in which clay sized particles accumulate. Additionally, RF% did not influence the prediction of clay stocks (line 326); if RF% data were unavailable, a standard or constant value could be assumed for predicting clay stocks. Further, these simplifications for calculating soil properties on a mass per area basis are standard corrections and assumptions that are made throughout the available literature. With missing or incomplete data, the complexities of measuring soil properties in the field, educated assumptions are usually required.

Response to remarks on Section 3.1 Bias in sampling and stratification of L_o:

The editor did not fully understand the model background as presented in the manuscript. L_o was not used for stratification; L_o is not directly expressed within the model structure. We removed L_o from Eq. 4 to produce Eq. 5, justifying this simplification as time partially accounts for the influence of topography and parent material variation. Soil residence time on a landscape is proportional to slope or curvature (Heimsath et al., 1997, 2002; Yoo et al., 2007). Additionally, the degree of weathering or alteration of the parent material and the presence of secondary minerals and products are also proportional to the soil residence time (Brimhall and Dietrich, 1987; Chadwick et al., 1990; Brimhall et al., 1992). We chose to break down model predictions using leave one out cross validation by parent material in Fig 4 to demonstrate the model was insensitive to different parent materials or landforms, the predictive ability of the model did not vary significantly between the 3 broad parent material categories. We did not calculate model parameters based on parent material, we presented global parameter values in Table 2. We have updated lines 124 and lines 155-157 to clarify this point.

Biased sampling due the use of chronosequence studies is an issue faced in all of soil science. Soil pits are generally preferentially sited in locations where it is possible to dig a soil pit of sufficient depth to sample the soil profile. Any chronosequence study or synthesis of chronosequence data is hampered by biases within soil sampling and presentation of selected data in the literature. Biases in estimated model parameters are based upon sampling techniques and availability of chronosequence data in the literature not due to selective sampling of chronosequence data used to calculate model parameters. We did not limit the data used to calculate the model parameters from the chronosequence literature as a way to minimize errors within the presented model.

Response to remarks on Line 346, clay content change:

In lines 151-152 we stated: "The model assumes all changes in soil physical properties are due to pedogenic processes.", and in lines 345-348 we stated: "Weathering and clay production are primary pedogenic processes (Birkeland, 1999; Schaetzl and Anderson, 2005), and because the model assumed all changes in the soil profile are due to these processes, the model was the most effective at predicting clay content." These statements are in agreement with each other. The model implicitly captures the net effect of all pedogenic processes, we assumed that all changes in the soil profiles are due to pedogenic processes, and the primary pedogenic processes are weathering and clay production, amongst a suite of other processes (Schaetzl and Anderson, 2005), meaning the model captures the influence of weathering and clay production in soil property change. There is no "pretending", we are not misrepresenting the model or its predictive power in any way. We did not claim to model soil forming process, only the end result of all soil forming processes at specific times and energetic inputs based on the available chronosequence literature; this is true for any chronosequence or time based representation of soil data that has been published over the last 70+ years.

Response to remarks on Section 4.1.1, and where the model underperformed:

In many areas, estimated TPE values likely do not account for the total flux of mass and energy into the soil system. Error in predicted clay percentages are likely partially a function of error in TPE estimates. We discussed underestimations of TPE due to changing climate, topography, parent material differences and intrinsic thresholds in soil formation in Section 4.3. Further, we did not constrain the chronosequence data set used to calculate the model parameters, as the formulated model is capable of handling soil data from a wide range of environments and locations due to its probabilistic component. We highlighted where the model failed to predict soil property values as a way to highlight locations where we still have an incomplete understanding of soil formation, or places where parent material greatly influences resultant soil formation (i.e. coral reef terraces). The inability of the model to predict soil properties in particular areas, suggests that a soil-forming factor not included in EEMT or TPE is highly influencing soil formation in this area, not that input data used to calculate model parameters need to be constrained. Models are only representations of reality and there is no logical need for a model to perform perfectly. It is generally beneficial to identify locations and conditions under which models do not work, as a way to identify potential model refinements.

We did not highlight model failures as an excuse to selectively choose data to achieve the best model predictions as suggested by the editor. Further, constraining data to achieve a successful model prediction is uninteresting, as one cannot identify locations or conditions under which the model breaks. Without the inclusion of coral reef terrace chronosequence, we would not have identified that the model has an inability to predict resultant soil formation under fine textured parent materials and tropical climates.

Response to remarks on Line 439, model assumptions about initial conditions:

The editor did not understand the model background as written in lines 115-127, we did not stratify the data by parent material:

"Explicitly including time in Eq. 4 through TPE partially captures variation in soil property change attributable to topography and parent material. Soil residence time may be directly related to landscape position through topographic control on soil production and sediment transport/deposition (Heimsath et al., 1997, 2002; Yoo et al., 2007). Additionally, parent material modulates soil residence time through control on soil depth (Rasmussen et al., 2005; Heckman and Rasmussen, 2011), soil production, and sediment transport rates (Andre and Anderson, 1961; Portenga and Bierman, 2011). The initial conditions of the soil forming system (L_o) are never fully known; however, representing the state of the soil system as a probable distribution of values, implicitly accounting for soil age, and not constraining the initial soil forming conditions, Eq. 4 can be stated simply as:

$$\mathbb{P}(s_1 \leq S \leq s_2) = f(TPE) \qquad (5)$$

where the probability state of the soil, $\mathbb{P}(s_1 \leq S \leq s_2)$, bounded by a lower and upper limit, is a function of one quantifiable variable."

We simply removed L_o from Eq. 4 to write Eq. 5, TPE partially accounts for variation in L_o due to the influence of topography and parent material on soil residence time, as discussed above. We did not use parent material to stratify model parameter estimates; we calculated model parameters for the entire chronosequence dataset. We did not make assumptions about the soil parent material, or include any data about the parent material within the presented model. The statement in Line 439 is accurate. We have updated lines 124 and lines 155-157 to clarify this point.

Response to remarks on Line 459, potential to model landscape evolution:

We strongly disagree with this statement. First, the application of the model that couples the geomorphic model of Pelletier and Rasmussen (2009) explicitly includes soil production and sediment transport to predict landscape variation in soil depth and residence time – these values coupled with TPE yield estimates of soil physical properties completely independent of any soil data. This coupled model may be used to predict soil and landscape evolution across any range of topographic and/or climate scenarios, and yield probabilistic estimates of soil clay content. As stated throughout the manuscript, the model was designed to capture Quaternary soil evolution;

additionally, the focus on clay content necessitates a geologic time scale perspective as this property changes not on human scales, but on pedogenic time scales. Changes induced by human activity could be incorporated into the sediment transport of the Pelletier and Rasmussen (2009) model, as well as incorporated into the energy and mas transfer terms, but in terms of changes in clay content over human time scales these changes will likely be insignificant. As stated in the manuscript, this approach could be used to investigate potential landscape scenarios. Using the geomorphic model (Pelletier and Rasmussen, 2009), potential landscape evolution scenarios could be investigated where changes in topography and soil thickness are used to determine changes in soil properties across small watersheds. We stress that potential landscape evolution scenarios could be investigated, assuming the landscape is at steady state, soil development and evolution could be teased apart using the presented approach; any predictions drawn from such hypothetical modeling exercises would only be a potential future for any landscape. Furthermore, as discussed in this review EEMT can be updated to include the influence from human impacts on the atmosphere and landscapes, and TPE can also be calculated to include the influence of a changing climate (Rasmussen et al., 2011).

