Report

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Soil Climate and Decomposer Activity in Sub-Saharan Africa Estimated from Standard Weather Station Data: A Simple Climate Index for Soil Carbon Balance Calculations

Soil biological activity was calculated on a daily basis, using standard meteorological data from African weather stations, a simple soil water model, and commonly used assumptions regarding the relations between temperature, soil water content, and biological activity. The activity factor r_{e_clim} is calculated from daily soil moisture and temperature, thereby taking the daily interaction between temperature and moisture into account. Annual mean r_{e_clim} was normalized to 1 in Central Sweden (clay loam soil, no crop), where the original calibration took place. Since soils vary in water storage capacity and plant cover will affect transpiration, we used this soil under no crop for all sites, thereby only including climate differences. The Swedish r_{e_clim} value, 1, corresponds to ca. 50% annual mass loss of, e.g., cereal straw incorporated into the topsoil. African mean annual r_{e_clim} values varied between 1.1 at a hot and dry site (Faya, Chad) and 4.7 at a warm and moist site (Brazzaville, Congo). Sites in Kenya ranged between $r_{e\_clim} = 2.1$ at high altitude (Matanya) and 4.1 in western Kenya (Ahero). This means that 4.1 times the Swedish C input to soil is necessary to maintain Swedish soil carbon levels in Ahero, if soil type and management are equal. Diagrams showing daily r_{e_clim} dynamics are presented for all sites, and differences in within-year dynamics are discussed. A model experiment indicated that a Swedish soil in balance with respect to soil carbon would lose 41% of its soil carbon during 30 y, if moved to Ahero, Kenya. If the soil was in balance in Ahero with respect to soil carbon, and then moved to Sweden, soil carbon mass would increase by 64% in 30 y. The validity of the methodology and results is discussed, and r_{e_clim} is compared with other climate indices. A simple method to produce a rough estimate of r_{e_clim} is suggested.

INTRODUCTION

Africa is the only region where average food production per person has declined over the past 40 y (1, 2). The average African consumes only about 87% of the calories needed for a healthy and productive life (3), and 16% of Africa's current arable land base is so eroded that it is not agriculturally useful anymore. Soil fertility depletion (mainly N, P, and C) has been described as the single most important constraint to food security in West Africa (4). The Sudano-Sahelian zone of West Africa is the home of the world's poorest people, of which 90% live in villages and gain their livelihood from subsistence agriculture (5). Increasing population pressure has decreased *per capita* arable land, and fallow periods to restore soil carbon levels and soil fertility are shortened. Soil fertility is closely linked to soil organic matter and thus soil carbon, whose status depends on biomass input and management, mineralization, leaching, and erosion (6–9).

Clearly, to maintain and improve African soils, it is necessary to be able to calculate trends in soil carbon mass (soil C constitutes about 58% of soil organic matter) and how this responds to different agricultural measures. Recently, carbon sequestration in soil as a means for reducing atmospheric CO_2 (8, 10, 11) has become a possible, but still largely potential, source of income for farmers. If and when mechanisms for C sequestration contracts (a farmer gets paid for sequestering x tonnes of carbon) become common, soil carbon modeling will have to be the main approach, since repeated measurements of soil C stocks are too expensive to make in every field.

In ecological, agricultural, and soil biological research, particularly modeling, the climate is a crucial factor controlling most processes. In fact, climate is the major determinant for ecosystem structure and function. Climate controls soil processes such as CO_2 evolution, soil C balances, and nutrient mineralization from plant litter and humus. Naturally, climate also affects primary production, but this is outside the scope of the present paper. The effects of climate on soil biological activity have been addressed in various ways; in fact, all generally applied soil biological models (e.g., RothC or Century; see reviews by Paustian [12], Powlson et al. [13], and more recently Grace et al. [14]) include or at least use modules that calculate soil biological activity from weather data. These calculations are usually performed with daily or monthly time steps.

