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Vegetation drastically reduces wind erosion: An implementation of the RWEQ in the Mongolian Gobi Steppe

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Abstract: Soil loss prevention is an important ecosystem service for protecting human and environmental health. Using spatio-temporal climate and environmental data of the Eastern Gobi Steppe, a region missing from previous studies of Mongolian wind erosion, we implement the revised wind erosion equation (RWEQ) model to estimate soil loss. A replicable pipeline is coded to perform these computations to allow similar analyses elsewhere. Soil loss is estimated on a monthly basis to analyze seasonal variations. The results show that the annual total soil loss is 61 * 1010 kg over an area of 69.3 * 103 km2, which is about 8800 tonnes (the weight of 1492 African elephants) over an area equivalent to 6930 football fields. Increasing fractional vegetation coverage to a uniform 50% coverage (doubling current vegetation coverage in every 1 km2) can reduce soil loss by 60%, highlighting the importance of protecting and increasing vegetation coverage in ecosystem service preservation.

Keywords: wind erosion, soil loss, ecosystem services, revised wind erosion equation, Gobi Steppe

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0. SOFTWARE AVAILABILITY

The Python code of the model implemented in this paper is available in: https://github.com/charlottegiseleweil/winderosion. The README file includes a usage example, as well as a link to a sample data set..

1. Introduction

Soil Loss causes both environmental and human health issues, like sandstorms, land infertility, and respiratory ailments.

Soil loss due to wind erosion is a grave problem for semiarid and arid areas, where the lack of precipitation and scant vegetation coverage cannot prevent surface materials from being blown away by strong and frequent winds (Zhibao, 2000). This can lead to desertification, to severe soil coarseness, infertility, and dryness, which affect the ability to grow crops for sustenance (Duniway, 2019; Zhao, 2006). Wind erosion also creates sandstorms, and air pollution which affect pulmonary health (Li, 2005). Indeed, the soil particles that enter the air from sandstorms are easily inhalable and can cause significant respiratory ailments due to oxidative stress, as they are embedded into deep lung tissue and the subepithelial environment (Saxton, 2001; Griffin, 2007). For all these reasons, soil erosion control is one of the fundamental ecosystem services for human welfare (Fu, 2011).

WEQ and its revised version (RWEQ) are the reference for calculating wind erosion, based on climate and soil factors.

Wind erosion is caused by a combination of climate factors, such as wind speeds, temperature, precipitation, and soil factors such as surface terrain roughness, and vegetation coverage. The Wind Erosion Equation (WEQ) published by Woodruff and Siddoway (1965), models this phenomenon. The Revised Wind Equation (RWEQ) extends the WEQ by utilizing wind as the primary factor rather than soil erodibility as WEQ does. Fryrear et al. show that RWEQ is a much more accurate model: the correlation between measured erosion and estimated erosion with WEQ was not significant (r2 = 0.01), whereas the correlation with RWEQ was highly significant (r2 = 0.927) (Fryrear, 2001). RWEQ also takes soil surface roughness into account unlike WEQ.

We used the RWEQ model to estimate wind erosion in the Gobi Steppe. In East Asia, the Gobi Steppe is a region sensitive to global climate change; where dust storms are regarded as one of the most severe environmental problems (Qi, 2010). Our area of interest specifically is the Eastern Gobi Steppe. The Eastern Gobi Steppe stretches from part of the Inner Mongolia Plateau in China into Mongolia at 1,000 to 1,500 m elevation, northward into Mongolia. Summer heat depends on elevation, ranging from warm to hot, and winters are severely cold. Winter conditions are harsher here than other parts of China at similar altitudes and latitudes, as there are no mountains to shelter the region from northerly winds. Annual total precipitation varies significantly, and most of the precipitation is in summer. Vegetation consists of drought-resistant shrubs and low grasses.

RWEQ has been validated in areas surrounding the Eastern Gobi Steppe, but never in the Eastern Gobi Steppe itself.

Closer to the Eastern Gobi Steppe, in the Inner Mongolia Province of China, wind erosion had been simulated using RWEQ by Jiang et. al, where they have shown that there is high correlation (r2 = 0.88) between RWEQ estimates of wind erosion and measurements obtained from remote sensing data (Jiang, 2016). They find that 23.2% of this erosion could be rated as severe between 2001 and 2010 (Jiang, 2016). Corroborating these findings, (Haiyan, 2018) find that 23.2% of the wind erosion can be rated as severe from 1990 to 2015, also using RWEQ-based models. Other approaches results in more variability - e.g., (Qi, 2010) finds annual soil erosion rates ranging from 53.12 tonnes/km2 to 479.63 tonnes/km2 over 8 sampling sites, using the Cs tracing technique (Fulajtár et al., 2017) which analyzes changes of 137-Caesium, which is found bound to soil colloids, inventories in soil to measure soil erosion on 8 sampling sites in the Mongolian Plateau; (Shi, 2009) finds a categorical map of wind erosion across the Mongolian Plateau, ranking wind erosion from none to severe, using a fuzzy c-means clustering technique which is an automatic classification method that expresses gradual spatial changes of physical geographic phenomena, such as wind erosion in this case, by using a continuously divided membership model (Shi, 2009).

Though wind erosion has been estimated in the Inner Mongolia Province in China, by Jiang et. al. and Haiyan et. al., estimates are missing for the Eastern Gobi Steppe. Based on the strong correlation of RWEQ estimates against wind erosion measurements shown by Fryrear et. al. and Jiang et. al., we aim here to use a RWEQ-based model to estimate wind erosion in the Mongolian Gobi Steppe and most importantly understand its main drivers, to simulate wind erosion under possible scenarios of evolution in climate and vegetation cover. This work also outputs a replicable implementation of the RWEQ-based wind erosion model, globally applicable with data at various resolutions.

1.1. The Eastern Gobi Steppe

The Eastern Gobi Steppe stretches from the Inner Mongolia Plateau in China into Mongolia at 1,000 to 1,500 m elevation, northward into Mongolia. Summer heat depends on elevation, ranging from warm to hot, and winters are severely cold. Winter conditions are harsher here than other parts of China at similar altitudes and latitudes, as there are no mountains to shelter the region from northerly winds. Annual total precipitation varies significantly, and most of the precipitation is in summer. Vegetation consists of drought-resistant shrubs and low grasses.

Our study area, where sensitivity analysis was conducted, is located along Mongolia's southern border and inside the Gobi desert. This area is characterized by extremely low rainfall and very little vegetation cover. We used the RWEQ model to estimate wind erosion in one region of the Mongolian Plateau (Figure 1). In East Asia, the Mongolian Plateau is a region sensitive to global climate change; where dust storms are regarded as one of the most severe environmental problems (Qi, 2010). We conducted a sensitivity analysis of the RWEQ model in a portion of the Eastern Gobi Steppe, outlined in the map with a red border, to analyze which environmental factors have the greatest influence in predicting wind erosion. The results of the analysis are detailed in further sections of this paper.

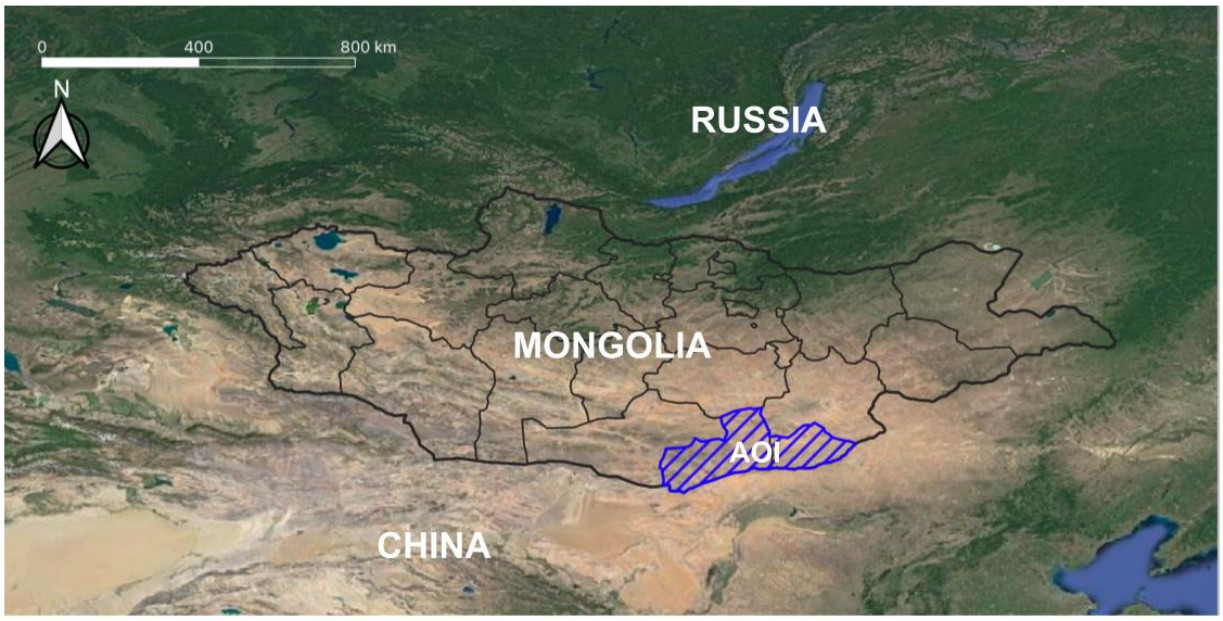


Figure 1. Map of Our Area of Interest (AOI) in Mongolia. Borders Overlayed on Google Earth Satellite Base Map.

2. METHODS

2.1. RWEQ Equations

The RWEQ (model estimates soil loss (SL) for a given location. Weather, soil erodibility, soil crust, surface terrain roughness and vegetation coverage factors are used to calculate the maximum transported capacity by wind (Qmax) and the critical field length (S) as shown (Visser, 2005; Jarrah, 2020):

$$Qmax = 109.8 * (WF * EF * K' * SCF * COG) \quad (1)$$

$$S = 105.71 * (WF * EF * K' * SCF * COG)^{-0.3711} \quad (2)$$

$$SL = 100/(S^2 + 0.01) * Qmax * (e^{-(50/(S+0.01))})^2 \quad (3)$$

where Qmax (in kg/m) is the transport capacity and S (in m) is the distance where 63% of the maximum transport capacity is reached, called the critical field length. SL (in kg/m2) is the rate of soil loss caused by wind erosion (Z from the original equation is 50 here, and is already factored in). WF is the weather factor, SCF is the soil crusting factor, EF is the soil erodible fraction, COG is the vegetation factor, and K' is the surface terrain roughness factor.

Weather factor (WF, in kg m^{-1}). Wind is the cornerstone of RWEQ, with soil moisture and snow cover as important factors influencing wind erosion. In this paper, the weather factor is calculated on a monthly basis. The weather factor represents the effect

of climate on wind erosion, and combines wind speed, soil moisture, and snow cover as shown:

$$WF_{monthly} = Wf * \rho / 9.8 * SW * SD \quad (4)$$

Where WF is the weather factor (in kg/m), Wf is the wind factor (in m3/s3), ϱ is air density (in kg/m3), 9.8 is acceleration due to gravity (in m/s2), SW represents soil moisture, and SD represents snow cover.