As stated in the manuscript and repeatedly above, we used modern EEMT integrated over the age of the soil as the estimate of "total" pedogenic energy input as the best available data that we have. We clearly recognize that this does not incorporate past climate change, leading to what could be under/over estimates of TPE depending on how the local climate system changed at each included location during glacial periods. The majority of sites were from northern hemisphere mid-latitude sites suggesting modern EEMT, and hence, TPE likely underestimates the total pedogenic energy transferred to each location. As noted spatially explicit estimates of LGM climate conditions are now available, but we currently lack a time resolved estimate of paleoclimate variation. As such, we used modern values as proxies for soil forming factors. This is true for any study of soil properties relative to modern climate. Based on the editor suggestion we have removed the reference to investigation of potential soil forming environments at lines 540-541 in the revised manuscript.

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Response to Reviewer J. Phillips.

We thank the reviewer for his helpful comments in the preparation of the manuscript titled: "A probabilistic approach to quantifying soil property change through time integration of energy and mass input". Below we have detailed our response to the reviewer's comments, including how the manuscript was edited.

Response to comments:

Lines 69-71: We have eliminated the first two "approaches".

Lines 128-131; 152-154. We choose the bivariate normal density function for its simplicity and ease of parameterization. We did not consider other bivariate distributions. We wanted to demonstrate the use of bivariate probability functions for modeling soil properties from a probabilistic viewpoint. We have added language to lines 134-136 to indicate that only the bivariate normal density function was considered for the present approach.

Lines 144-154: Modeling soil properties over time requires a number of assumptions, as such every soil formation model is an approximation of reality. We made these assumptions to reduce model complexity and to make the model as mathematically simplistic and easily parameterized as possible. We are aware of many issues with these assumptions, and we discuss at length the implications of these assumptions in lines 464-514 on model outputs and model failures. We disagree with the reviewer that these assumptions are unrealistic, as the present approach is effective at prediction soil property across wide variety of environments and ecosystems.

Line 159: We have replaced "over" with "more than" based on the reviewer's comment.

Line 161-162: We have edited the manuscript to reflect the reviewer's comment, and removed one of the phrases "within the present study" from the revised manuscript.

Lines 164-166: We agree with the reviewer that Southern Hemisphere and mid-latitude sites are underrepresented within the current dataset; however, we are limited about the availability of published datasets. A number of studies from South America, Africa and the Tropics were initially identified, but only a small number of these studies included horizon-level texture data or numerical or approximate ages for the described soil profiles.

Lines 168-177: Based on the reviewer's suggestion we have added additional explanation and description of EEMT, at lines 184-187 in the revised manuscript.

Lines 182: We agree there are many chemical and biological changes that occur over time that are not dependent on soil textural changes, we do discuss intrinsic changes in soil properties from lines 490-502. We have updated the manuscript based on the reviewer's comments, replacing the word "proxies" with "examples of soil property change with time".

Line 213: We have deleted the first "terrain" based on the reviewer's comment at lines 236 in the revised manuscript.

Lines 232-236, Lines 389-390: As discussed in the manuscript and acknowledged by the reviewer, soil depth is correlated to and dependent upon topography and hillslope redistributive processes. Soil depth varies systemically across hillslope as indicated by the contemporary work of Dietrich, Heimsath, Pelletier, amongst many more, and was discussed in the manuscript. We only stated that soil depth incorporates the strength of these processes in lines 232-234, and we have changed “correct” to “incorporate” based on the reviewer’s comments. Further in lines 389-390, we simply state the soil depth acts as a proxy for hillslope processes, not that soil depth accounts for all hillslope processes or the complexity of sediment redistribution on a hillslope. We acknowledge the incomplete understanding of soil depth and weaknesses of soil depth predictions at lines 335-336. Soil depth only partly accounts for the complexity of hillslope processes.

Lines 248-263: The outputs from the process-based numerical soil depth model and the topographically resolved EEMT model were used to calculate the necessary model inputs to the probabilistic model. Soil depth was used to calculate soil residence time, and TPE values were calculated from topographically resolved EEMT and soil residence time values. TPE values were used in the probabilistic model to calculate depth weighted clay content values, and Eq. 9 was used along with predicted soil depth values to calculate mass per area clay across the small-forested catchment. Based on the reviewer’s suggestion we have added language to clarify Section 2.4.1 from lines 306-309 in the revised manuscript and a flow chart to the revised manuscript.

Line 271: We updated line 271 to indicate that Pearson’s correlation was used to parameterize the probability distributions. Further, we updated lines 276 and 281 to indicate the Pearson’s correlation is represented in the reported statistics.

Lines 322: We have added the word “regression” to indicate that we are discussing the slope of the regression line presented in Fig 6b.

Lines 359-372: We agree with the reviewer’s comment, the sand and silt fractions are both dominated by resistant primary minerals. We have added a statement to the revised manuscript at lines 423-425.

Lines 377-379: We have added additional references that indicate the non-linear dynamics of soil depth and soil deepening at lines 407 in the revised manuscript.

Lines 413: We agree with the reviewer that scale is likely an important factor in predicting soil properties. Finer spatial scales will likely better match the local variation in soil properties, but may also lead to greater potential for prediction errors. Further, finer scale information about local lithology differences and weathering rates are likely required. We have added discussion of the issue of scale in predicting soil properties in lines 464-467 in the revised manuscript. Further, the issue of scale in lithology and weathering rates is discussed from lines 468-479 in the revised manuscript.

Lines 421-424: We have added language clarifying the difficulty of including differing weathering rates based on lithology to the revised manuscript at lines 477-478 in the revised manuscript.

Lines 426-462: The model predicts ranges of clay contents. The bivariate normal distribution predicts the conditional parameters of a univariate normal distribution for the soil property of interest. With the conditional univariate parameters, the model user can determine the probability of observing a particular range of clay values. This approach represents a first attempt at a true probabilistic prediction of soil property values, more complex probabilistic approaches that incorporate explicit change with time are possible. However, these more complex probabilistic approaches would require an equation over which probabilistic predictions can be updated over time.

Lines 464-514: With the appropriate updates and additions to the probabilistic model many of these caveats and issues with the model are correctable. Further, many of these caveats specifically address the assumptions and simplifications that are discussed in lines 174-185 in the revised manuscript.

Lines 467-470: We agree with the reviewer's comment, parent material can greatly influence rates of pedogenesis or weathering, regardless of controlling for the other soil forming factors. We have added language to the revised manuscript at line 527 to reflect this issue.

Table 2: We have updated the caption for Table 2 with the explanations of the column headings. We use a "rho" or ρ to represent Pearson's correlation.

Response to Anonymous Reviewer #2

We thank the reviewer for their comments on the manuscript titled: "A probabilistic approach to quantifying soil property change through time integration of energy and mass input". Below we have detailed our response to the reviewer's comments, including how the manuscript was edited.

We disagree with a number of the assertions made by the reviewer. The objective of the presented work was to present the development of a probabilistic model of soil property change using time integrated energy and mass inputs. We added language clarifying this hypothesis at lines 78-80 in the revised manuscript. We think the title is appropriate for the manuscript as written; the manuscript discusses modeling the change in soil properties using energy and mass inputs integrated with time or the age of the soil system, as such we did not change the manuscript title. Further, we did not attempt to model any soil forming process. The presented probabilistic approach is based upon the soil state factor model, which only considers the state of the soil forming environment to understand soil formation or soil structures (Jenny, 1941, 1961). Similarly, the effective energy and mass transfer model only quantifies the amount of potential heat and chemical energy added to the soil, it does not describe any soil forming processes (Rasmussen et al., 2005, 2011, 2015; Rasmussen and Tabor, 2007). This is clearly stated in lines 85-87 and 145-152 in the original manuscript. The model simply quantifies the net effect of all soil forming processes operating within the soil forming system. The revised manuscript has been edited to clarify this point at lines 154. Further, the discussion focused on the reasons for poor or acceptable model fits for the modeled soil properties, and discusses advantages and disadvantages to the probabilistic approach. Nowhere within the discussion do we claim that the presented approach models any soil forming process or soil formation. As was stated in lines 145-152 of the original manuscript, the model assumes all changes within the soil are due to pedogenic processes, this aligns with what is stated in the discussion in lines 345-348 in the original manuscript. EEMT and TPE quantify the amount of energy added to the soil system capable of doing pedogenic work, e.g. chemical weathering, which is most representative of clay formation.