Coarse estimates of the climatic effect can be made from annual mean values of air temperature and annual sums of precipitation and calculated potential evaporation. For example, aridity index, calculated as the ratio of annual potential evaporation to precipitation, is commonly used as a measure of climatic influence (15). However, the climatic condition for soil biological activity at a given instant, r_e, is controlled (mainly, other factors exist) by both temperature and soil water content in a multiplicative manner ($r_e = r_{e\_water} \times r_{e\_temperature}$). In other words, if there is no water available ($r_{e\_water} = 0$), no activity will occur even if the temperature is optimal for soil biological activity, and *vice versa*. Therefore, calculations based on annual means can be inaccurate. For example, a region that is hot and dry ($r_{e\_water} = 0$) for 6 mo and cold and wet ($r_{e\_temperature}$ low) for 6 mo can have the same annual aridity index as a region that is temperate and moist for the entire year. The soil biological activity, however, will be much lower in the first example. This means that high-resolution (daily) rainfall data combined with a soil water model with a daily time step will give a more realistic activity estimate than, e.g., monthly data. Also, almost all meteorological observations are made with daily or higher resolution in time, so with today's computing power and data storage capacity it seems unnecessary to first make, e.g., decadal or monthly means.

This paper describes a method to convert daily weather station data to an annual (or daily) climate factor, which summarizes the soil climate and its influence on soil biological

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Table 1. Assumed soil depth (topsoil horizon thickness) for water storage and calculated calibration factors (CF) for normalization of calculated r_{e_clim} relative to the Swedish calibration sites representing Uppsala, Sweden. The calculated r_{e_clim} for a given site is divided by the value given here to normalize against the calibration site. In this application, a soil depth of 250 mm was used (bold).

Soil depth (mm)	CF (−)
50	0.073104
100	0.087827
150	0.095979
200	0.10143
250	0.10535
300	0.10838
500	0.11575

activity in one variable, r_{e_clim}. Its value is based on the daily product of $r_{e\_water} \times r_{e\_temperature}$ and thus it should in principle give correct annual estimates of soil biological activity. The calculated r_{e_clim} is normalized to the calibration site in Uppsala, Sweden (= 1) (see Tables 1 and 2 and Fig. 1). For example, $r_{e\_clim} = 4$ indicates that a given plant residue will decompose four times as fast as in central Sweden. Thus climate influence on decomposition is condensed into one value, including effects of precipitation, evaporation, transpiration, and air temperature and their daily interactions—and this value allows immediate comparisons of climate-induced decomposition rates between sites and regions. Since soils vary in water storage and plant cover will affect transpiration, we used the clay loam soil from the calibration site assuming no crop/plant cover for all sites, thereby only including climatic differences. This approach is used on weather data sets from West and Central Africa and Kenya, and a map showing the various results from different climate zones is presented. An example of the long-term consequences for soil carbon balances of differences in r_{e_clim} (e.g., a radical climate change) is calculated using the introductory carbon balance model (ICBM [16]), and the results are discussed in a global context.

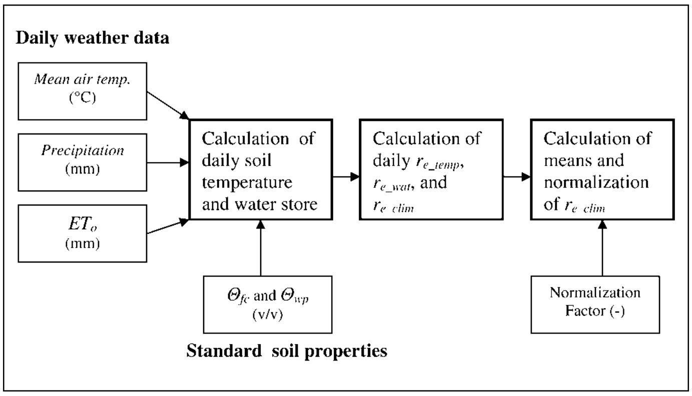

Figure 1. Flow chart showing input variables and calculation of annual r_{e_clim}. Daily mean air temperature, daily precipitation, and daily reference crop evapotranspiration (ET_0) are used to calculate daily soil temperature and water store in topsoil, assuming soil water properties (field capacity, Θ_{fc}, and wilting point, Θ_{wp}, expressed as volumetric fraction) from the soil at the Swedish calibration site. Activity multipliers (r_{e_temp}, r_{e_wat}, and r_{e_clim}) are calculated from the daily data and activity functions. Annual and Julian day means are then calculated and normalized to the initial calibration site ($r_{e\_clim} = 1$).