Wind factor is calculated from daily wind speed (ws, in m/s) using the equation shown below (Jarrah, 2020) when the wind speed value is higher than the threshold of 5 m/s. For all wind speed values less than this threshold, the wind factor is set to 0 (Stetler, 1997):

$$Wf = ws * (ws - 5)^2 \quad (5)$$

The soil moisture factor is calculated from monthly potential evapotranspiration (ETp, in mm), monthly total precipitation (PRCP, in mm), monthly number of rainy days (PRCP_DAYS) as shown (Jarrah, 2020):

$$SW = (ETp - PRCP * PRCP_DAYS) / ETp \quad (8)$$

Monthly potential evapotranspiration is calculated from monthly total solar radiation (SOL, in MJ/m2) and monthly average temperature (TEMP, in °C) as shown (Jarrah 2020):

$$ETp = 0.0135 * (SOL / 2.54) * (TEMP + 17.8) \quad (9)$$

SD is the snow cover factor determined as 1 – probability of snow depth > 25.4 mm (Jarrah, 2020)

Soil crusting factor (SCF). When rain hits the soil surface, there is a formation of surface crust because of redistributed soil particles. That soil surface can be hard or weak and may affect wind erosion potential (Jiang, 2016). The soil crusting factor is a non-temporal value calculated from clay (CL, %) and organic matter (OM, %) as shown (Jiang, 2016):

$$SCF = 1 / (1 + 0.0066 * CL^2 + 0.021 * OM^2) \quad (10)$$

Soil erodible fraction (EF). The erodible fraction is the fraction of the surface 25 mm of soil that is lower than 0.84 mm in diameter as determined by a standard compact rotary sieve, and the highest value of EF for a year is related to the physical and chemical properties of the soil (Jiang, 2016) The erodible fraction is a non-temporal value calculated from the ratios of sand (SND, %), silt (SILT, %), clay (CL, %), and organic matter (OM, %) in the soil as shown (Jarrah, 2020):

$$EF = (29.09 + 0.31 * SND + 0.17 * SILT + 0.33 * SND / CL - 2.59 * OM - 0.95 * 0) / 100 \quad (11)$$

Vegetation factor (COG). The amount of vegetation coverage over the soil can have a significant impact on how well the soil is protected from erosion. The monthly vegetation factor can be calculated from the monthly fraction of vegetation coverage (FVC, %) as shown (Jarrah, 2020):

$$COG = \boldsymbol{e}^{(-0.00438 * FVC)} \quad (12)$$

The original equation has additional factors as shown (Jarrah, 2020). However, due to limited availability of data, only the term related to FVC was used. This was based on the work done by Jiang (2016) in the same geographical region:

$$\boldsymbol{COG} = \boldsymbol{e}^{(-0.00438 * FVC)} + e^{(-0.0344 SA^{0.6413})} + e^{(5.614 CC^{0.7366})} \quad (13)$$

Where FVC is the percent of land covered by crop residue, SA is the standing stem area index and CC is the percent soil surface covered by crop canopy.

Surface terrain roughness factor (K'). Surface terrain roughness is calculated on a monthly basis from topographical roughness (Kr) and the Chain Random Roughness (Crr) as shown (Jiang, 2016):

$$K' = e^{(1.86 * Kr - 2.41 * Kr^{0.934} - 0.127 Crr)} \quad (14)$$

Topographical roughness is calculated for 3x3 grid of pixels of the raster data from the difference between the minimum and maximum elevations in the selected area (H, in m) and the length of the edge of the area (L = 3 * resolution of raster) as shown (Jiang, 2016):

$$Kr = 0.2 * (H^2/L) \quad (15)$$

Chain Random Roughness is calculated from the monthly fraction of vegetation coverage (FVC, fraction) as shown. It is computed in two steps. First, a random roughness is computed from FVC (Zhibao, 1996). Then the computed random roughness is used to calculate chain random roughness (Borelli, 2016)

$$RR = 0.025 + 2.464FVC^{3.56} \quad (16)$$

$$Crr = 17.46 * (RR)^{0.738} \quad (17)$$

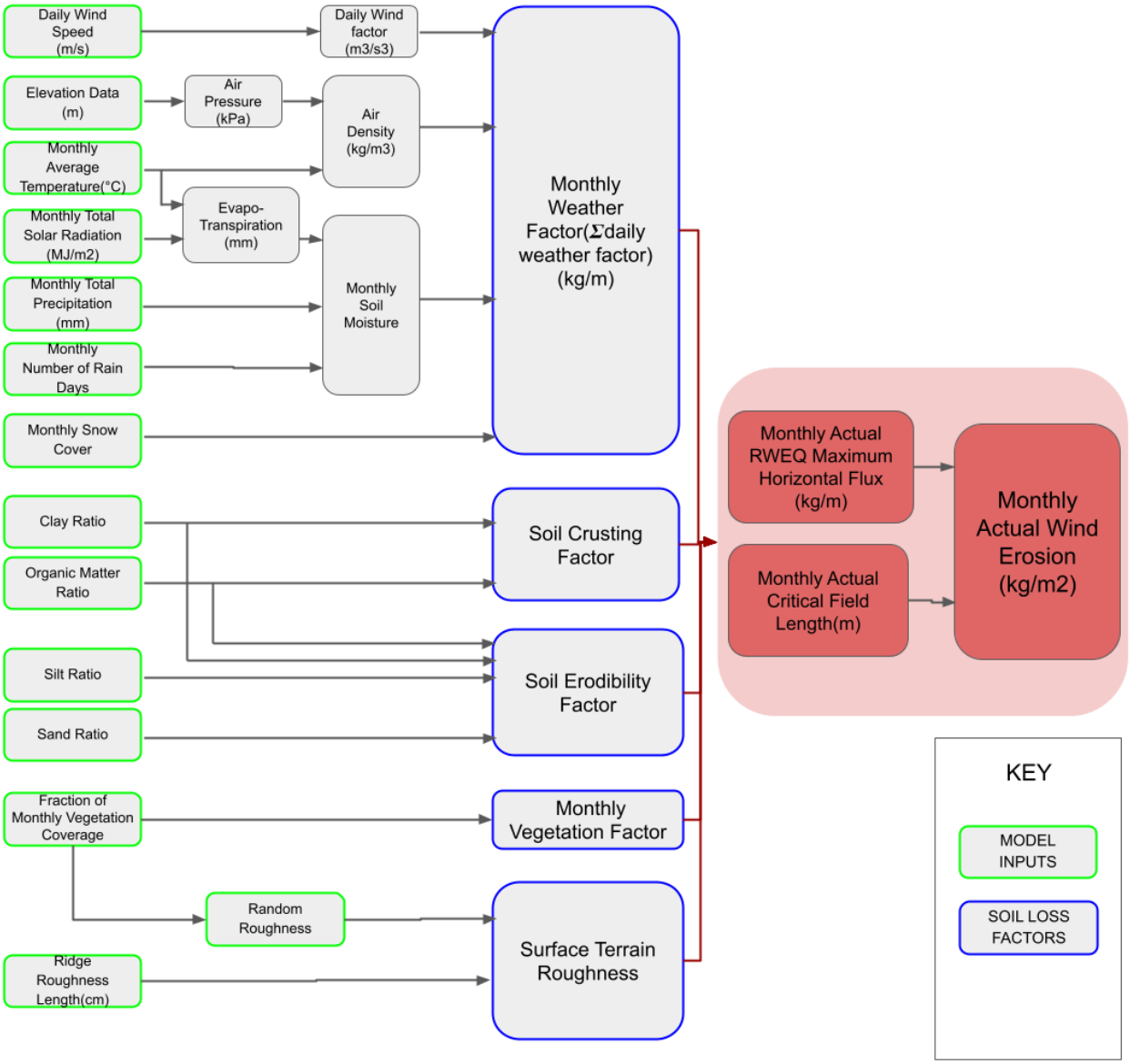


Figure 2. Model flowchart Summary. Demonstrates how inputs are utilized to calculate factors used for final soil loss calculation.

2.2. Input Data Sources

The Digital Elevation Model (DEM) data is downloaded from the Shuttle Radar Topography Mission (SRTM) website for the country of Mongolia (Survey, 2020). Wind speed is sourced from the ERA5-Land Dataset on the Copernicus Climate Data Store (Muñoz, 2019). Monthly average temperature and total precipitation come directly from Worldclim current conditions (Fick, 2017). Solar radiation is calculated according to Penman (1948). Precipitation Days information from a public website is used (Amicus Travel, 2020). To justify the use of this website, the data was compared to Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), and found to be only 1 or 2 days apart. As varying number of rain days was shown to have almost no impact on wind erosion results based on the sensitivity analyses, the travel website data served as a reasonable source of the number of rain days. Clay, silt, and sand fractions are from ISRIC SoilGrids 250m (Hengl, 2017). Soil organic matter and monthly snow cover are outputs of the Rangeland Production model (Kowal et al., 2021), driven by Worldclim historical vegetation. Monthly herbaceous vegetation cover is calculated from herbaceous biomass outputs from the Rangeland Production Model, and a simple linear regression relating standing biomass to vegetation cover estimated from vegetation collected in the study area as described by Ahlborn (Ahlborn, 2020). The temporal inputs are collected on a monthly basis, excepting wind speed, which is a daily data value, that is used to calculate a total monthly wind factor.

Category	**Dataset**	**Source**	**Temporal Range (Year)**	**Unit**	**Original Resolution**	**Format**
Elevation	Elevation Data (DEM)	SRTM	2000	m	0.05985 degrees² per pixel	GeoTIF
Climate	Monthly Average Temperature	Worldclim current conditions	1970–2000	°C	0.00833 degrees² per pixel	GeoTIF
	Monthly Total Precipitation	Worldclim current conditions	1970–2000	mm	0.00833 degrees² per pixel	GeoTIF
	Monthly Solar Radiation	Rangeland Production Model Output	2014-2015	MJ/m²	0.00324 degrees² per pixel	GeoTIF
	Monthly Snow Cover	Rangeland Production Model Output	2014-2015	% (probability)	0.05003 degrees² per pixel	GeoTIF

	Monthly number of Rain days	Amicus Travel	2020	day	0.05985 degrees^2 per pixel	GeoTIF
	Daily Wind Speed	Copernicus Climate Data Store	1981-2019	m/s	0.00833 degrees^2 per pixel	GeoTIF
Soil	Sand Ratio	ISRIC SoilGrids	2014-2016	%	0.00208 degrees^2 per pixel	GeoTIF
	Silt Ratio	ISRIC SoilGrids	2014-2016	%	0.00208 degrees^2 per pixel	GeoTIF
	Clay Ratio	ISRIC SoilGrids	2014-2016	%	0.00208 degrees^2 per pixel	GeoTIF
	Organic Matter Ratio	Rangeland Production Model Output	2014-2016	%	0.00324 degrees^2 per pixel	GeoTIF
Vegetation	Monthly fraction of vegetation coverage	Rangeland Production Model Output	2014-2016	%	0.05003 degrees^2 per pixel	GeoTIF

Table 1: Data Collection This table summarizes the data used for this paper, including the source, unit, original resolution and format.

2.3. Sensitivity Analysis

In the smaller study area in the Gobi desert, we explore the sensitivity of soil loss to each input by varying their value, and re-computing soil loss. Specifically, each model input (wind speed, temperature, etc), and each of the five intermediate factor (weather factor, erodible fraction, etc) are multiplied by a scaling factor: [50%, 75%, 90%, 100%, 110%, 125%, 150%]. For each parameter, in addition to the actual soil loss, 3 additional estimates are done with 3 different theoretical vegetation coverage scenarios: uniform 0%, 50% and 100% vegetation cover. For these theoretical vegetation coverage scenarios, fractional vegetation coverage rasters are pre-computed by assigning every pixel within the area of interest a value of 0, 50, and 100, respectively, as the equations are expecting a percentage representation. The soil loss is summed temporally as well as spatially to generate a single value representation of the scaling effect for each parameter. Line graphs are generated for each model input to show the scaling effect.

In addition, a percentage change of the annual soil loss compared to the actual annual soil loss is computed for 6 different theoretical vegetation coverage scenarios. 3 of the scenarios use absolute, uniform fractional vegetation coverage of 0%, 50%, and 100%. The

other 3 scenarios use 110%, 120%, and 150% of the original values for each pixel. Soil loss maps are generated for each month and then summed temporally to generate annual soil loss maps for visual comparison.

Another sensitivity analysis is done by computing the percentage change of the annual soil loss compared to the actual annual soil loss at the maximum and minimum values for each model input. The computation is done by setting only 1 input to the maximum or minimum at a time. For each analysis, each pixel in the area of interest for the selected input parameter is set uniformly to the maximum or minimum value. The soil loss is summed temporally as well as spatially to have a single value representation of the scaling effect for each parameter. Results are captured in Table 3 for comparison.

3. RESULTS AND DISCUSSION

3.1. Model results are coherent and show Eastern Gobi Steppe area is prone to soil loss.

Results from our model are consistent with previous studies done in the same area.