The influence of climatic variability on the model results is discussed in length in lines 503-514 in the original manuscript. While palecolimatic reconstructions are available, such as the spatially explicit LGM paleoclimate reconstruction from the CIMP4 general circulation model, time resolved paleoclimatic reconstructions are still largely unavailable for many locations. We chose to use modern climate values as they represent the best available data. We did not discuss human or anthropogenic impacts on soil formation or evolution. We are exclusively focused on Quaternary soil formation. In this manuscript, we focused on clay formation, which occurs on a geologic timescale and does not readily change on human timescales. Additionally, the EEMT model is easily adaptable to accommodate human influences on the energy and mass inputs into soil, such as fertilizer inputs (Rasmussen et al., 2011).

We have added the age span and depth ranges to the revised manuscript at lines 179-180. Data on vegetation and stoniness were not available across all the sequences and were not included. Further, many of these data are included in Table S1, where all of the chronosequences are listed along with location, dating method, mean annual precipitation, mean annual temperature, parent material and geomorphic surface.

Based on the reviewer's suggestion we have added additional language about the EEMT model at lines 184-187 in the revised manuscript.

The reviewer added comments about the influence of primary minerals on the sand fraction, variability of weathering, and poor prediction with regards to soil formation on amphibolite. The influence of parent material and lithology is discussed at length in lines 403-424 and lines 467-479 in the original manuscript. Further, we did not claim that the model was insensitive to parent material; we discussed the role of parent material and differential weathering rates as a possible explanation for poor model fits and suggest including parent material within the model apparatus a possible correction. The model makes no assumptions about the parent material, in that parent material is not directly expressed within the probability distributions, all soils are considered equally and global values are used to parameterize the probability distributions. We have added language to the revised manuscript at lines 417-419 about the dominance of primary minerals in the sand and silt fractions and have revised lines 580-581 to reflect the role of initial conditions within the model.

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Rasmussen, C., P.A. Troch, J. Chorover, P. Brooks, J. Pelletier, and T.E. Huxman. 2011. An open system framework for integrating critical zone structure and function.

Biogeochemistry 102(1-3): 15–29Available at http://link.springer.com/10.1007/s10533-010-9476-8 (verified 21 October 2014).

List of Revisions
Christopher Shepard, Marcel G. Schaap, Jon D. Pelletier, and Craig Rasmussen.

Below is a complete list of revisions and changes that were made to the manuscript titled: "Probabilistic approach to quantifying soil property change through time integrated mass and energy input."

We changed the title to reflect comments from the reviewers from "Probabilistic approach to quantifying soil property change through time integrated mass and energy input" to "Probabilistic approach to quantifying soil physical properties via time-integrated mass and energy input".

Lines 73-74: We have eliminated the first two "approaches".

Lines 84-86: The objective of the presented work was to present the development of a probabilistic model of soil property change using time integrated energy and mass inputs. We added language clarifying this hypothesis.

Lines 123-125, 172-173: We have updated the manuscript to clarify the role of parent material and initial conditions in the model structure.

Line 139-141: We have added language indicating that we choose to force the data to a bivariate normal structure and that other density functions are available and may provide a better fit to the soil physical property of interest.

Lines 167-169: We have removed the word "implicitly".

Line 182: We have replaced "over" with "more than" based on the reviewer's comment.

Line 161-162: We have edited the manuscript to reflect the reviewer's comment, and removed one of the phrases "within the present study" from the revised manuscript.

Lines 163-164: Added language indicating the model does not consider the distribution of soil properties with depth.

Lines 168-177: Based on the reviewer's suggestion we have added additional explanation and description of EEMT, at lines 184-187 in the revised manuscript.

Lines 194-197: We have added the age span and depth ranges to the revised manuscript.

Lines 222: We have updated the manuscript based on the reviewer's comments, replacing the word "proxies" with "examples of soil property change with time".

Lines 202-208: Based on the reviewer's suggestion we have added additional language about the EEMT model.

Lines 196-197: Commented on biases within the available literature.

Line 226: Based on the reviewer’s suggestion we have removed these soils from the current dataset. Only buried horizon have been removed from the dataset presented in the revised manuscript. We have updated all tables and figures to reflect this change accordingly.

Lines 205-208: We have added language to indicate the adaptability of the EEMT model for differing soil environments.

Line 265: We have deleted the first “terrain” based on the reviewer’s comment at lines 236 in the revised manuscript.

Lines 291: We have changed “correct” to “incorporate” based on the reviewer’s comments.

Line 271: We updated line 271 to indicate that Pearson’s correlation was used to parameterize the probability distributions. Further, we updated lines 276 and 281 to indicate the Pearson’s correlation is represented in the reported statistics.

Lines 319-322: Based on the reviewer’s suggestion we have added language to clarify Section 2.4.1 from lines 306-309 in the revised manuscript and a flow chart to the revised manuscript as a Figure 3 and updated the figure numbers accordingly.

Lines 322: We have added the word “regression” to indicate that we are discussing the slope of the regression line presented in Fig 6b (now Fig 7b).

Lines 508-510: We have added additional references that indicate the non-linear dynamics of soil depth and soil deepening.

Lines 498-500: We have added language to the revised manuscript about the dominance of primary minerals in the sand and silt fractions and revised lines 580-581 to reflect the role of initial conditions within the model.

Lines 545-548: We have added discussion of the issue of scale in predicting soil properties.

Lines 558-559: We have added language clarifying the difficulty of including differing weathering rates based on lithology.

Lines 608-609: We agree with the reviewer’s comment, parent material can greatly influence rates of pedogenesis or weathering, regardless of controlling for the other soil forming factors.

Lines 593: Based on the editor suggestion we have removed the reference to investigation of potential soil forming environments.

Lines 597-600: We commented on the potential of the current approach to predict future soil-landscapes.

Lines 635-645: We commented on the issue of human impacts on soil property

Lines 659-670: We commented on the issue of determining soil age relative to other soil properties.

Table 2: We have updated the caption for Table 2 with the explanations of the column headings. We use a "rho" or ρ to represent Pearson's correlation.

A probabilistic approach to quantifying soil physical properties via time-integrated energy and mass input

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Abstract

Soils form as the result of a complex suite of biogeochemical and physical processes; however, effective modeling of soil property change and variability is still limited, and does not yield widely applicable results. We suggest that predicting a distribution of probable values based upon the soil-forming state factors is more effective and applicable than predicting discrete values. Here we present a probabilistic approach for quantifying soil property variability through integrating energy and mass inputs over time. We analyzed changes in the distributions of soil texture and solum thickness as a function of increasing time and pedogenic energy (effective energy and mass transfer, EEMT) using soil chronosequence data compiled from literature. Bivariate normal probability distributions of soil properties were parameterized using the chronosequence data; from the bivariate distributions, conditional univariate distributions based on the age and flux of matter and energy into the soil were calculated, and probable ranges of each soil property determined. We tested the ability of this approach to predict the soil properties of the original soil chronosequence database, and soil properties in complex terrain at several Critical Zone Observatories in the U.S. The presented probabilistic framework has the potential to greatly inform our understanding of soil evolution over geologic time-scales. Considering soils probabilistically captures soil variability across multiple scales and explicitly quantifies uncertainty in soil property change with time.

1. Introduction

The need for pedogenic models that can be widely applied and easily utilized is paramount for understanding soil-landscape evolution, soil property change with time, and predicting future soil conditions. A mathematically simple, easily parameterized approach has yet to be developed that is capable of predicting current soil properties or recreating potential soil evolution with time. Here we address this knowledge gap through development of a probabilistic model of soil property change capable of predicting soil properties across a wide range of terrains, climates, and ecosystems.