MATERIALS AND METHODS

Meteorological Variables

Characteristics for the weather stations used are listed in Table 2. We used a comprehensive and freely available collection of long-term daily meteorological observations from West and Central Africa (17), together with selected weather station data from Kenya (see Acknowledgements [34] for sources). The data from West Africa included air temperature (daily minimum and maximum), daily precipitation, and daily reference crop evapotranspiration (ET_0). While all stations in Kenya reported precipitation and temperature, ET_0 was not available and had to be calculated using available additional climate variables. For Kabete, Kalalu, Matanya, and Ahero we used daily air temperatures, relative humidity (RH), wind speed, and irradiation to calculate ET_0 according to equation 6 in Allen et al. (18). For Ahero and Muranga, RH was missing and was calculated from actual vapor pressure data and minimum and maximum temperatures according to the procedures given by Allen et al. (18) equations 10, 11, and 12. Daily air temperature was calculated as the mean value of available measurements during the day, or the average between daily minimum and daily maximum temperatures. Daily rainfall was used as reported. When possible, r_{e_clim} was calculated as a mean over 10 y, but in some cases only 1 y of measurements was available (cf. Table 2).

Swedish Sites

Karlstad, Sweden is located in the western part the central Swedish plains agricultural region, close to lake Vänern. Stockholm, Sweden is on the eastern edge of the region, on the coast of the Baltic Sea. Typical crops for the region are

Table 2. Meteorological stations used for calculations of r_{e_clim}. Country, station name, latitude, longitude, altitude (m), Mean annual temperature (°C), annual precipitation (mm), reference crop evapotranspiration (ET_0, mm), aridity index (ET_0/precipitation), r_{e_clim}, observation period (start year–end year).

Country	Place	Latitude	Longitude	Altitude (m)	Mean temp. (°C)	Precip. (annual sum, mm)	ET_0 (annual sum, mm)	Aridity index	r_{e_clim}	Observation period
Sweden	Karlstad	59°24′N	13°30′E	107	6.0	644.4	523.4	0.8	1[a]	1970–1999
Sweden	Stockholm	59°18′N	18°03′E	44	7.0	542.2	595.1	1.1	1[a]	1970–1999
Chad	Faya	18°00′N	19°10′E	234	28.4	6.5	5808.3	896.3	1.1	1967–1977
Senegal	Saint Louis	16°01′N	16°30′W	2	25.8	215.0	1746.2	8.1	2.3	1970–1980
Togo	Mango	10°22′N	00°22′E	145	27.9	1093.6	2163.5	2.0	4.3	1967–1977
Congo	Pointe Noire	04°49′S	11°54′E	17	24.9	1062.0	685.8	0.7	4.2	1970–1980
Congo	Brazzaville	04°15′S	15°15′E	314	25.3	1319.0	740.3	0.6	4.7	1970–1980
Kenya	Kalalu	0°05′N	37°10′E	2080	16.6	740.0	1254.5	1.7	2.2	1986–2000
Kenya	Matanya	0°04′S	36°57′E	1840	18.1	794.0	1493.7	1.9	2.1	1986–2000
Kenya	Muranga	0°06′S	37°00′E	1067	19.9	1083.0	1468.0	1.4	2.2	2002–2002
Kenya	Ahero	0°09′S	34°36′E	1200	22.5	1265.0	1730.0	1.4	4.1	1986–1986
Kenya	Kabete	01°15′S	36°46′E	1650	18.0	1069.8	1132.1	1.1	2.4	1992–1997

[a] r_{e_clim} is by default set to 1 as the mean for the two Swedish stations, representing the calibration site.