A RWEQ-based wind erosion analysis has been done over the Inner Mongolia province of China (Haiyan, 2018). The equations are identical, excepting the equation for potential evapotranspiration. Our coefficient that multiples solar radiation and temperature after combining the numerical factors in the equation is 0.00531, while the Haiyan coefficient is 0.000277. However, this is accounted for as Haiyan 2018 uses temperature in degrees Kelvin while our paper uses degrees Celsius. Our area of interest, the Eastern Mongolian Steppe, overlaps part of the region covered by their study. That paper categorized wind erosion into different classes of severity from tolerable to destructive. A visual comparison of their figures shows that that overlapping area falls into the Severe and Very Severe categories. According to Haiyan 2018, the Severe category has a soil erosion range of 5000 to 8000 tonnes/km2/a and the Very Severe category has a soil erosion range of 8000 to 15000 tonnes/km2/a. Our estimated total soil erosion was 61 * 1010 kg over an area of 69.3 * 109 m2 which corresponds to 8800 tonnes/km2. That shows that the results of this study are consistent with prior published results in the overlapping areas of Inner Mongolia.

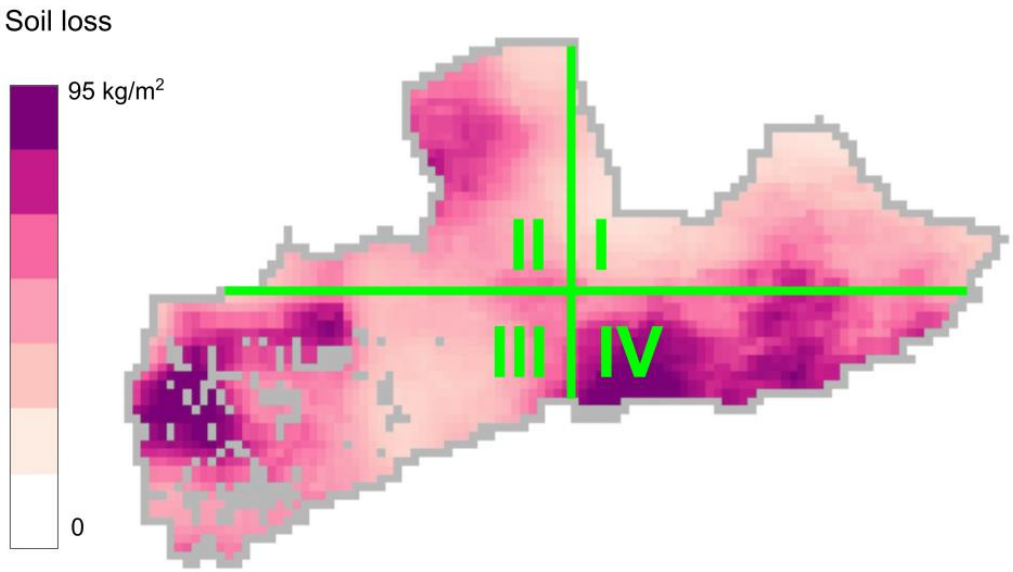


Figure 3. Map of Annual Soil Erosion in our area of interest split into 4 quadrants. For each quadrant, the spatial maximum and minimum soil erosion will be represented as categories according to Haiyan, 2018.

Area	Erosion Level as defined by Haiyan, 2018 (tonnes/km2)	Annual Wind Erosion, as calculated in this study (tonnes/km2)
Total Soil Loss / Total Area	Very Severe (8000 - 15000)	8800
Quadrant I (North East)	Moderate (2500 - 5000) - Destructive (> 15000)	2600 - 63000
Quadrant II (North West)	Very Severe (8000 - 15000) - Destructive (> 15000)	8900 - 69000
Quadrant III (South West)	Very Severe (8000 - 15000) - Destructive (> 15000)	8200 - 93000
Quadrant IV (South East)	Destructive (> 15000) - Destructive (> 15000)	21000 - 95000

Table 2: Data Comparison This table summarizes the categories of severity of wind erosion from Haiyan, 2018 and compares them with our annual wind erosions based on each quadrant of the area of interest.

The Eastern Gobi Steppe Area has almost double the soil loss per unit area of Inner Mongolia because it is less vegetated

Our model estimates the total annual soil loss for the Mongolian Eastern Gobi Steppe to be 0.61 * 109 tonnes. Another study on soil loss in Inner Mongolia of China, a nearby region, estimates the annual soil losses to be in the range of 4 to 5.7 billion tonnes (Jiang, 2016). In comparison, our model estimates the total annual soil loss for the Mongolian Eastern Gobi Steppe to be 0.61 * 109 tonnes (61 * 1010 kg). The area of interest in that study is 1.2 million km2, whereas our area of interest has an area of 69300 km2. Comparing these numbers, we see that the Eastern Gobi Steppe Area has almost double the soil loss per unit area of Inner Mongolia. This is because the Inner Mongolia area of interest is larger and contains areas with a large range of vegetation coverage, so there is less wind erosion on average due to the influence of vegetation-heavy areas, which are not present in the Eastern Gobi Steppe.

3.2. Multiple Environmental Factors Contribute to Soil Loss with Varying Impact

3.2.1. Significant impact of 5 primary RWEQ factors

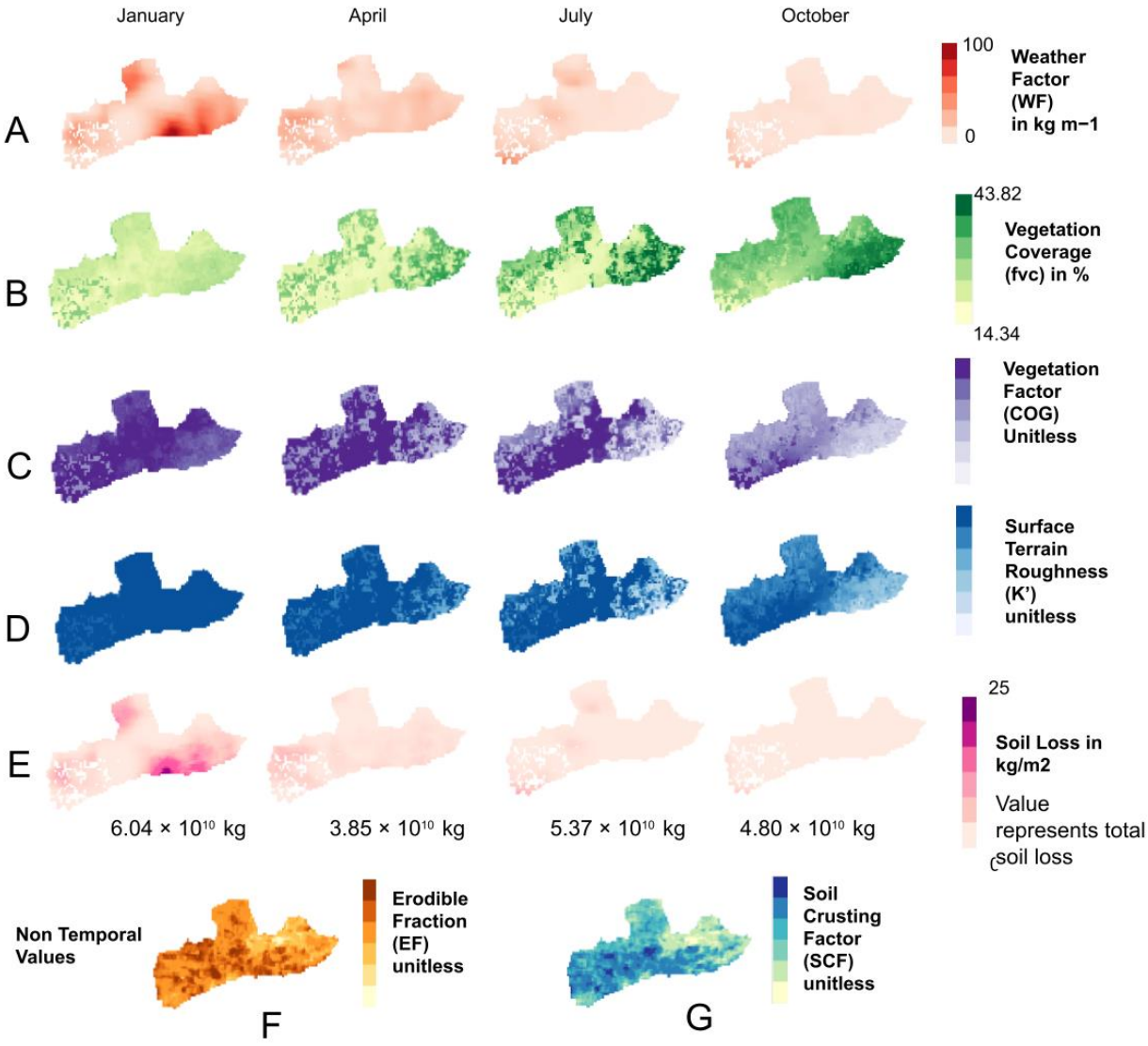


Figure 4. Soil loss factors per season. Inputs are monthly, this figure highlights one month per season.

Soil erosion is affected by the seasonal variation of the weather factor and vegetation coverage.

RWEQ's primary factors are weather factor (WF), vegetation factor (COG), Surface Terrain Roughness (K'), Erodible Fraction (EF), and Soil Crusting Factor (SCF). Figure 4 displays maps of each of these five primary factors, along with the estimated soil loss, for our area of interest. Though the spatial distribution of each factor varies across months, we have chosen four months, January, April, July, and October to represent the four seasons. In addition to the primary factors, fractional vegetation coverage maps are shown to highlight the relation between seasonal soil loss and vegetation coverage. The weather factor represents the effect of climate on wind erosion, and combines wind speed, soil moisture, and snow cover. As shown in Figure 4-A and 4-E, the higher weather factor in January leads to a higher soil loss for the month. Figure 4-C also shows that COG is high for January. COG is inverse to fractional vegetation coverage, which implies lower vegetation coverage. Indeed, the fractional vegetation coverage in January is the lowest of the

four seasons which contributes to the high soil loss in that month. Similarly, in October, the Weather Factor was low and fractional vegetation coverage was high, resulting in comparatively lo[illegible] soil loss in that month. K' shows similar variability across the seasons as COG since both factors are dependent on fractional vegetation coverage. The seasonal variation of SCF and EF is not expected in this region and this project used non-temporally variable soil composition data.

3.2.2. Soil loss is most sensitive to changes in wind speed data, followed by soil composition input data.

Variable	Affected Soil Loss Factors	Global Average of Variable	Global Range {min - max}	Maximum Spatial Range {min - max}	Maximum Seasonal Range {min - max}	SL sum% difference with variable= 50% of actual value	SL sum% difference with variable= 150% of actual value	SL sum %diff when variable= min (of Global Range) uniformly	SL sum %diff when variable= max (of Global Range)
Wind_speed (m/s)	WF	1.2	0 - 13	0.7 - 17	NA	-100	309	-100	322
Temp (℃)	WF	-0.13	-24 - 20	5.8 - 7.4	33 - 40	-3.06	2.70	52.5	-9.43
Precip (mm)	WF	8.8	0 - 47	2 - 28	19 - 46	2.61	-1.92	5.60	-2.91
Precip days	WF	0.75	0 - 3	NA	0 - 3	2.61	-1.92	5.60	-17.7
Solar_rad (MJ/m^2)	WF	667	260 - 1050	0.58 - 42	748 - 789	-2.79	1.69	-3.17	0.73
Sand (ratio)	EF	0.43	0.32 - 0.50	0.19 - 0.19	NA	-16.6	15.5	-8.70	4.66
silt (ratio)	EF	0.39	0.32 - 0.48	0.16 - 0.16	NA	-7.52	7.30	-2.68	3.39
Clay (ratio)	EF, SCF	0.18	0.14 - 0.25	0.11 - 0.11	NA	75.0	-46.1	27.2	-42.2
som (%)	EF, SCF	2.7	2.3 - 3.2	0.88 - 0.88	NA	11.6	-13.4	3.56	-4.65
fvc (%)	COG, K'	25	14 - 49	13 - 34	0 - 30	10.3	-17.4	8.59	-50.3
WF (kg/m)		25	0 - 520	22 - 510	15 - 516	-52.5	43.4	NA[1]	NA[1]

EF		0.43	0.39 - 0.45	0.05 - 0.05	0.00 - 0.00				
SCF		0.18	0.10 - 0.25	0.15 - 0.15	0.00 - 0.00				
K′		0.79	0.48 - 0.86	0.07 - 0.37	0.00 - 0.35				
COG		0.89	0.79 - 0.94	0.06 - 0.14	0.00 - 0.12				

Table 3. Sensitivity Analysis of Soil Loss (SL) against Model Inputs. Sensitivity is measured as the perfect change in the annual, spatial soil loss sum if an input is increased or decreased by a percentage of the original value, or uniformly set to the minimum or maximum value of the spatial data. The actual annual soil loss rate is 8800 tonnes/km2.