The state factor approach has been one of the primary pedogenic models since it's development in the late 1800's and early 1900's (Dokuchaev, 1883; Jenny, 1941). The soil state factor approach (Jenny, 1941) assumes the state of the soil system or specific soil properties (S) may be described as a function of the external environment, represented by climate (cl), biology (o), relief (r), parent material (p), and time (t): S = f(cl, o, r, p, t). This approach increased our understanding of soil variation across each factor, but more complex, multivariate approaches are generally not possible or difficult to derive from this formulation (Yaalon, 1975). From the original state factor model have evolved pedogenic models that include functional (Jenny, 1961), energetic (Rasmussen and Tabor, 2007; Rasmussen et al., 2005, 2011; Runge, 1973; Smeck et al., 1983; Volobuyev, 1964), and mechanistic approaches (Finke, 2012; Minasny and McBratney, 1999; Salvador-Blanes et al., 2007; Vanwalleghem et al., 2013). However, many of these approaches are either limited to a site-specific basis, require a high degree of parameterization, or lack wide-scale applicability.

Here we develop a simple probabilistic approach to predict soil physical properties using a large dataset of chronosequence studies. The model compresses state factor variability into two

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key components (parent material and total pedogenic energy, defined in Section 1.1) that were parameterized and calibrated using the chronosequence database. We hypothesized that a probabilistic approach predicts accurate ranges of soil physical properties based on the soil-forming environment. Additionally, we modified the model to include soil depth to capture the influence of redistributive hillslope processes to predict soil properties. We hypothesized that by including soil depth, the model would effectively predict the clay content in an independent dataset synthesizing soil and landscape variability in complex, hilly terrain from a wide range of environments.

1.1 Probabilistic model of soil property change

The model presented here is based on a reformulated state-factor model, where a location has a probability of displaying a range of differing soil morphologies and properties based upon the state factors, with some range of values more probable than others, meaning the state-factor model (Jenny, 1941) may be restated as:

$$\mathbb{P}(s_1 \leq S \leq s_2) = f(cl, o, r, p, t) \qquad (1)$$

where, the left hand side of the equation, $\mathbb{P}(s_1 \leq S \leq s_2)$, represents the probability that a given soil will have a value located between a lower limit (s_1) and an upper limit (s_2) (Phillips, 1993b). Eq. 1 can be restated more simply as:

$$\mathbb{P}(s_1 \leq S \leq s_2) = f(L_o, P_x, t) \qquad (2)$$

where, the original soil forming state factors have been simplified to represent the fluxes of matter and energy into the soil system (P_x), incorporating the influence of climate and biology, and the initial state of the soil forming conditions (L_o), incorporating the influence of the initial topography and original soil parent material, and time or age of the soil system (t) (Jenny, 1961).

Equation 2 was further simplified to make the approach operational. A quantitative measure of climate and biology was needed to represent the influence of P_x on soil formation. We used a quantification of P_x calculated from effective precipitation and biological productivity, termed effective energy and mass transfer (EEMT, J m^{-2} yr^{-1})(Rasmussen and Tabor, 2007; Rasmussen et al., 2005, 2011). EEMT provides a measure of the energy transferred to the subsurface, in the form of reduced carbon from primary productivity and heat transfer from effective precipitation, which has the potential to perform pedogenic work, e.g., chemical weathering and carbon cycling. Using EEMT as a simplification of P_x, Eq. 2 was restated as (Rasmussen et al., 2011):

$$\mathbb{P}(s_1 \leq S \leq s_2) = f(L_o, EEMT, t) \qquad (3)$$

We further simplified Eq. 3 by combining the flux term EEMT and the age of the soil system (t). EEMT multiplied by the age of the soil system, i.e. EEMT*t, provides an estimate of the total energy transferred to the soil system over the course of its evolution, referred to here as "total pedogenic energy" (TPE, J m^{-2}). The TPE provides an estimate of P_x that incorporates soil age, thus Eq. 3 may be restated as:

$$\mathbb{P}(s_1 \leq S \leq s_2) = f(L_o, TPE) \qquad (4)$$

where at a certain point in time the probability of a soil property existing between s_1 and s_2 is a function of L_o and TPE. L_o controls the spread or variation of the probability distribution $\mathbb{P}(s_1 \leq S \leq s_2)$ over time and the potential observable soil states, whereas TPE is proportional to the internal soil state at a given time (Jenny, 1961). Explicitly including time in Eq. 4 through TPE partially captures variation in soil property change attributable to topography and parent material. Soil residence time may be directly related to landscape position through topographic control on soil production and sediment transport/deposition (Heimsath et al., 1997, 2002; Yoo et al., 2007). Additionally, parent material modulates soil residence time through control on soil depth (Heckman and Rasmussen, 2011; Rasmussen et al., 2005), soil production, and sediment transport rates (Andre and Anderson, 1961; Portenga and Bierman, 2011). The initial conditions of the soil forming system (L_o) are never fully known; however, representing the state of the soil system as a probable distribution of values, implicitly accounting for soil age, and not constraining the initial soil forming conditions, the influence of initial conditions can be partially ignored and hence herein focus on modeling soil properties using only TPE.

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Quantitatively realizing Eq. 4 required the use of predetermined joint probability density functions parameterized with TPE and a selected soil physical property. Bivariate normal density functions were calculated to determine the probability of a soil property range given a TPE value. The bivariate density function was selected due to its simplicity and ease of parameterization, other bivariate density functions are available that may better fit the selected soil property data but are not considered here. The bivariate normal density distribution (Ugarte et al., 2008) was calculated as:

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$$f(x,y) = \frac{1}{2\pi\sigma_x\sigma_y\sqrt{1-\rho^2}} \exp\left(-\frac{1}{2(1-\rho^2)}\left[\frac{(x-\mu_x)^2}{\sigma_x^2} + \frac{(y-\mu_y)^2}{\sigma_y^2} - \frac{2\rho(x-\mu_x)(y-\mu_y)}{\sigma_x\sigma_y}\right]\right) \qquad (5)$$

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where, ρ represents the Pearson correlation coefficient, μ_x is the mean of TPE, μ_y is the mean of the selected soil physical property, σ_x is the standard deviation of TPE, σ_y is the standard deviation of the selected soil physical property. Using the bivariate normal density functions, conditional mean and variance values were calculated given a value of TPE; the conditional means and variances parameterized conditional univariate normal distributions for the selected soil physical properties. The conditional mean (Ugarte et al., 2008) was calculated as:

$$\mu_{Y|X=x} = \mu_y + \rho\frac{\sigma_y}{\sigma_x}(x - \mu_x) \qquad (6)$$

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where, $\mu_{Y|X=x}$ is the conditional mean soil property value given a value for TPE. The conditional variance (Ugarte et al., 2008) was calculated as:

$$\sigma^2_{Y|X=x} = \sigma^2_y(1-\rho^2) \qquad (7)$$

where, $\sigma^2_{Y|X=x}$ is the conditional variance of the soil property given a value of TPE.

Applying this approach required certain assumptions and simplifications. The model assumes that climate was constant over the entire duration of pedogenesis. The model makes no assumptions about the progressive and regressive processes that drive pedogenesis; by weighing all profiles equally, the net effects of both progressive (e.g., horizonation, clay accumulation, reddening, etc.) and regressive (e.g., haplodization, erosion, pedoturbation, etc.) pedogenic processes (Johnson and Watson-Stegner, 1987; Phillips, 1993a), are captured in the model structure. The model also does not consider the net effect of progressive and regressive pedogenic processes on the distribution of selected soil properties with depth. The model makes no assumptions about the initial soil forming system, and we did not constrain the model to any particular initial condition for either parent material or geomorphic landform; the model simply describes the probability of a location exhibiting a range of soil properties based on TPE. The model assumes all changes in soil physical properties are due to pedogenic processes. We used a bivariate normal distribution; consequently the model assumes the data conforms to a normal distribution.