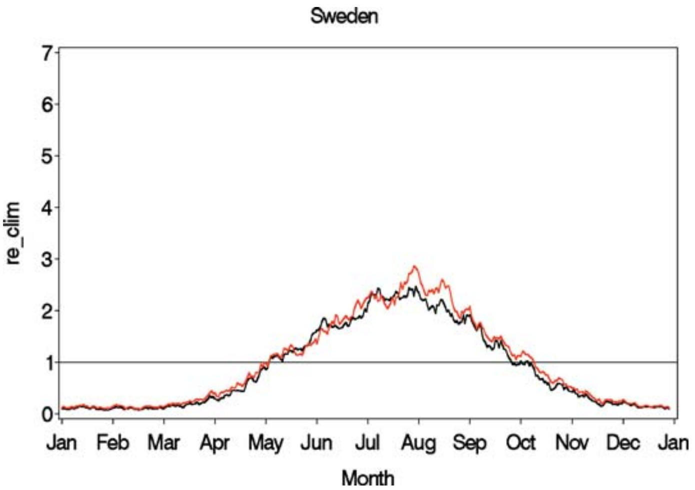

Figure 2. Mean (30 y) within-year dynamics of r_{e_clim} in the two Swedish weather stations used for calibration. Karlstad (black) and Stockholm (red). The normalized mean value (= 1) is also indicated.

barley, wheat, oilseed, and grass leys for hay and silage production. The region is cold temperate, with an annual mean temperature of +6°C to 7°C and annual precipitation of around 600 mm (Table 2, Fig. 2). Frost in the soil and/or snow cover is common from November to April, and the growing season is May to September. Climate, soils, and infrastructure are favorable for productive agriculture, which together with the cold winters (slow decomposition) leads to a high soil carbon content, over 7 kg m^{-2} (0–25 cm).

West and Central African Sites

Faya is located in northern Chad with a desert climate (Fig. 3). Rainfall is very low, on average 6.5 mm y^{-1}, with some years having no rain, and the highest annual rainfall over the data period (1967–1977) was 15.6 mm. Of all stations discussed here, Faya has the highest annual evapotranspiration, an average of 5808 mm, with an annual low of 5440 mm and a high of 6265 mm, and this leads to a very high aridity index as shown in Table 2. Average daily temperature is 28.4°C with the coolest day being 12.6°C and the warmest being 37.8°C.

Saint Louis is a coastal station situated in the northwestern corner of Senegal. The local climate is tropical with well-defined dry and humid seasons that result from northeast winter winds and southwest summer winds. With climate data for 1970–1980, annual rainfall in Saint Louis was on average 215 mm, with 100 mm in the driest year and 380 mm in the wettest year. Rainfall occurs mainly between June and October, when daily mean temperatures can reach 34°C. In the cooler period, December to February, minimum temperatures are about 17°C. Evapotranspiration averages 1391 mm, with an annual range of 1295 to 1483 mm. Annual aridity index over the 11 y had a high of 14.5 and a low of 3.4.

Mango station is located in Sansanné-Mango city in Togo. It is situated in the Savanes region (characterized by a gently rolling savanna), in northern Togo, about 550 km from the capital Lome. Average annual precipitation for the period 1970–1980 was 1130 mm, with a minimum and maximum of 890 and 1360 mm, respectively. Average daily temperature of 27.8°C was observed with a variation of between 20.6°C and 35°C. Average evapotranspiration was 2164 mm *per annum*, with the lowest recorded being 1581 mm and the highest 2670 mm.

Pointe Noire is a station in the coastal plain by the South Atlantic Ocean, in the southwest corner of Congo Brazzaville. The station receives an annual average rainfall of 1067 mm (1970–1980) with an annual low and high of 457 and 1694 mm, respectively. Mean daily temperature ranged between 18.2°C and 29.3°C, with an average of 24.9°C. Annual evapotranspiration varied between 658 and 799 mm, with an average of 685 mm.