Note 1: The Sensitivity analysis for the soil loss factors (wf, scf, ef, kprime, cog) is done by applying a single scale factor to the product of these factors in the RWEQ equations for maximum transported capacity by wind (Qmax) and the critical field length (S). As such, there is no representative min or max value that could be used.

Soil loss is most sensitive to changes in wind speed, as expected when using RWEQ which emphasizes the effect of wind.

Of all inputs to the RWEQ equation, sensitivity of soil loss to wind speed is greatest (Table 3). A couple of results deserve special attention. When the wind speed for every day is set to the maximum wind speed spatially, the soil loss increases by 322% (First Row, Table 3). In our area of interest, the wind speed values are mostly less than the threshold, hence when the value is forced to the maximum, there is a significant increase in soil loss. This observation is more pronounced when all spatio-temporal wind speed values are increased by 150%. As most of the wind speed values are between 3 m/s and 5 m/s, a 150% increase makes many of them higher than the threshold and contributes to the soil loss. In addition, the wind speed has a cubic relation to the weather factor, so a small increase in non-zero entries of wind speed values results in significantly higher weather factor, hence, soil loss. This is in line with the general principle of RWEQ's reliance on wind as a corner-stone (Fryrear, 2001).

Fractional vegetation and clay ratio are the most significant soil-based factors.

The soil parameters (sand, silt, clay, organic matter) also have significant effects on soil loss (Table 3); in particular the clay ratio especially affects soil loss as higher clay in the soil allows it to maintain larger clumps which could reduce the impact of wind erosion (Purdue). Similarly, fractional vegetation coverage also has a significant effect on soil loss.

Precipitation and Solar Radiation are not as significant.

The results show a lack of sensitivity of soil loss to precipitation, number of rain days, and solar radiation as shown by less than 10% change in the corresponding rows of Table 3.

3.3. Increased Vegetation Coverage Reduces Soil Loss

3.3.1. Vegetation Protects from Soil Loss

Increasing vegetation coverage significantly reduces wind erosion.

Vegetation coverage has a significant impact on soil loss, as observed by the soil loss percent change with varying magnitudes of fractional vegetation coverage (Figure 5). The areas with minimal vegetation coverage (Map B) result in more soil loss (Map A), such as

the western side of the area of interest. At fractional vegetation coverage in the range of 30% to 50%, the soil loss is in the range of 0.001 kg/m2 to 0.002 kg/m2 as shown in the eastern side of the area in Maps A and B. A potential soil loss estimation with 0% fractional vegetation coverage (FVC) shows more soil loss as shown in Map C. Specifically, the eastern side shows higher percent change in soil loss in the range of 70% to 100% more (Map C). This is consistent with the higher FVC in that area (Map B) where the soil loss is minimized by the higher vegetation coverage. If that coverage is removed, the area becomes susceptible to higher soil loss. On the other hand, the theoretical scenarios where FVC is uniformly 50% (Map D) and 100% (Map E) indicate that soil loss could be significantly reduced with substantially increased vegetation. Soil loss would decrease by 60% to 80% with 50% FVC and decrease by 90% to 100% with 100% FVC. If the vegetation coverage in each area is increased to 110% (Map F), 120% (Map G), or 150% (Map H) of the original vegetation coverage, it results in reduced soil loss to a lesser degree, from 20% to 60% decrease.

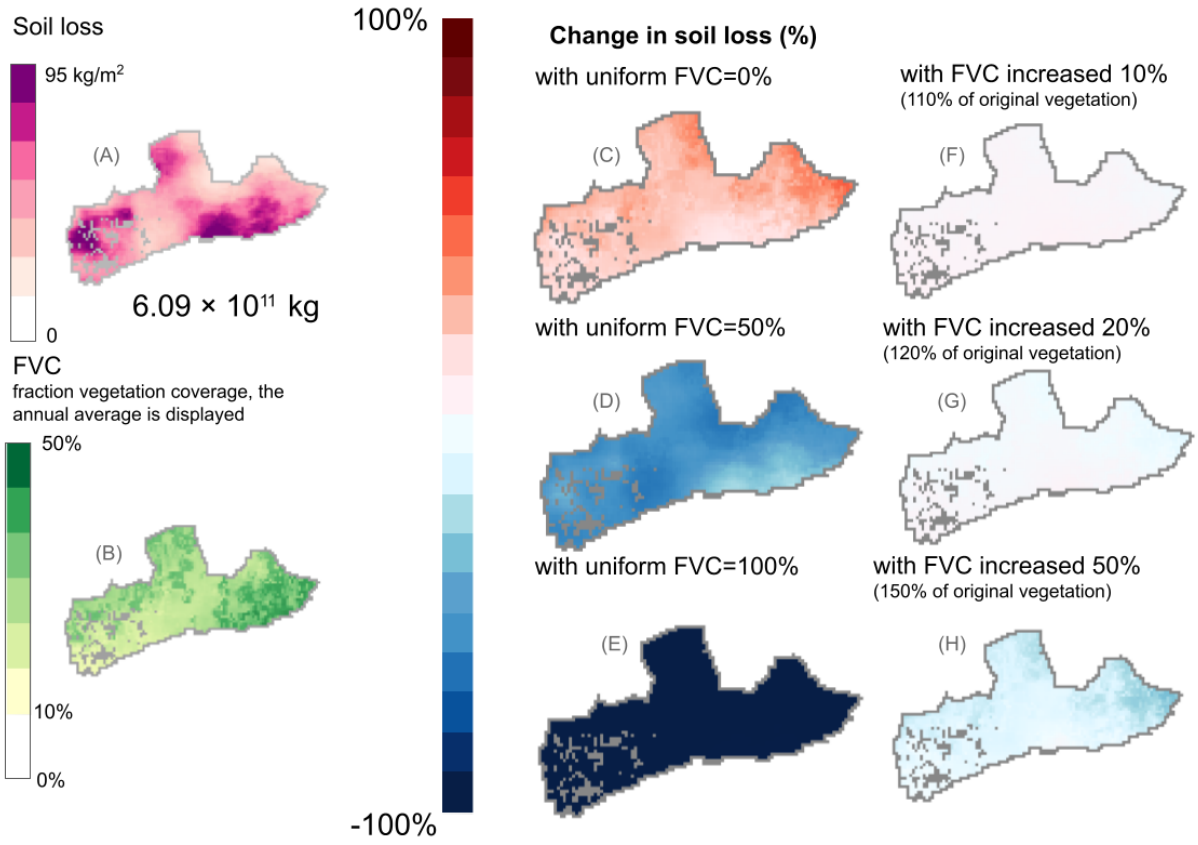


Figure 5. Soil loss with current vegetation, and 6 scenarios of vegetation cover.

3.3.2. Vegetation coverage management is a powerful tool to mitigate wind erosion

Increasing vegetation coverage seems like an effective way of decreasing wind erosion.

Based on our 6 vegetation cover scenarios, we show that increasing the original vegetation cover by only 10% or 20% is needed to achieve 13% to 25% decrease in soil loss. The current average annual vegetation coverage is 25% which means that the vegetation coverage must be doubled (increased by a factor of 1.4 to 3.3 depending on area) to enable the more drastic reductions in soil loss (60% to 80%) that are achieved with a uniform vegetation cover of 50%. As reported by the sensitivity analysis of Table 3, a lack of sensitivity was observed for climate factors such as precipitation, solar radiation and temperature.

These results suggest that while future climate change may bring higher wind speeds to the region, increasing vegetation cover is a powerfully effective tool to reduce soil loss. This finding suggests that protecting and increasing vegetation coverage would be effective in decreasing wind erosion.

4. CONCLUSION

The fractional vegetation coverage has a significant impact on soil loss.

Our results show that the RWEQ based model that we developed is applicable to estimating soil loss in the Mongolian Eastern Gobi Steppe, as our estimated total soil erosion was consistent with prior published results in neighboring areas. Our findings indicate that in addition to the weather and soil related model inputs, the vegetation coverage has a significant impact on soil loss. Indeed, our sensitivity analysis shows that varying vegetation coverage results in the second largest percent change in soil loss, following wind speed. This is especially significant for this area as wind speeds are often below the threshold for wind erosion. The estimated soil loss is lower in the eastern part of the area of interest, which has a higher vegetation coverage. The spatial soil loss estimates using different theoretical vegetation coverages show that increasing fractional vegetation coverage can reduce soil loss. Even an increase of 10 to 20% can have measurable reductions in soil loss. As demonstrated by Table 3, changes in wind speed and soil composition also have significant impact on soil loss.

Protection and increase of vegetation coverage is vital to decreasing wind erosion.

These results highlight the importance of safeguarding vegetation coverage as it can have significant contributions for ecosystem service preservation by preventing wind erosion. A similar conclusion is reached in Jiang 2016: promoting forest and grassland restoration from farmland, restricting grassland cultivation, limiting the number of livestock heads on grassland, and allowing a timely recovery for degraded grassland can lead to reduced soil loss. A possible follow-up study of our research could explore the type of vegetation that causes the greatest reduction in soil loss, similar to the study done by Zhang et al. on the impact of different groundcover plants in combating soil erosion (Zhang, 2020).

The Chinese government implemented measures to prevent sandstorms and wind erosion via the Beijing-Tianjin Sandstorm Source Control Project to be implemented from 2013 to 2022. ("Counties Benefit from Beijing-Tianjin Sandstorm Source Control Project", 2020). This project is focused on the Chinese provinces of Beijing, Tianjin, Hebei, Shanxi, Shaanxi and Inner Mongolia. In this project, resources are invested into afforestation, sand fixation, and degraded shelter forest reconstruction. Afforestation, the planting of new trees, and forest reconstruction increase vegetation coverage significantly. The benefits of this project are widespread. For example, the income of farmers and herdsmen in the area has been increased, and the more stable ecosystem bolstered by the increase in vegetation coverage will contribute to conservation of animal and plant species. If such a project is implemented in our area of interest, the Eastern Gobi Steppe, increasing vegetation coverage to decrease wind erosion, valuable ecosystem services can be preserved.

Prediction of future wind erosion in this area must be explored.

It is important to further investigate the impact of climate evolutions on future wind erosion. As described in the Supplementary Material, a scenario of extreme climate change generated by the Rangeland Production Model was utilized to predict the percent change in soil loss from the current data to the future climate scenario. The Rangeland Production Model primarily considered changes in temperature and precipitation, but lacked future wind speed data, which limited the analysis using our model. Further analysis of future soil erosion should be done with predicted wind speed data for this region.

5. SUPPLEMENTARY MATERIAL

5.1. Use Case of Model on Rangeland Data of Extreme Climate Scenario

To implement a use case for our model, we use a scenario of extreme climate change generated by the Rangeland Production Model (Kowal, 2021) and analyze the change in wind erosion from the current scenario. The future scenario describes monthly average conditions during the time period 2061–2080 under the SSP3-7.0 land use and emissions scenario (Fick and Hijmans 2017). Among the nine global climate models (GCM) for which downscaled global data are currently available, the simulation was derived from outputs of the CanESM5 GCM. We chose this GCM because for the selected time period and scenario, this model shows the largest change in temperature and precipitation for the study area (Kowal et al. 2021). While the modeling procedure that we follow here could be applied to examine the impacts of any future climate scenario, our choice of the SSP3-7.0 scenario and CanESM5 GCM was guided by our desire to explore Mongolia's likely future. The results, therefore, indicate a reasonable outer bound for likely climatic changes under a "business as usual" emissions and land-use scenario.

One major limitation to estimating wind erosion under future climate is the lack of projections of wind speed under future climate. Because of this data availability constraint, we set the wind speed constant in this future scenario. However, this is a serious limitation to the accuracy of our estimations, as wind speed and hence the weather factor is an important contributor to soil loss. Nevertheless, near-surface wind speeds have been reported to be decreasing in China, and the trend is predicted to continue (Zha, 2020).