2. Methods

2.1 Data collection and preparation

The probability distributions were parameterized using an extensive literature review of chronosequence studies. More than 140 chronosequence publications were identified using

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Google Scholar (scholar.google.com) and ThomsonReuters Web of Science (webofknowledge.com), forty-four of which contained the required data. Inclusion within the present study required: profile descriptions with horizon-level clay, sand, and silt content, soil depth; well-defined ages of the soil-geomorphic surfaces; and geographic coordinates or maps showing locations of the described profiles. The chronosequences spanned a wide range of geographic locations, ecosystems, climates, rock types, and geomorphic landforms (Fig 1, Table S1). The chronosequence soils spanned ages from 10 years to 4.35 Myr and depth ranges from 3.0 cm to 1460 cm, with mean annual temperature and precipitation ranging from -11.2 to 28.0 °C and 3.0 to 400 cm yr^{-1}, respectively. We were limited in site selection by the available data; as such we could not control for any bias that may exist with regards to site selection and reported soil property values.

2.2 Total Pedogenic Energy

The influence of both climate and vegetation at the locations of each soil profile was determined using effective energy and mass transfer (EEMT) (Rasmussen and Tabor, 2007; Rasmussen et al., 2005). EEMT quantifies the heat and chemical energy from effective precipitation and net primary productivity added to the soil system (Rasmussen and Tabor, 2007; Rasmussen et al., 2005, 2011). EEMT describes the energy added to the soil system that can perform pedogenic work, such as chemical weathering and carbon cycling. EEMT is adaptable to include specific energetic inputs to the soil system based upon the prevailing soil forming environment, e.g. the energetics from added fertilizer in an agriculture field or the impact of human induced erosion (Rasmussen et al., 2011). The EEMT values for each soil profile were extracted from a global map of EEMT derived from the monthly global climate dataset of New et

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al. (1999) at 0.5°x0.5° resolution using ArcMap 10.1 (ESRI, Redlands, CA) (Rasmussen et al., 2011). For the chronosequence soils, EEMT values ranged from 2,235 to >200,000 kJ m^{-2} yr^{-1}. Total pedogenic energy (TPE, J m^{-2}) was derived simply by multiplying EEMT (J m^{-2} yr^{-1}) for each soil profile by its reported age (yr). TPE was used because it was a better predictor of soil physical properties relative to mean annual temperature, mean annual precipitation, or net primary productivity (Table 3).

2.3 Application to chronosequence data

The chronosequence database included 44 distinct chronosequences representing 405 different soil profiles. We focused here on changes in sand, silt, and clay content and solum thickness as examples of soil property change with time. We tested the approach on depth weighted (DWT) sand, silt and clay content (reported as weight %), as well as the maximum measured value of sand, silt, and clay content within each soil profile. Buried horizons were removed from the soil profiles before either the maximum or DWT content values were calculated. Solum thickness was extracted for each profile, defined as the thickness of the horizons influenced by pedogenic processes or the depth to C horizons (Schaetzl and Anderson, 2005). The site RW-14 from McFadden and Weldon (1987) was not included in the solum thickness model calculations, the measured solum thickness of RW-14 was 1460 cm, an order of magnitude greater than all other soil profiles included in the study. Four hundred and five profiles reported clay content data, only 387 profiles reported sand and silt content, and 399 soil profiles contained a developed solum. We classified the soil profiles by parent material in terms of igneous, metamorphic, or sedimentary and by geomorphic landform, e.g., alluvial surface,

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marine terrace, or moraine, etc. (Shoeneberger et al., 2012); for example, if a soil was formed on an alluvial fan from granitic parent material, it would be defined as alluvial and igneous.

Using the soils data, we calculated bivariate normal probability distributions using TPE and the soil physical properties (Eq. 5). The soil data were transformed using logarithmic and square root transformations when appropriate to meet the normality assumption of the bivariate normal probability distribution. Conditional univariate normal distributions (Eqs. 6, 7) were calculated to approximate probable ranges of soil properties using leave one out cross validation (LOOCV). Each of the soil chronosequences was removed from the model dataset, with the all remaining chronosequence data used to calculate the parameters of the bivariate and conditional univariate normal distributions. The conditional univariate normal distributions were calculated using the TPE values for the profiles within the left-out chronosequence.

2.4 Application to complex terrain

By design, soil chronosequences are generally sited on gentle, low sloping terrain to minimize the influence of topography and erosion/deposition on soil formation (Harden, 1982). However, much of the Earth's surface is characterized by complex topography with high relief, steep slopes, and differences in slope aspect. Any predictive soil model or approach must be effective in both simple and complex terrain. To test the ability of the model to predict soil properties in complex terrain, we compiled data from upland catchments with variable parent material and topography from the literature, as well as data available from the US NSF Critical Zone Observatory Network (CZO, wwww.criticalzone.org) (Table 1) (Bacon et al., 2012; Dethier et al., 2012; Foster et al., 2015; Holleran et al., 2015; Lybrand and Rasmussen, 2015; Rasmussen, 2008; West et al., 2013). Data from several additional studies from complex terrain

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were also included to test the model (Table 1) (Dixon et al., 2009; Yoo et al., 2007). These data were accessed from: www.criticalzone.org, or Google Scholar (scholar.google.com). These studies were included because they all contained horizon-level soil texture data, soil depth, percent volume rock fragment data, and ^{10}Be or U-series measures of soil erosion rates or residence time, where mean residence time (MRT) was calculated as: MRT=h/E, where h is soil depth (m) and E is erosion rate (m/yr) (Pelletier and Rasmussen, 2009b). We used published coordinates to extract EEMT values, calculated from New et al. (1999), for each soil profile using ArcGIS 10.1, and used EEMT and MRT to calculate TPE. It should be noted the coarse resolution of New et al. (1999) EEMT values do not account for local scale variation in water redistribution and primary productivity that can lead to significant topographic variation in EEMT (Rasmussen et al., 2015). Using Eq. 5 and the parameters generated from the chronosequence database, conditional mean depth weighted clay content was calculated for each profile.

Due to the influence of redistributive hillslope processes on soil development (Yoo et al., 2007), soil depth varies systematically across hillslopes (Heimsath et al., 1997); thus, soil depth can be used to incorporate information about these processes within the model calculations. We calculated the mass per area clay content of these profiles using soil depth to incorporate this variation as:

$$\text{Mass per area clay (kg m}^{-2}) = (\rho_b)(h)\left(\frac{\mu_{Y|X=x,\text{DWT CLAY}}}{100}\right)\left(1-\left(\frac{\text{RF\%}}{100}\right)\right) \qquad (8)$$

where, ρ_b is the soil bulk density assumed to be 1500 kg m^{-3} for all soil profiles, $\mu_{Y|X=x,\text{ DWT CLAY}}$ is the predicted conditional mean for depth weighted clay content (DWT CLAY) using Eq. 6, RF% is the measured depth weighted percent volume rock fragments within the soil, when no RF% data were available we assumed a value of 41.7%, which was the average RF% for profiles

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with reported values, and h is the soil depth in meters. Using Eq. 8, mass per area clay was calculated for each soil profile. Further, we examined the impact of depth, rock fragment percentage, and predicted conditional mean DWT clay on the predicted mass per area clay predictions using multiple linear regression.