Under the "extreme climate" scenario, using elevated temperatures and decreased precipitation, wind erosion is estimated to decrease (Figure 5) - but with less than 38.4% change in the Eastern Gobi Steppe.

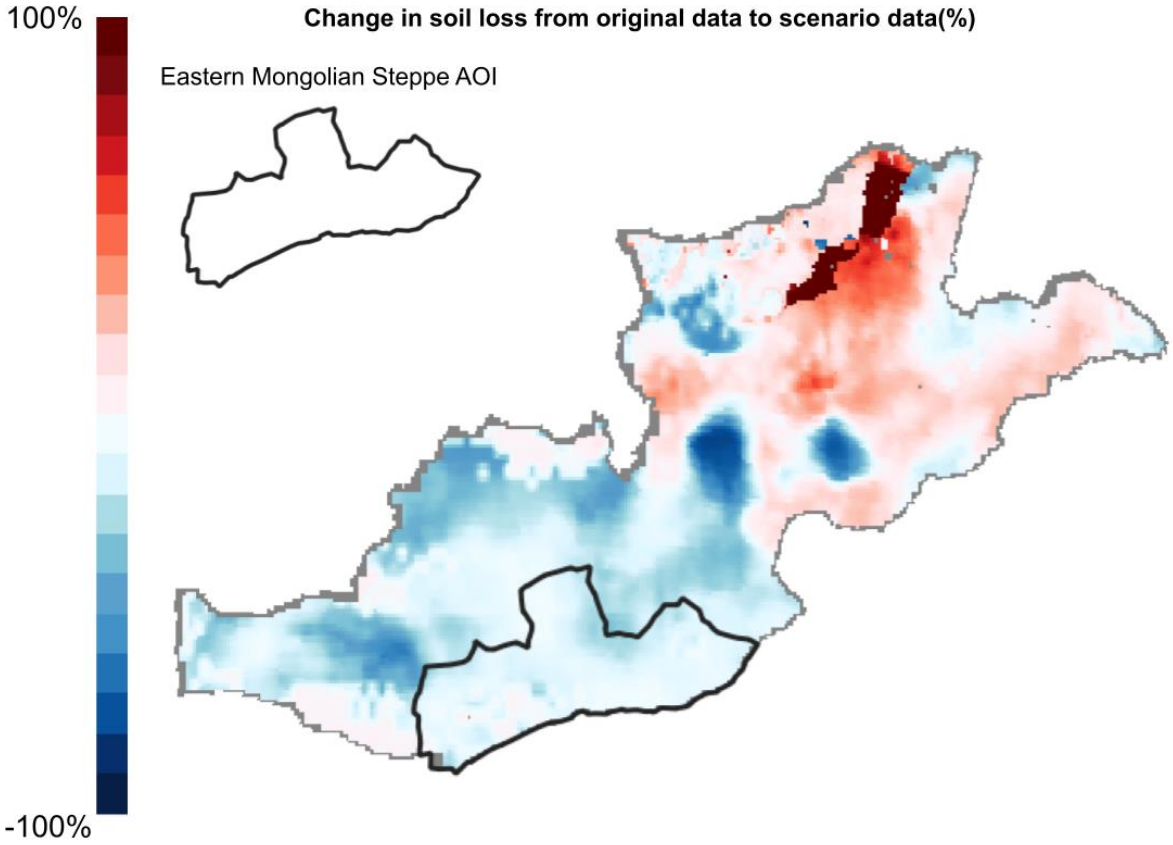


Figure 6. Percent Change in Soil Loss from current data to a future Extreme Climate Scenario.

An artifact of the data appears in the northeastern part of the larger area of interest: an approximately 10 km2 area with percent change in soil loss up to 2000% (Figure 6) -

this extreme change is explained by the fact that original soil loss values were extremely small (below 0.001 kg/m2), thus this is not considered meaningful.

5.2 Correlations of all model inputs to weather factor (WF)

	Wind speed	Temp	Precip	Sol Rad	Sand Ratio	Silt Ratio	Clay Ratio	SOM Ratio	FVC
WF Correlation	-0.6 (5), 0 (1)	0 (1), 0.5 (5)	0 (1), 0.04 (5)	0 (1), 0.5 (5)	-0.01 (5), 0.27 (4)	-0.17 (4), 0 (1)	-0.2 (4), 0.05 (5)	0 (1), 0.23 (5)	-0.27 (4), 0 (1)

Table 4: **Correlation of model inputs to weather factor** This table conveys the minimum, the first value, and maximum correlations of each input, which are comma separated. In parentheses next to the minimum and maximum, there is the number of the month (January is 1, February is 2, etc.) where said correlation is found.

The weather factor is calculated using wind speed along with precipitation, number of rain days, temperature, and solar radiation. The analysis of the correlations of the model inputs to the weather factor does not show a specific parameter to have significantly high correlation in all months. This indicates that all the model inputs are significant and have complex interdependent relationships to their contribution to the weather factor. The Pearson correlation coefficient that is used for these analyses has less accuracy for non-linear correlations.

5.3. Plots of Sensitivity of Soil Loss to Model Inputs

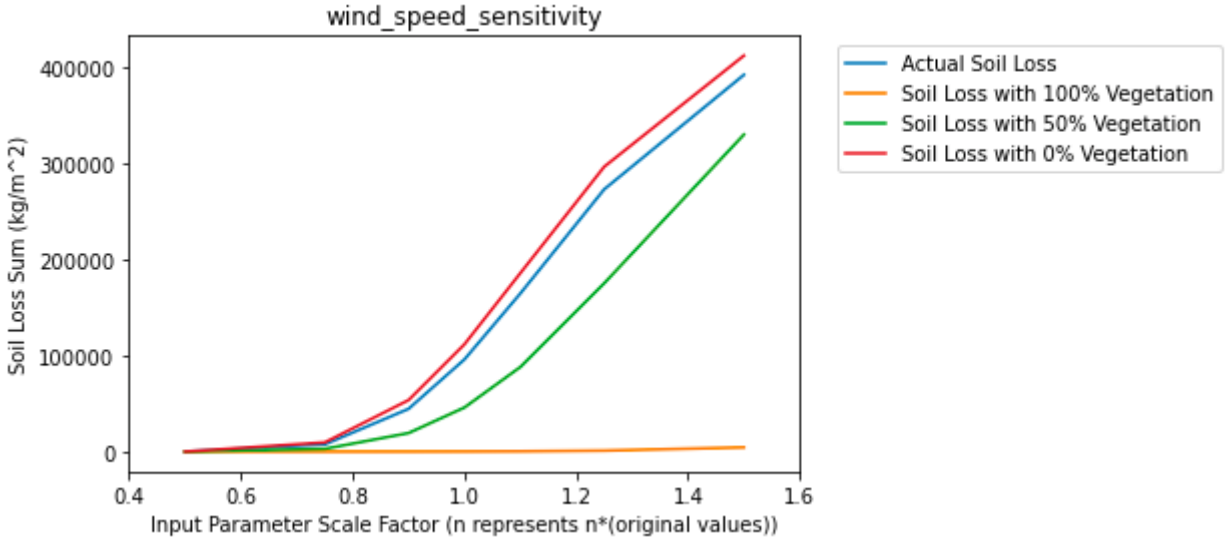


Figure 7. Wind Speed (m/s) Sensitivity Global Average of Factor (Original 100%) = 4.03.

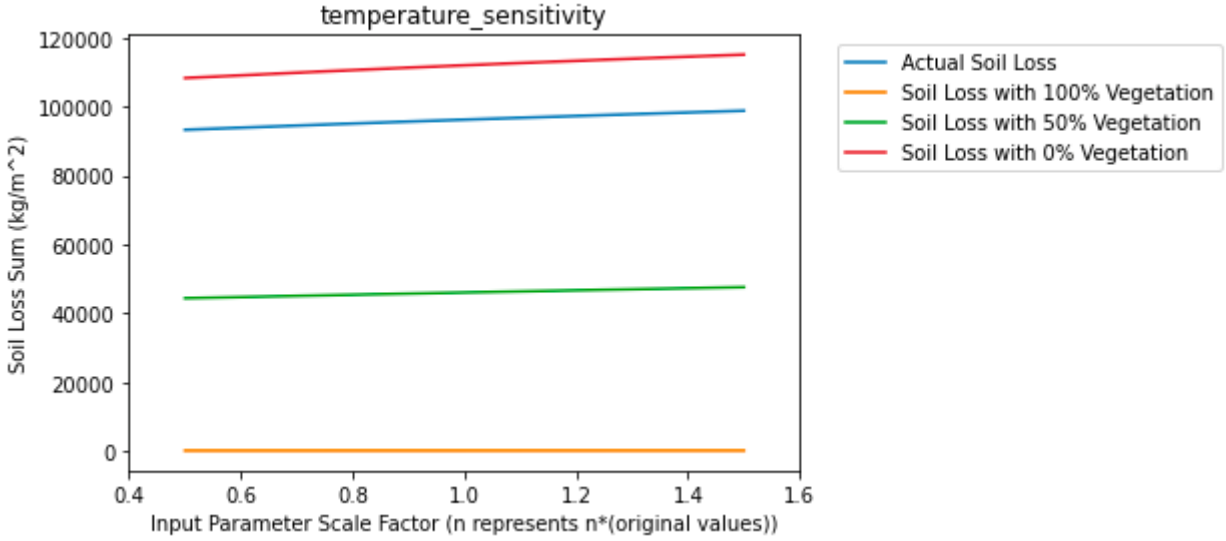


Figure 8. Temperature (deg C) Sensitivity Global Average of Factor (Original 100%) = -0.13.

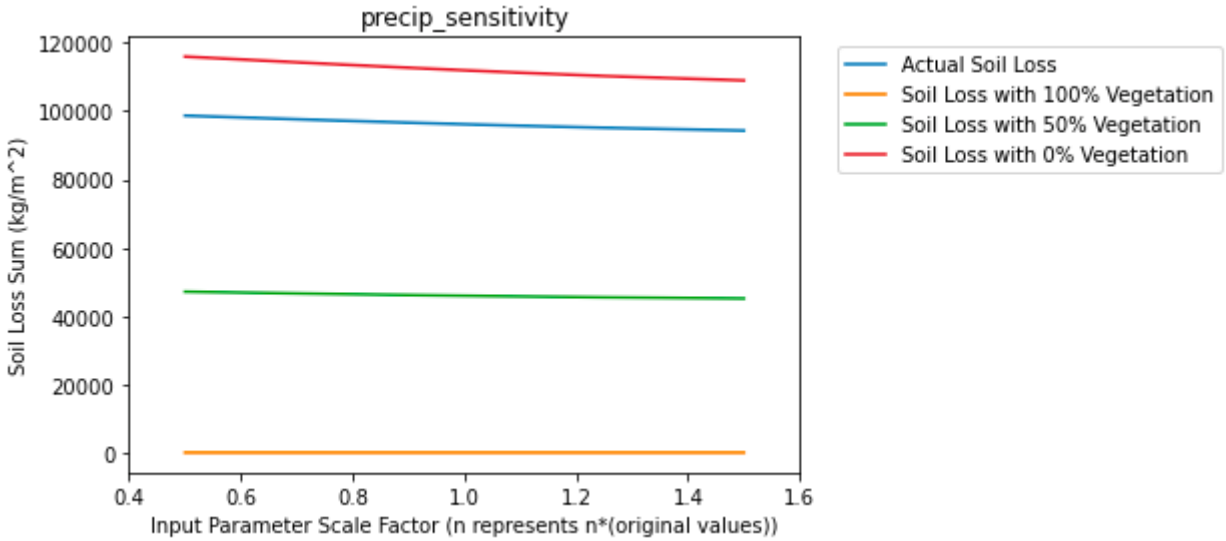


Figure 9. Precipitation (mm) Sensitivity Global Average of Factor (Original 100%) = 8.79.