2.4.1 Coupling geomorphic model with probabilistic model

Additionally, we applied the probabilistic model independent of measured soil data, across a small complex catchment in the Santa Catalina Mountains (Catalina-Jemez CZO, Fig 2a-b, Table 1) (Holleran et al., 2015; Lybrand and Rasmussen, 2015). The ~6 ha catchment is located at an elevation between 2300-2500 m with mixed conifer vegetation, approximately 30 km northeast of Tucson, AZ (Fig 2, Table 1). The approach utilized soil depth and residence time output from a process-based numerical soil depth model (Pelletier and Rasmussen, 2009a). The model used high resolution LiDAR derived topographic data to estimate 2 m pixel resolution soil depth and erosion rates (Fig 2c) (Pelletier and Rasmussen, 2009a). These data were coupled with topographically resolved EEMT values that accounted for local hillslope scale variation in water redistribution and primary productivity at a 10 m pixel resolution (Rasmussen et al., 2015) (Fig 2d). We used calculated TPE from the topographically-resolved EEMT and soil residence time values to predict DWT clay, and coupled predicted DWT clay values with modeled depth from Pelletier and Rasmussen (2009a) in Eq. 8 to predict mass per area clay at 2 m pixel resolution; the data processing and model apparatus are shown in Fig 3. We assumed a constant 50% rock fragment value for each location. The coupled geomorphic-TPE model outputs were compared with point measures of mass per area clay from Holleran et al. (2015) and Lybrand and

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Rasmussen (2015). Model data were completely independent from the Holleran et al. and Lybrand and Rasmussen datasets such that they served as validation data for the modeled output.

2.5 Model domain

The model was parameterized using chronosequence studies; as such, the model is best suited for generally low, sloping terrain. The model was extended to complex terrain using the described correction above (Section 2.4), widening the model domain to steeply sloping terrain. The model does not consider human activities or aeolian additions, and should not be extended to soils significantly impacted by either humans or dust. The model was trained on a diverse array of parent materials and ecosystems, and could be utilized in climates with MAT ranging from -10 to 28°C and MAP ranging from 3 to 400 cm yr^{-1}. The model could be utilized on soils spanning multiple magnitudes in age, from 10 yr to greater than 4Myr.

3. Results

3.1 Application and parameterization to chronosequences

The relationships between TPE and soil texture and solum thickness were used to calculate the bivariate probability distributions. The bivariate probability distributions (Eq. 5) were parameterized using the means, standard deviations and Pearson's correlation from the chronosequence database (Table 2). Furthermore, the relationship between TPE and the soil properties was stronger than just using age, NPP, MAP, or MAT alone (Table 3). Age was expected to strongly correlate to the soil properties due to the design of chronosequence studies; however, comparing age and TPE separately, the percent increase in Spearman rank correlations (r) ranged from 8.7% (DWT Silt) to 25.6% (Max Sand). Maximum and depth weighted silt

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content were weakly correlated to both age and TPE and exhibited only a minimal change in Spearman's rank correlation with TPE relative to age.

The correlation between TPE and maximum clay content (Fig 4, Pearson's ρ=0.78, r^2=0.62, $\sqrt{\text{Max Clay}} = -7.38 + 1.37 * \log(\text{TPE})$, df=403) was highly significant, and presented the strongest probabilistic relationship determined between TPE and the soil properties. The bivariate probability surface displayed the greatest probability around the joint means between TPE and maximum clay content (Fig 4). Solum thickness and TPE were also strongly related, but weaker relative to the maximum clay-TPE relationship (Fig S1, Pearson's ρ=0.65, r^2=0.42, $\log(\text{solum thickness}) = -0.58 + 0.27 * \log(\text{TPE})$, df=397). The relationships between TPE and max sand (Fig S2) and silt (Fig S3) contents were generally weaker, relative to clay and solum thickness, with little to no relationship between TPE and silt content.

The conditional univariate normal distribution parameters were determined for the soil physical properties from the bivariate distribution and using Eqs. 6 and 7. The bivariate normal distribution effectively predicted maximum clay content (Fig 5) with an r^2 = 0.54 (RMSE=14.8%) between the measured maximum clay content and predicted conditional mean maximum clay content (Eq. 6) across all sites based on LOOCV (Fig 5d). The model effectively predicted maximum clay content regardless of parent material with r^2 of 0.61 (RMSE=14.4%), 0.56 (RMSE=12.0%), and 0.59 (RMSE=16.8%), for igneous, metamorphic, and sedimentary parent materials, respectively. The r^2 between the measured values and predicted values for solum thickness, max sand, and max silt were 0.28 (RMSE=101.0 cm, Fig S4), 0.17 (RMSE=23.4%, Fig S5), and 0.04 (RMSE=18.0%, Fig S6), respectively.

The relationship of predicted to actual maximum clay content varied significantly across individual studies. The predicted values represent the predicted conditional means (Eq. 6)

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bounded by the conditional standard deviation (Eq. 7), which approximates a 50% probability that the measured maximum clay content will be within 1 standard deviation of the conditional mean (Fig 6). The individual studies presented in Fig 6 were selected to represent a broad range of climates and landforms, and demonstrate both the strengths and weaknesses of the model. For Harden (1987) (Fig 6a, r^2=0.88, p<0.0001, df=20, RMSE=9.4%) and Howard et al. (1993) (Fig 6b, r^2=0.86, p<0.001, df=6, RMSE=10.2%), the model was generally successful at predicting the maximum clay content values; both the Harden (1987) and Howard et al. (1993) sequences were located in alluvial deposits but in vastly different climates, xeric (winter-dominated annual rainfall regime) vs. udic (evenly distributed annual rainfall regime), respectively. The model was capable of predicting maximum clay content values for glacial moraine deposits, in a frigid climate (Fig 6c, r^2=0.87, p<0.0001, df=12, RMSE=6.0% Birkeland, 1984) and on marine terraces in Northern California with a xeric climate (Fig 6f, r^2=0.98, p<0.001, df=4, RMSE=8.9%, Merritts et al., 1991). The model was incapable of predicting clay accumulation on marine terraces in hot, wet climates in Barbados (Fig 6d, r^2=0.31, p=0.08, df=9, RMSE=44.9% Muhs, 2001) or Taiwan (Fig 6e, r^2=0.67, p<0.001, df=11, RMSE=23.1%, Huang et al., 2010).

3.2 Application in complex terrain

The model was much less effective in complex terrain and highly overpredicted DWT clay contents in soils located in complex landscapes (Fig 7a, r^2=0.26, y=0.39x+7.36, p<0.0001, RMSE=5.4%). The model highly over predicted the clay content of the South Carolina site and the Gordon Gulch soils, and under predicted the clay content of the Rincon, Santa Catalina, Jemez sites.

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When correcting for the influence of hillslope processes by explicitly including soil depth and calculating mass per area clay, the approach effectively predicted clay content, with an r^2=0.81 (Fig 7b, y=1.58x-15.5, p<0.0001, RMSE=86.4 kg clay m^{-2}), only slightly overpredicting clay content, with a regression slope of 1.58. Soil depth was the strongest contributing factor to the mass per area clay prediction with the greatest sums of squares in a simple multiple linear regression including depth, RF%, and DWT clay% (Table 4); predicted conditional mean clay content percentage was the second strongest contributing factor to the mass per area clay prediction. Rock fragment percentage did not influence the mass per area clay content prediction.

3.3 Coupled geomorphic-TPE model

The coupled geomorphic-TPE model effectively predicted mass per area clay for the majority of soils located within the Marshall Gulch subcatchment with an r^2=0.74 (Fig 8a, y=0.86x-5.06, p<0.0001, RMSE=17.7 kg clay m^{-2}). For a subset of soils, the model did not effectively predict mass per area clay, and were excluded from the regression in Fig 8a; four of these soils were located on the east-facing ridge of the catchment, and an additional two soils were formed on amphibolite rather than the granite or quartzite materials that all of the other soils in the catchment were derived from. All of these locations also exhibited a poor fit between modeled and measured soil depth (Fig 2e). The spatial distribution of mass per area clay was also predicted across the catchment (Fig 8b), independently of measured data, and generally conformed to previously predicted spatial distribution of clay stocks in the Marshall Gulch catchment (Holleran et al., 2015).