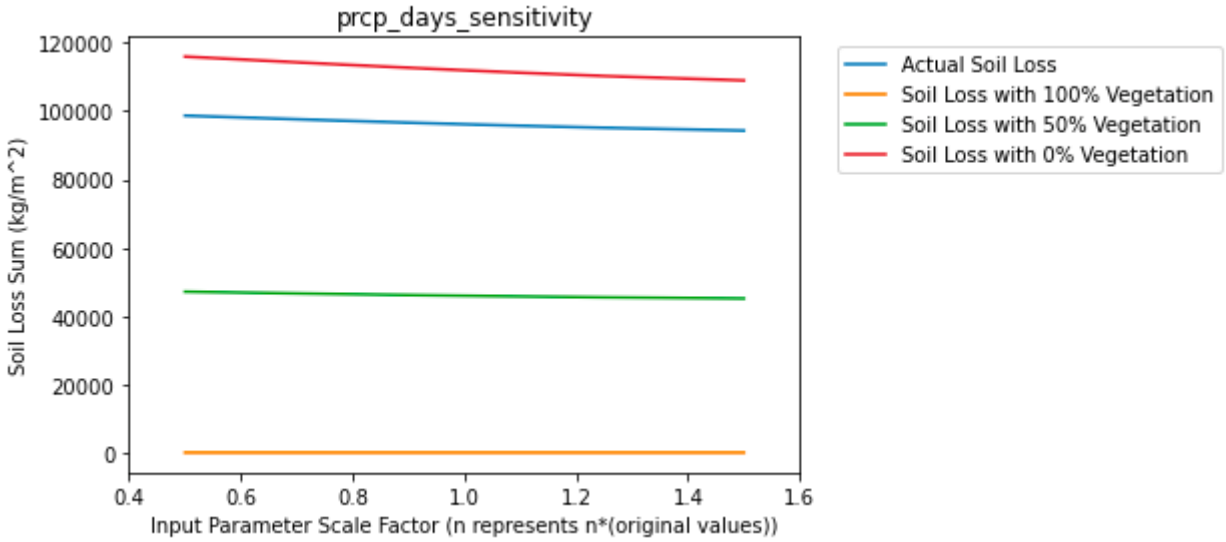
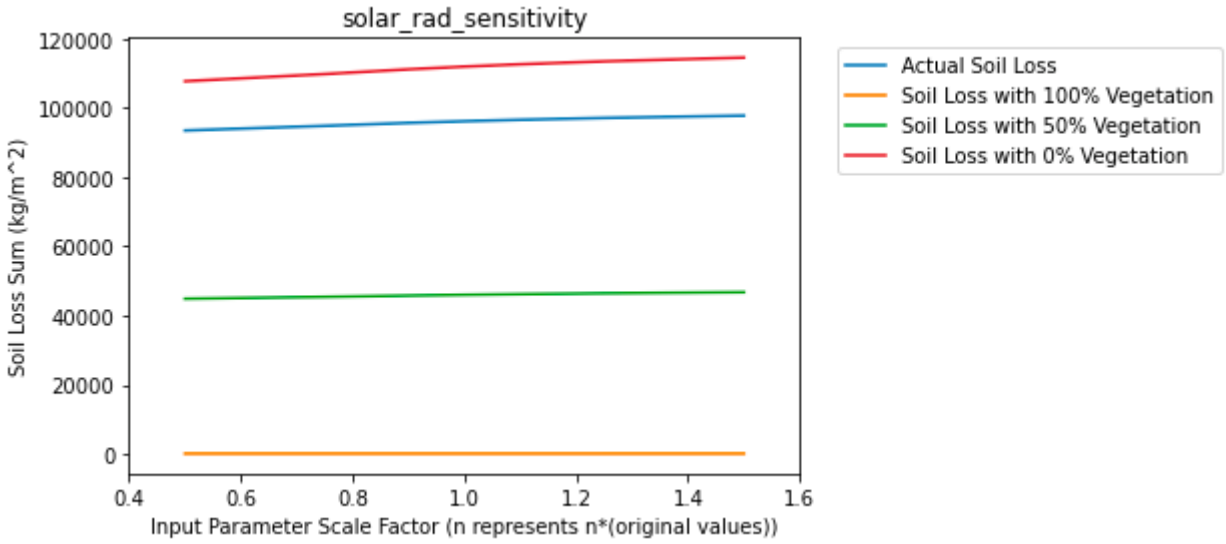
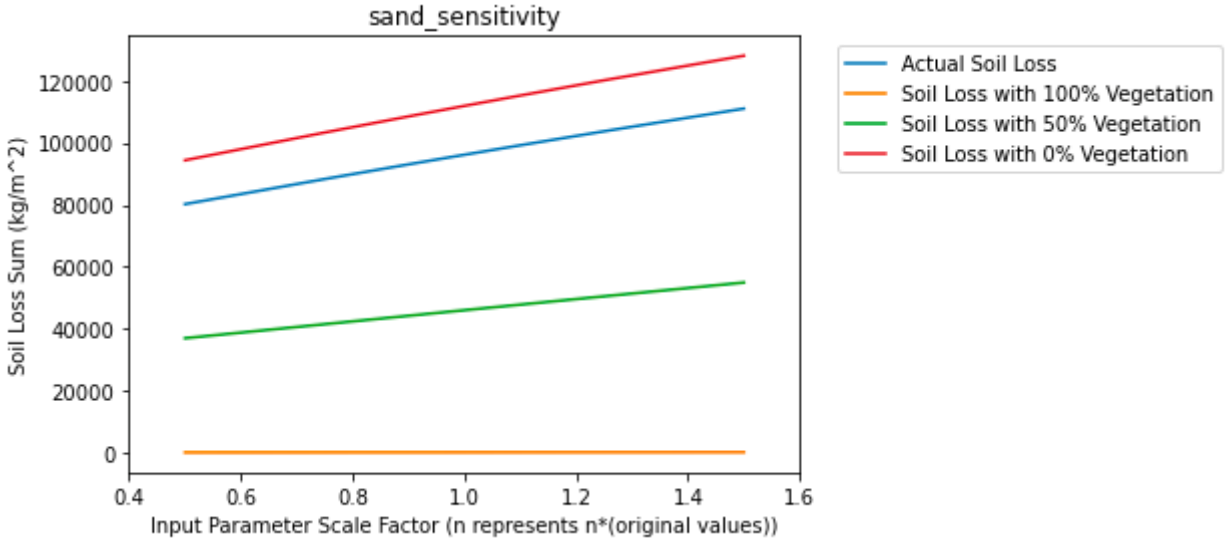


Figure 10. Number of Rain Days Sensitivity Global Average of Factor (Original 100%) = 0.75. 467



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Figure 11. Solar Radiation (MJ/m2) Sensitivity Global Average of Factor (Original 100%) = 667.16. 469



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Figure 12. Sand Ratio Sensitivity Global Average of Factor (Original 100%) = 0.43. 471

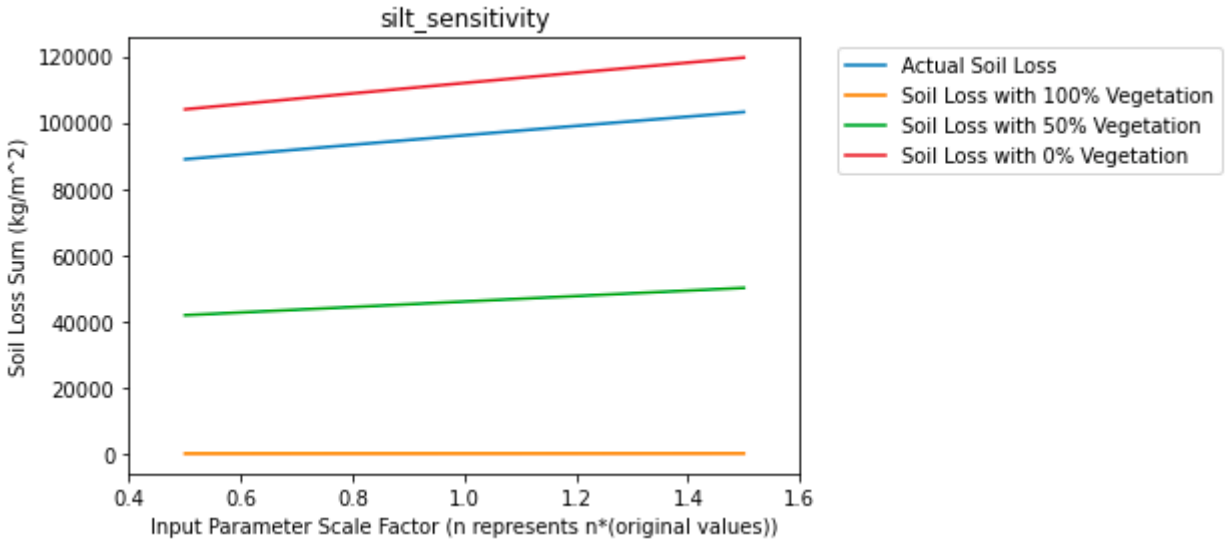


Figure 13. Silt Ratio Sensitivity Global Average of Factor (Original 100%) = 0.39.

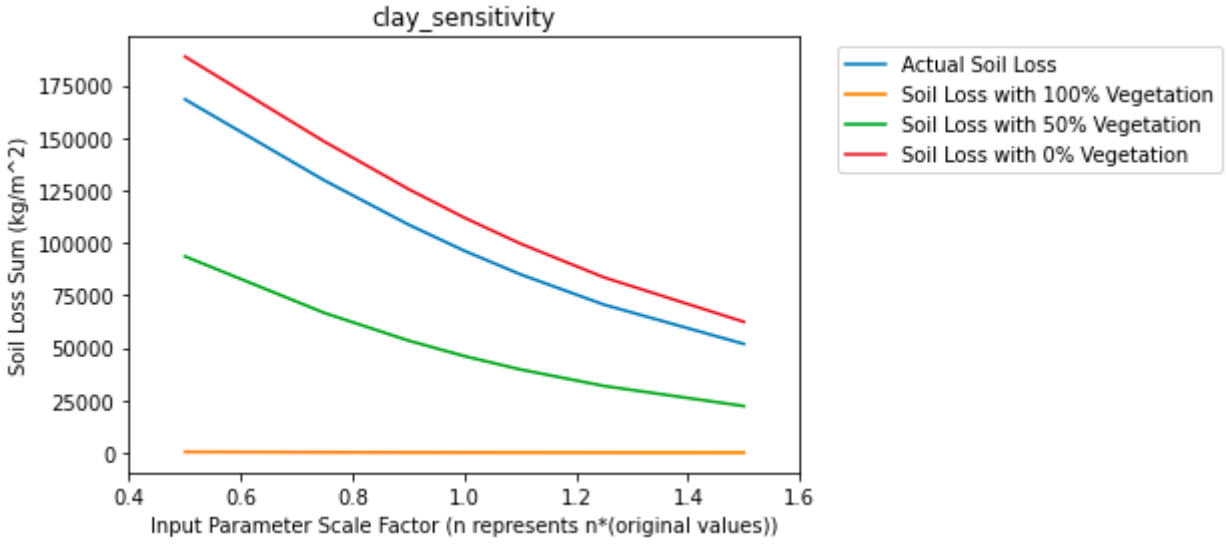


Figure 14. Clay Ratio Sensitivity Global Average of Factor (Original 100%) = 0.18.

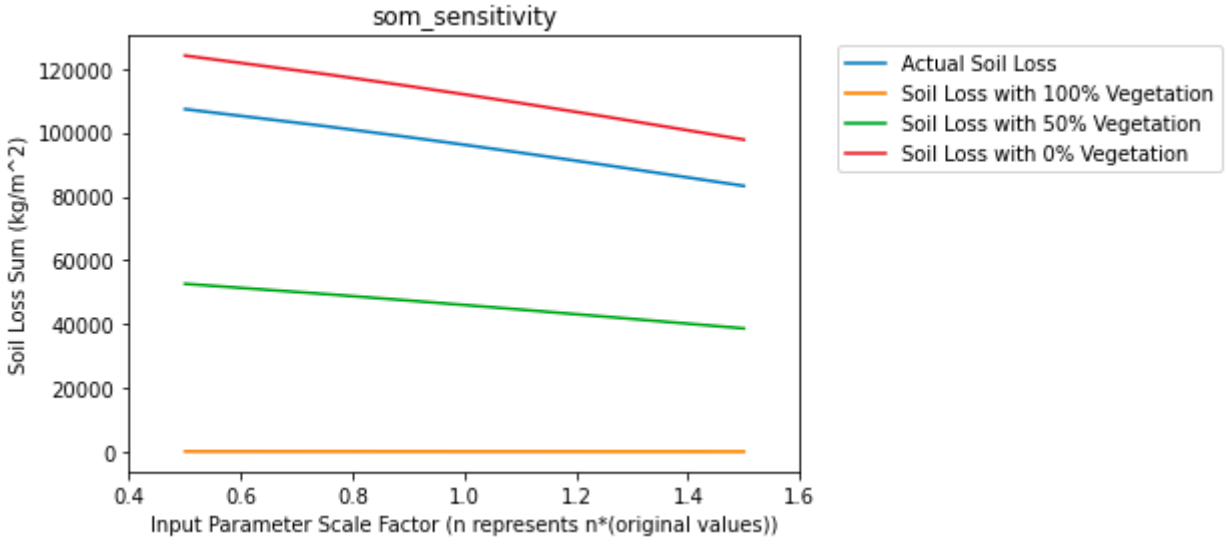


Figure 15. Soil Organic Matter (%) Sensitivity Global Average of Factor (Original 100%) = 2.74.

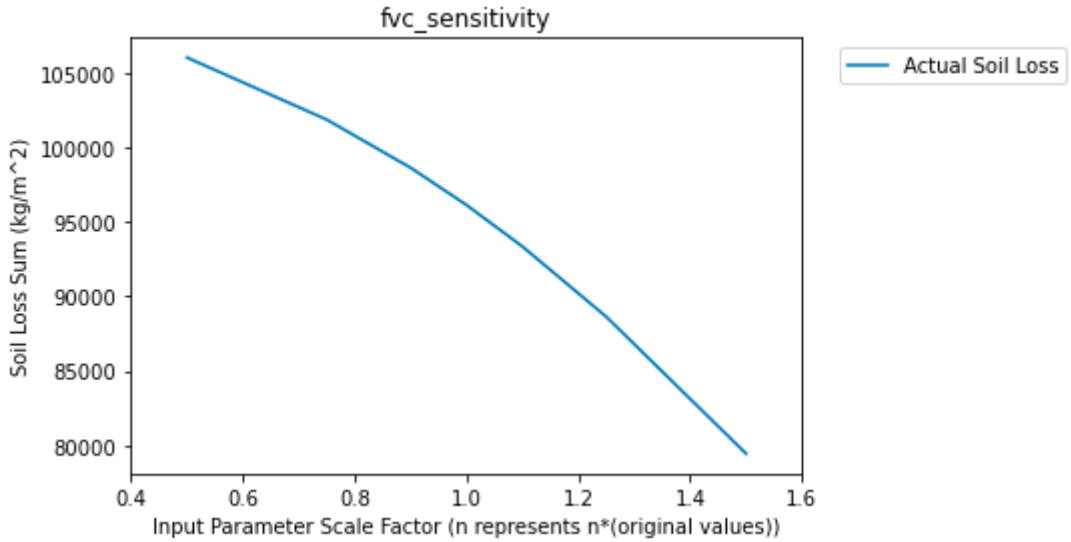


Figure 16. Fractional Vegetation Coverage (%) Sensitivity Global Average of Factor (Original 100%) = 24.74.

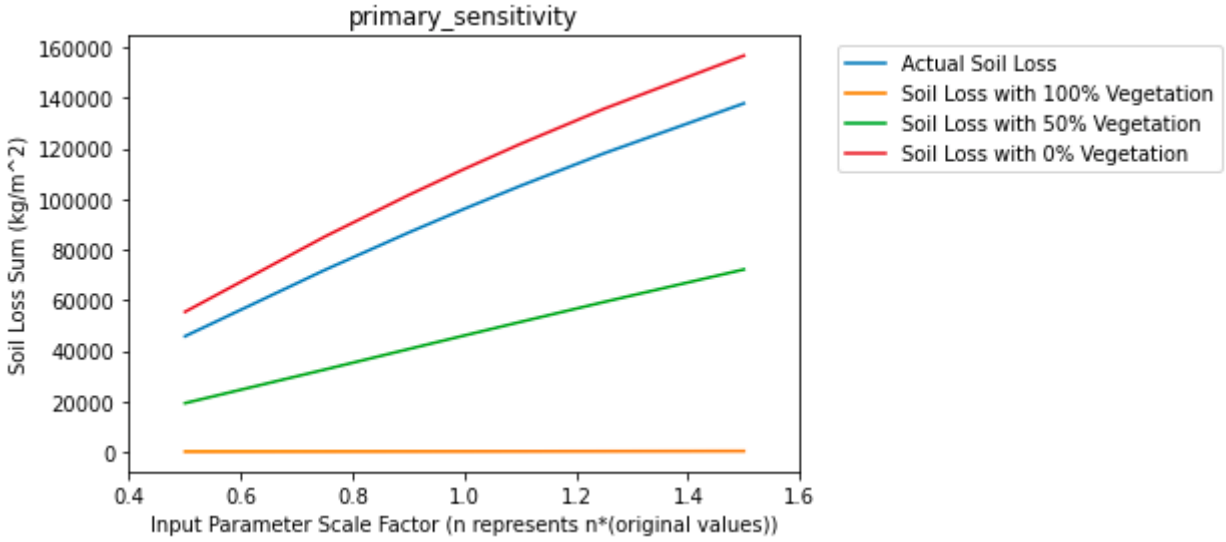


Figure 17. Primary RWEQ input Sensitivity Sensitivity of weather factor, soil crusting factor, erodible fraction, surface terrain roughness and vegetation factor (all fives impact similarly Soil Loss, as they get multiplied).

5.4. Histograms of Soil Loss Factors

Here are the histograms for the soil loss factors of RWEQ: weather factor, erodible fraction, Soil Crust Factor, surface terrain roughness, and vegetation factor.

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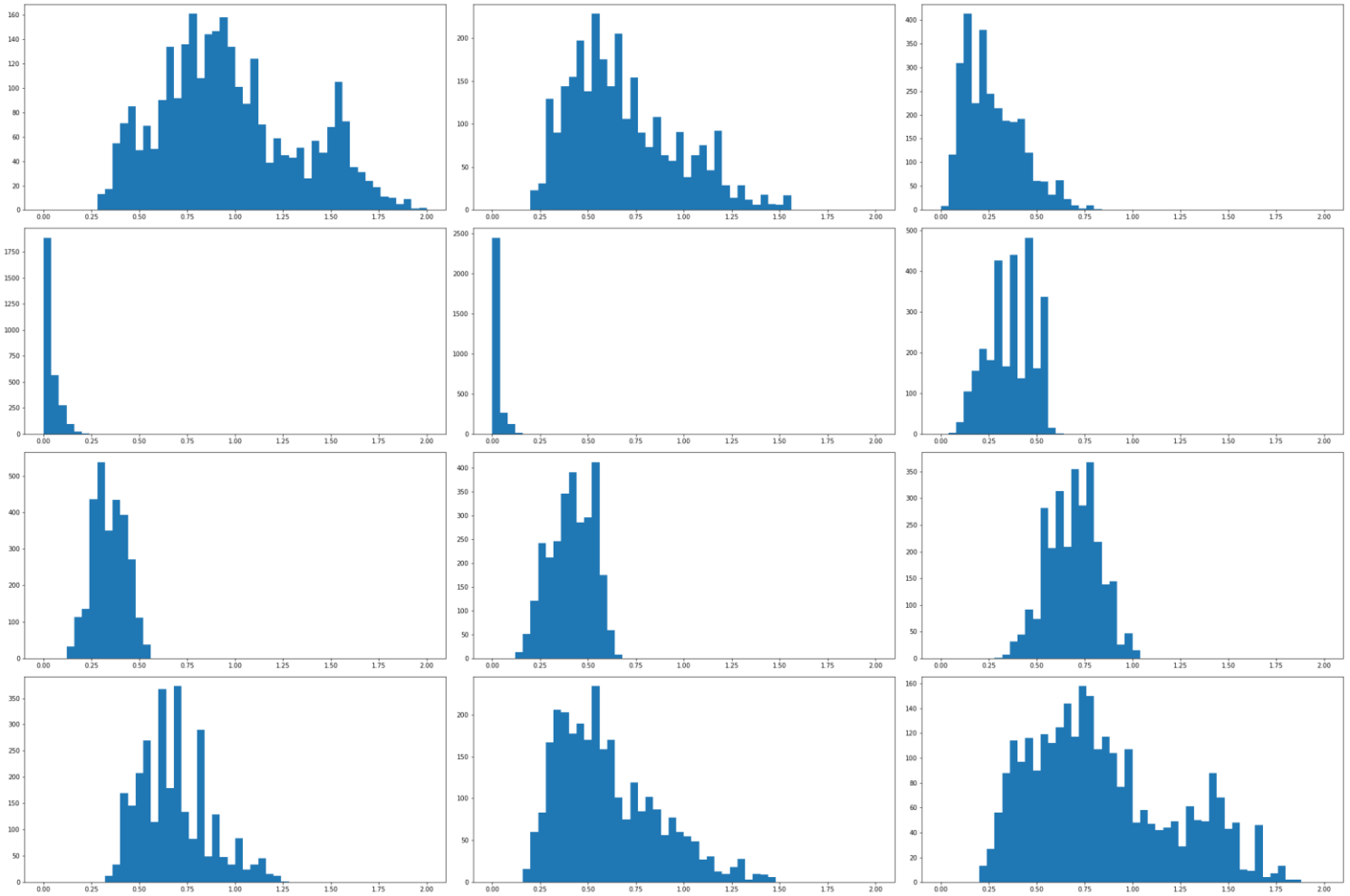
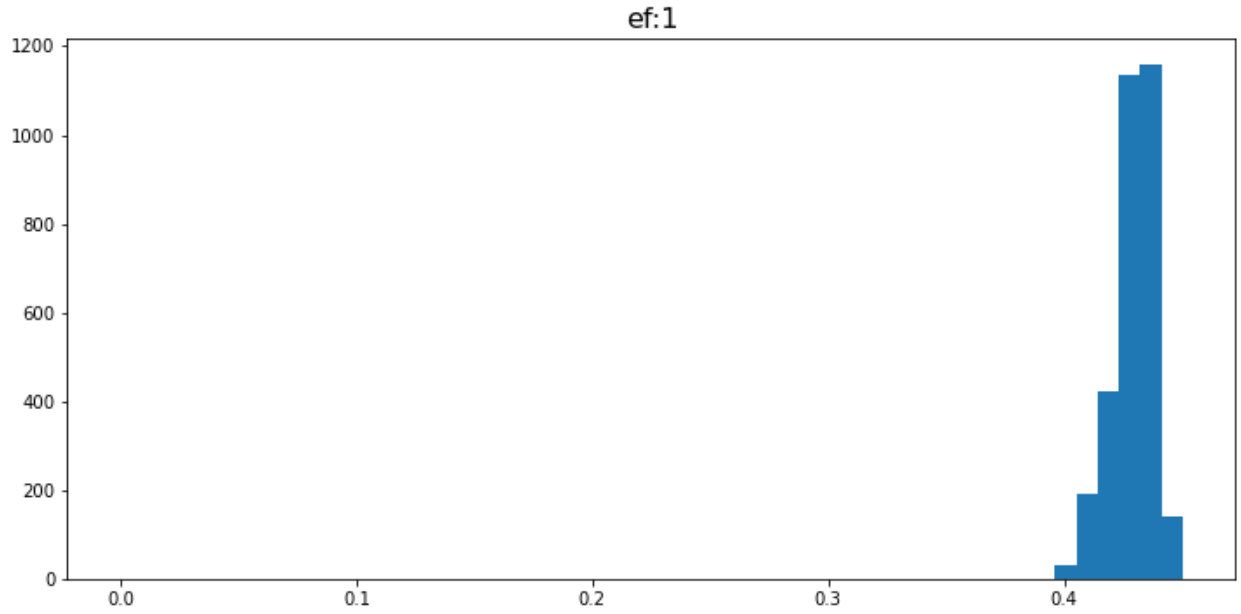


Figure 18. Monthly Weather Factor (WF).