4. Discussion

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4.1 Model effectiveness

4.1.1 Model results for chronosequences

The model predicted maximum clay content across a diverse range of lithologies, climates, and landforms. Weathering and clay production are primary pedogenic processes (Birkeland, 1999; Schaetzl and Anderson, 2005), and because the model assumed all changes in the soil profile are due to these processes and TPE is closely related to degree of weathering, the model was the most effective at predicting clay content. For initial soil states that begin pedogenesis with a potentially significant amount of clay-sized particles the model was much less effective. The soils of the Taiwanese chronosequence formed from conglomerates (Huang et al., 2010); conglomerates are typically poorly sorted, such that these soils initially formed with high clay contents slowing clay accumulation, limiting the effectiveness of the model to predict clay contents in these soils. Additionally, the model highly underestimated the clay content of soils located on coral reef terraces in tropical environments (Maejima et al., 2005; Muhs, 2001). Coral reef terraces represent a relatively unique landform that weathers rapidly to fine sized particles, especially under tropical climates, and generally have complicated parent material compositions (Muhs et al., 1987). The combination of these factors limited the ability of the model to predict the soil properties on these surfaces.

Sand and silt displayed weaker relationships with increasing total pedogenic energy. The lack of correlation of sand and silt to TPE may result in part from the definitions of the particle size classes. Sand sized particles span several orders of magnitude difference in particle size, ranging from particles of 2 mm to 0.05 mm (Soil Survery Staff, 2010), whereas clays are constrained to particles less than 0.002 mm. The sequential weathering of rock fragments and coarse sand to fine and very fine sands therefore is not reflected in total sand content and likely diminishes the relationship between sand content and total pedogenic energy and time (Pye and Sperling, 1983; Pye, 1983; Sharmeen and Willgoose, 2006). The relationship between silt content and pedogenic energy was the weakest of the three broad particles size classes (Tables 2, 3). Similar to sand, the silt size fractions span an order of magnitude in particle size ranging from 0.05 to 0.002 mm in diameter. Further, the sand and silt fractions are dominated by resistant primary minerals (Pye, 1983), and would not change greatly in response to increased TPE or weathering, which may partly account for the weaker correlations with TPE. Additionally, the silt fraction may also be heavily influenced by deposition of eolian material and thereby introduce an additional mass of silt that was not derived from the direct weathering of the initial soil forming system (McFadden et al., 1987) effectively uncoupling silt content from total pedogenic energy.

Solum thickness displayed a relatively strong relationship with increasing pedogenic energy, with TPE explaining up to 42% of the variance in solum thickness (Tables 2, 3). Soil production is related to climatic variation (Amundson et al., 2015), with this variation partly captured by EEMT and TPE, leading to the slightly stronger predictive power of the model. However, soil production is also highly influenced by redistributive hillslope process, chemical and physical weathering, and tectonic uplift (Heimsath et al., 1997; Riebe et al., 2004; Yoo and Mudd, 2008b), and can be a highly non-linear process (Pelletier and Rasmussen, 2009a). These factors were not directly accounted for in this study in that topography was not a quantified factor, which likely represents a large proportion of the remaining unexplained variance in solum thickness.

4.1.2 Model results in complex terrain

Due to using soil chronosequence data to parameterize the approach, the influence of redistributive hillslope processes was not captured. Additionally, in the amount of time required to transport soil across a hillslope, chemical and physical alterations of the soil particles are possible and may not be reflected in mean residence time calculations (Yoo and Mudd, 2008a; Yoo et al., 2007). Soil thickness is highly dependent upon hillslope position and landscape morphology (Dietrich et al., 2003; Heimsath et al., 1997; Pelletier and Rasmussen, 2009a). By using soil thickness as a proxy for the strength of these redistributive hillslope processes, and converting the predicted conditional mean clay content value to a mass per area basis, the model was able to capture differences in clay content across complex terrain for a variety of lithologies and climates. The differing lithologies, climates, or vegetation types did not appear to impact the ability of the model to predict clay contents, likely because local variation in soil depth accounts for many of these controls. Parent material and climate influence the weathering process and production of clay in soils (Harden and Taylor, 1983; Muhs et al., 2001); however, these factors are collinear with soil depth (Heckman and Rasmussen, 2011; Lybrand and Rasmussen, 2015; Pelletier and Rasmussen, 2009a), such that by including soil depth, differences due to lithology or climate were partly incorporated in the model prediction.

4.1.3 Results from coupled geomorphic-TPE model

For the majority of sites in the Marshall Gulch sub-catchment, the coupled geomorphic-TPE model was highly effective at predicting clay content, and the spatial distribution of clay stocks. Large differences were found for four soils located on the east-facing ridge of the catchment underlain by granite with the model generally over-predicting soil depth and clay content. Discrepancies between the modeled and measured depths were likely the primary sources of error within the mass per area clay predictions for the four east-facing ridge soils (Fig 2e). The geomorphic model predicted deeper soil depths due to the presence of an apparent convergent zone on the east-facing ridge of the sub-catchment; however, this convergent zone is only a small feeder tributary to the larger catchment drainage. The inability of the model to effectively predict clay contents and the mismatch between modeled and actual soil depths in the four soils located on the east-facing ridge is likely due to this local, fine-scale topographic variation. The fine-scale topographic variation may indicate that the scale of soil property predictions is important in achieving accurate predictions. Fine spatial scales match the scale of local soil-landscape variation and processes, but fine scale variation in weathering rates and lithology is also required to better predict soil depth within the catchment (McKenzie and Ryan, 1999).

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Error in predicted soil depths due to fine-scale differences in lithology within the Marshall Gulch sub-catchment partly explains the discrepancies between measured and predicted mass per area clay contents. For two amphibolite-derived soils, the model greatly underestimated mass per area clay. The geomorphic soil depth model assumed a uniform weathering rate based on the granitic soils (Pelletier and Rasmussen, 2009a); due to differences in primary mineral assemblage, the amphibolite materials are likely weathering at a faster rate compared to the granite derived soils (White et al., 2001; Wilson, 2004), resulting in greater clay production and likely explaining the underestimated clay contents. Inclusion of differential weathering rates for varying lithologies within the geomorphic model would likely lead to better prediction of clay contents, but in areas of complex lithology this would require detailed information about distributions of differing lithologies. With these adjustments, the coupled geomorphic-TPE model represents an effective, independent prediction of clay stocks.

4.2 Advantages of probabilistic approach

Simplifying and representing the soil-forming factors as multivariate distributions and probabilities has the potential to quantitatively represent the general state-factor model, making the approach universally applicable. The initial state of the soil can likely never be fully known, leading to variability in soil properties over time that cannot necessarily, or ever, be attributed to any external factor (Phillips, 1989, 1993b). A probabilistic approach utilizes that variability to drive predictions and understanding of these systems. Similar to the approach taken here, building distributions of the soil-forming state factors that are associated with distributions of particular soil properties could yield probabilistic predictions of soil formation and change. We selected to use a representation of climate and biology (EEMT), however, depending on the soil property of interest the variables needed to parameterize the distributions would likely change; for example, if interested in organic matter content, aboveground net primary productivity or normalized difference vegetation index may be better predictors of organic matter accumulation. The strength of this approach lies in the fact that no assumptions are made about the initial conditions of the soil forming system or the specific soil forming processes. Predicting probable distributions of soil physical properties implicitly acknowledges that our understanding of any system is incomplete, but explicitly quantifies uncertainty in predictions and constrains the potential observable values to a predicted range. Utilizing this approach will require the necessary data to build distributions that are widely representative and applicable to most locations (Yaalon, 1975). With wide accessibility to large databases of soil information, such as the US National Soil Information System (NASIS) and the FAO Harmonized World Soil Database, access to the required amount and quality of data may be possible. Similar to the present study, simple bivariate distributions could be solved to calculate conditional distributions based on the soil-forming state factors, effectively producing quantitative probabilistic representations of Jenny's original equation (Jenny, 1941).