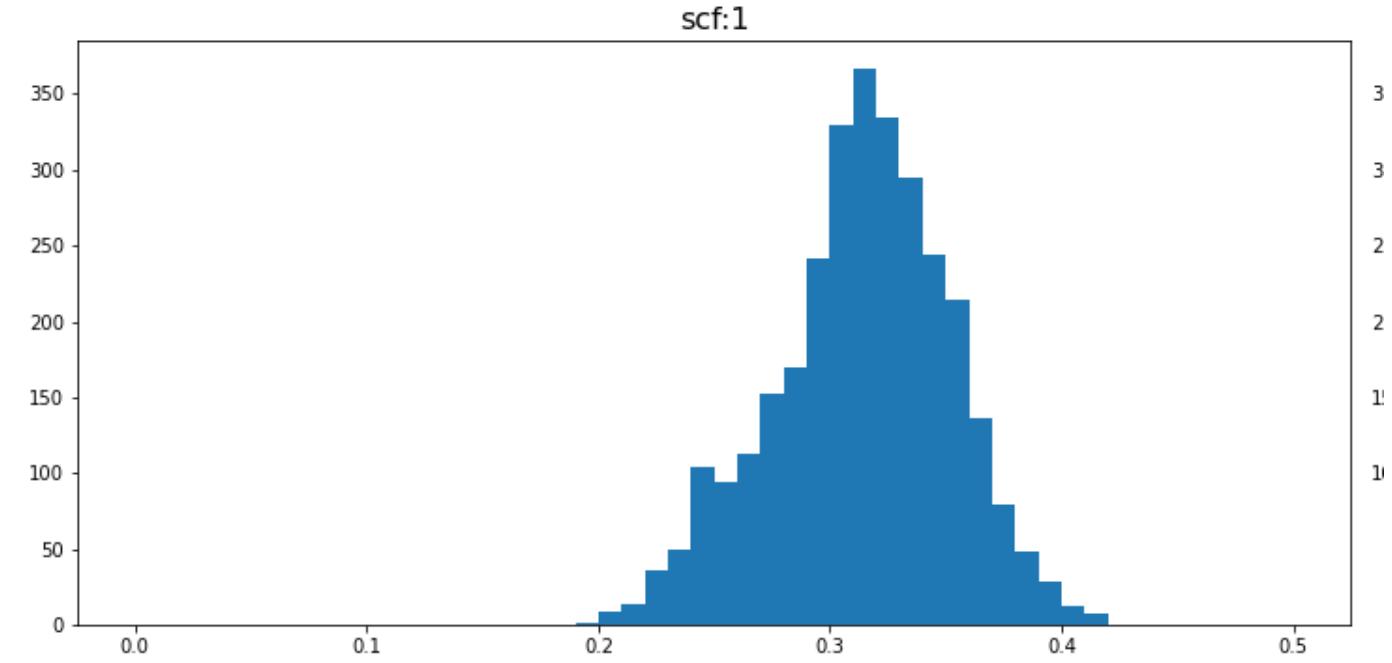
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Figure 19. Erodible Fraction (EF).

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Figure 20. Soil Crusting Factor (SCF).

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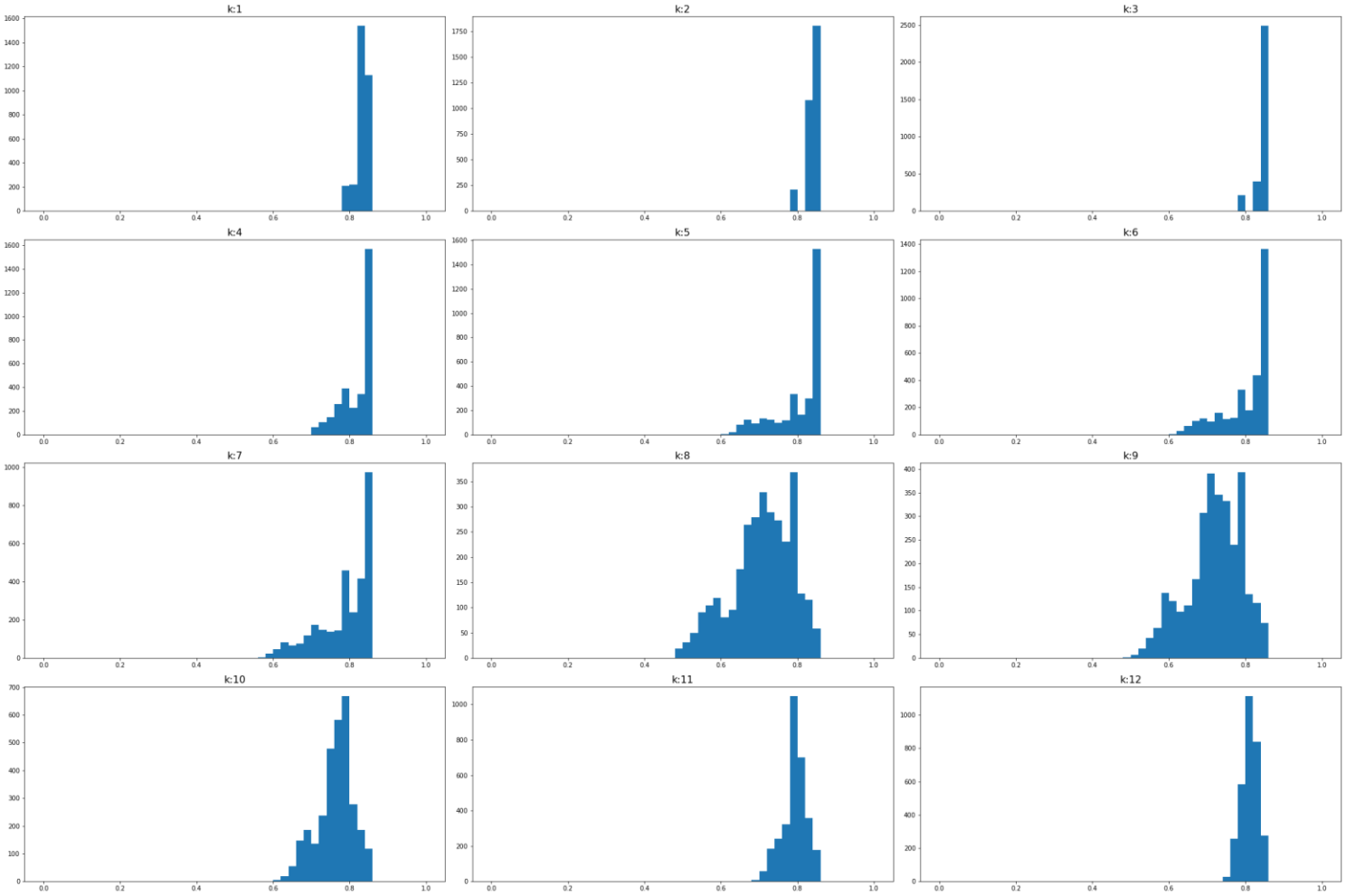


Figure 21. Monthly Surface Terrain Roughness (K').

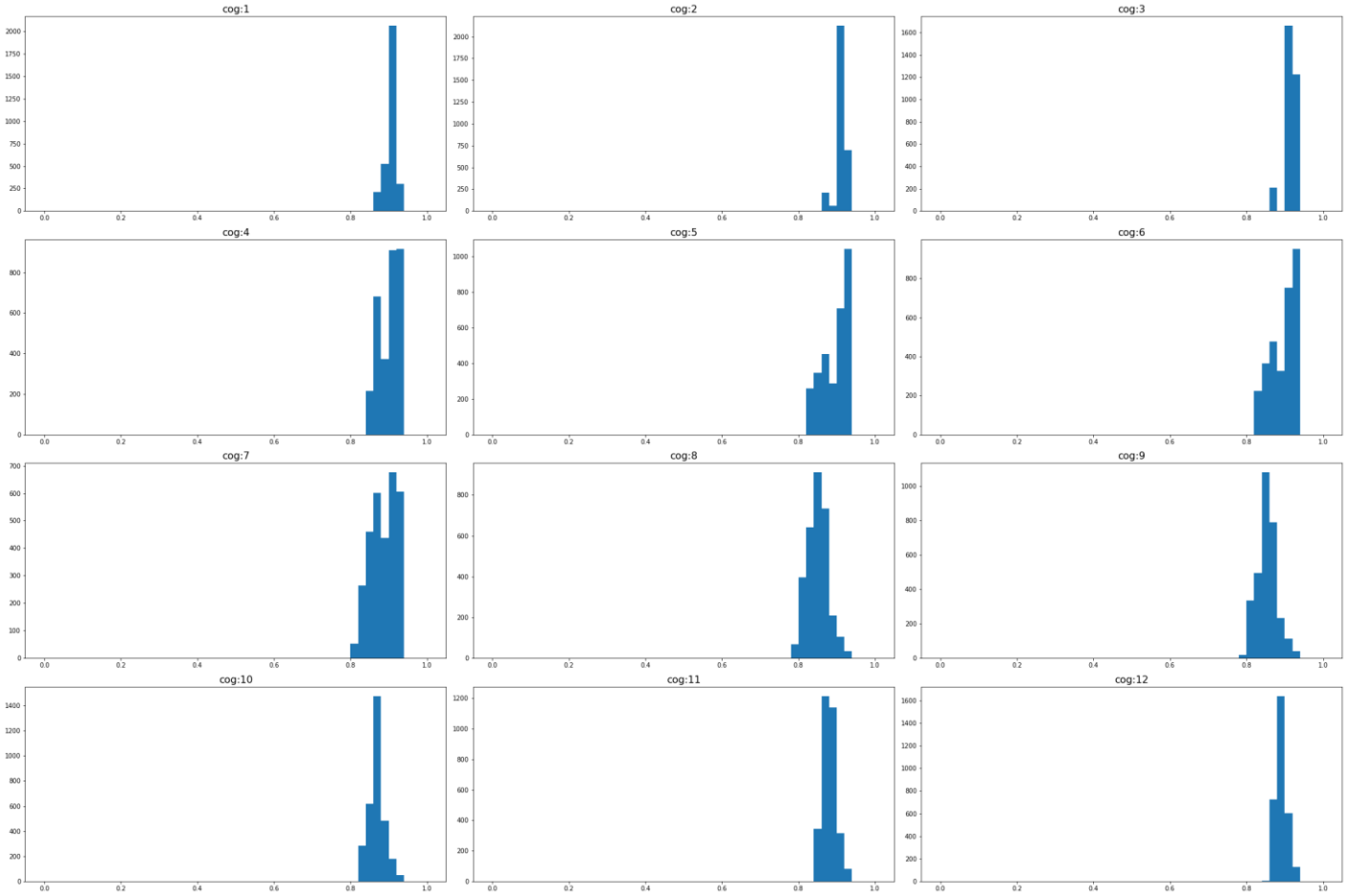


Figure 22. Monthly Vegetation Factor (COG).

Supplementary Materials: The following supporting information can be downloaded at: www.mdpi.com/xxx/s1, Figure S1: title; Table S1: title; Video S1: title.

Author Contributions: For research articles with several authors, a short paragraph specifying their individual contributions must be provided. The following statements should be used "Conceptualization, X.X. and Y.Y.; methodology, X.X.; software, X.X.; validation, X.X., Y.Y. and Z.Z.; formal analysis, X.X.; investigation, X.X.; resources, X.X.; data curation, X.X.; writing—original draft preparation, X.X.; writing—review and editing, X.X.; visualization, X.X.; supervision, X.X.; project administration, X.X.; funding acquisition, Y.Y. All authors have read and agreed to the published version of the manuscript." Please turn to the CRediT taxonomy for the term explanation. Authorship must be limited to those who have contributed substantially to the work reported.

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Data Availability Statement: In this section, please provide details regarding where data supporting reported results can be found, including links to publicly archived datasets analyzed or generated during the study. Please refer to suggested Data Availability Statements in section "MDPI Research Data Policies" at https://www.mdpi.com/ethics. If the study did not report any data, you might add "Not applicable" here.

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Conflicts of Interest: Declare conflicts of interest or state "The authors declare no conflict of interest." Authors must identify and declare any personal circumstances or interest that may be perceived as inappropriately influencing the representation or interpretation of reported research results. Any role of the funders in the design of the study; in the collection, analyses or interpretation of data; in the writing of the manuscript, or in the decision to publish the results must be declared in this section. If there is no role, please state "The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results".

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