The simplicity of the present approach allows easy integration into pre-existing geomorphic models of landscape evolution. Past approaches that have combined pedogenic and landscape evolution models have generally focused on producing hypothetical soil-landscape relationships that progress forward through time (Minasny and McBratney, 2001; Vanwalleghem et al., 2013), or have focused on idealized landscapes (Temme and Vanwalleghem, 2015). However, by combining probabilistic approaches parameterized using known landscapes, and geomorphically based landscape evolution models, predictions of the current state of the soil-landscape can be investigated. As was demonstrated in Fig 7B, combining the present approach with geomorphically based soil depth models generated from DEMs has great potential to predict soil properties across a diverse range of environments, without needing prior knowledge of the landscape other than topography and climate. Further, potential soil-landscapes can be investigated by updating EEMT values to incorporate future climate scenarios available from predictive climate models (Gent et al., 2011; Taylor et al., 2012) and topographic and hydrological impacts due to changes in topography over time (Rasmussen et al., 2015).

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4.3 Limitations and potential refinements

There are obvious limitations within the current model: lack of consideration of parent material influences, topographic variation, human impacts, internal soil feedbacks and thresholds, determination of landscape and soil age, and differences in paleoclimate variation. Parent material control on the relative proportion of weatherable minerals and mineral

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weathering rates (Jackson et al., 1948) can manifest as vastly different soil morphologies and rates of pedogenesis when controlling for other soil forming factors or even without controlling for other factors (Heckman and Rasmussen, 2011; Parsons and Herriman, 1975; Phillips, 1993b). The current approach implicitly assumes no information about the initial conditions, only that all clay production is a pedogenic process. Applying this approach to parent materials, where a large fraction of clay-sized particles formed through non-pedogenic processes, is thus limited and may explain why the model was ineffective for some soils. Refining the current approach would require normalization of soil to the particle size distribution of the soil parent material. Past studies have utilized highly characterized parent material data to model soil property change with time (Chadwick et al., 1990; Harden, 1982), but these data are generally difficult to obtain and often not reported in the available chronosequence literature.

Topography dictates soil chemical and physical properties and residence times, especially in complex terrain (Almond et al., 2007; Egli et al., 2008; Lybrand and Rasmussen, 2015), where non-linear diffusive hillslope processes control the fluxes of matter and energy into and out of the soil system (Heimsath et al., 1997; Pelletier and Rasmussen, 2009a; Rasmussen et al., 2015; Yoo and Mudd, 2008b; Yoo et al., 2007). Using earlier versions of EEMT (Rasmussen and Tabor, 2007; Rasmussen et al., 2005), the current formulation of the model and TPE does not explicitly quantify topographic variation, which may account for error within current soil property distributions and predictions. With the inclusion of topographic variation in EEMT (Rasmussen et al., 2015) and topographic control of soil residence times (Foster et al., 2015; West et al., 2013), we were able to correct this error with the present approach and effectively predicted clay stocks in complex terrain.

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Human activities significantly alter soil physical properties (Grieve, 2001; Neff et al., 2005; Pouyat et al., 2007). For example, differences in land use and increased grazing activity can alter soil physical properties such as clay and sand content across landscapes (Neff et al., 2005; Pouyat et al., 2007), or compaction from farming equipment leading to increased bulk density and increased erosion rates (Fullen, 1985; Hamza and Anderson, 2005). Human impacts on soil physical properties were not included in the presented model. The energetic contributions due to human impacts can be incorporated within the EEMT apparatus, and adjusted model parameters can be calculated (Rasmussen et al., 2011). Human impacts on soil physical properties may be locally important, but for the majority of locations, human energetic contributions to the soil system are generally orders of magnitude smaller compared to the energetic inputs from solar radiation, precipitation, or primary productivity.

Internal or intrinsic feedbacks and thresholds within the soil system drive pedogenic development without changes in the external state factors (Chadwick and Chorover, 2001; Muhs, 1984). For example, greater chemical weathering and clay production due to increased water residence time caused by argillic horizon development is the result of an internal feedback that is independent of the external climatic and biological system (Schaetzl and Anderson, 2005). These thresholds can operate as progressive or regressive processes, driving soil formation forward or hindering further development (Johnson and Watson-Stegner, 1987; Phillips, 1993a). Internal soil development feedbacks were not explicitly considered in the present model formulation. The presence of these internal feedbacks may partially explain error within the model predictions. Changes in EEMT would not explain all observed differences in soil properties over the age of the soil. However, if these feedbacks were operating in the included soils, the influence of intrinsic thresholds was implicitly captured within the probability distributions, partially accounting for the role of internal soil development feedbacks on soil formation.

Soil age is typically unmeasured in most geomorphological and pedological studies, limiting the applicability of the current model. Numerical age dating, e.g. cosmogenic radionuclides or optically stimulated luminescence, is expensive and requires time-consuming preparation to be broadly utilized and can be complicated by transport and burial histories of soil and sediment (Anderson et al., 1996; Bierman, 1994; Gosse and Phillips, 2001; Granger and Muzikar, 2001; Schaetzl and Anderson, 2005). Fortunately, relative age dating methods using landscape position are easily utilized and can provide the necessary age constraint needed to make model predictions (Burke and Birkeland, 1979; Favilli et al., 2009; Huggett, 1998; Matthews and Shakesby, 1984; Nicholas and Butler, 1996; Schaetzl and Anderson, 2005). Age constraint may also be achieved using landscape or hillslope morphology derived from elevation transects or digital elevation models to estimate a "diffusivity age" for the soil (Hsu and Pelletier, 2004; Pelletier et al., 2006).

Global climate patterns have shifted dramatically over the last 65 Myr, (Zachos et al., 2001). The majority of soils observed in the compiled chronosequence database span the Quaternary, including both the Holocene and Pleistocene. The Pleistocene was marked by a number of major glacial-interglacial cycles at approximately 100,000-year intervals (Imbrie et al., 1992; Wallace and Hobbs, 2006), which corresponded with shifting climatic conditions, e.g., for large portions of the northern mid-latitudes glacial periods were generally cooler and wetter, and interglacial periods were warmer and drier (Connin et al., 1998; Petit et al., 1999). Further, the Pleistocene climate shifts likely influenced the rates of weathering and clay production (Hotchkiss et al., 2000). Taking into account the differences in past and modern climate would

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partially reduce prediction errors between observed and modeled soil physical properties. Reconstructed global paleo-EEMT values would improve model accuracy, and limit uncertainty in the probabilistic ranges of soil properties for soils older than Holocene age.

5. Conclusion

The present approach effectively predicts soil physical properties across a diverse range of geomorphic surfaces, lithologies, ecosystems, and climates. Further, this approach is mathematically simple and only requires knowledge of the probable age of a geomorphic surface and the effective energy and mass transfer value associated with a given location, making this approach universally applicable. The simplicity of the probabilistic approach lies in the lack of the need to consider the initial conditions of the soil forming state or the processes driving soil property change. A probabilistic approach does not exactly predict a soil physical property value at a given location, but constrains the probable values based upon the state of the external environment to the soil. Using probabilistic approaches, we can model probable soil-landscape evolution scenarios, greatly informing our understanding of the evolution of critical zone structure.

Acknowledgements

We thank Molly Holleran, Rebecca Lybrand, and Ashlee Dere for providing data for this study. Support for C.S. was provided by the University Fellows program at the University of Arizona and by the University of Arizona/NASA Space Grant Graduate Fellowship. This research was funded by the U.S. National Science Foundation grant no. EAR-1331408 provided in support of

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