Brazzaville is located in Congo Brazzaville, about 350 km from the south Atlantic coastline and has an average annual mean precipitation of 1320 mm, which varied between 1000 and 1500 mm during the period 1970–1980. Annual evapotranspiration averaged 740 mm, with little variation over the 10 y

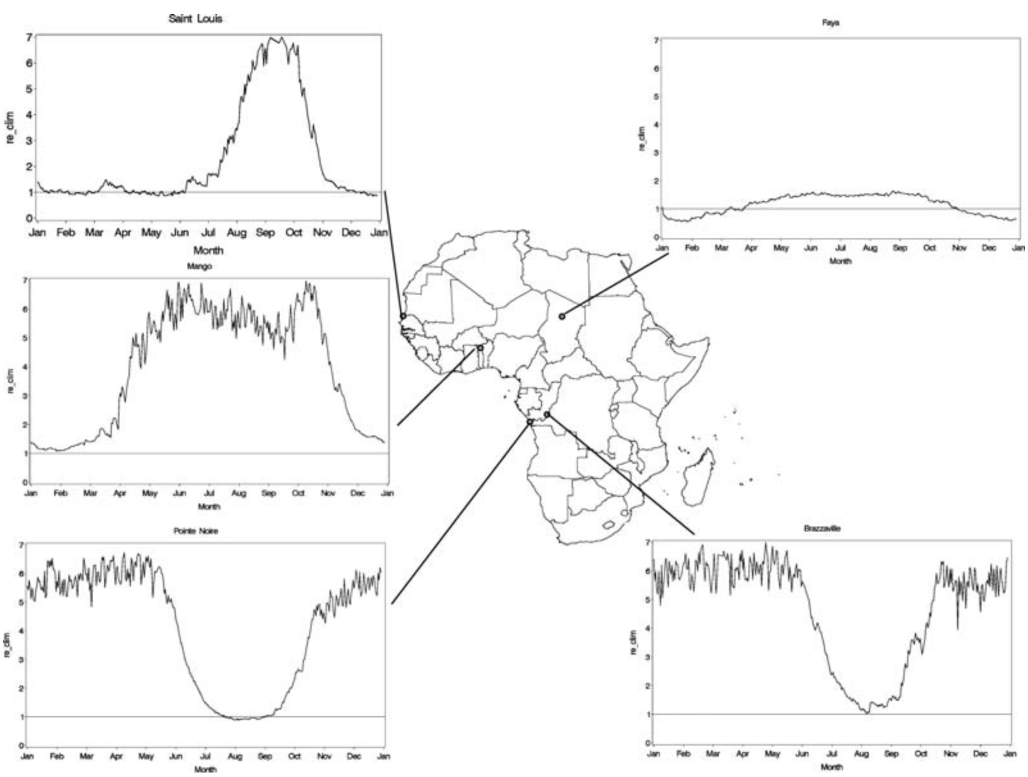

Figure 3. Mean within-year dynamics of r_{e_clim} in West and Central African sites. See Table 1 for more information.

Gräsö, Sweden, annual r_{e_clim} ca. 1. When photo was taken, daily r_{e_clim} was close to zero. Photo: O. Andrén.

(standard deviation of 55 mm). Daily mean temperature is 25.3°C, and it varies between 17.2°C and 29.6°C.

Kenyan Sites

Kalalu station is located at the northern foothills of Mount Kenya and is characterized by a semiarid climate (Fig. 4). It receives a weakly trimodal pattern of rainfall, i.e., rain occurs between March and May, July and August, and October and November, with an annual average of 750 mm. For the period 1986–2000, maximum and minimum annual rainfall was 1410 and 356 mm, respectively. Mean annual reference evapotranspiration (ET_0) was 1254 mm, with a range of 1115–1548 mm, while the mean daily temperature varied between 16°C and 18.5°C. The region was a livestock and wheat production area in the 1960s, but now it comprises small-scale settlements as well as large-scale farming operations.

Like Kalalu, Matanya station is located at the northern foothills of Mount Kenya, but more to the west (Fig. 4). Annual rainfall in Matanya ranged between 458 and 1085 mm during 1986–2000. The rainfall has a bimodal distribution; long rains from March to May and short rains from October to December. Average annual evapotranspiration was 1490 mm, and it ranged between 1332 and 1641 mm. The growing period lasts only 2 mo during the "long" rains and 3 mo during "short" rains. The mean annual temperatures ranged between 17°C and 19°C. The area is mainly grassland but has seen an increase in cultivated land in the last 10 y.

Kabete station is located in the outskirts of Nairobi about 12 km from the city center. The mean annual rainfall ranged between 710 and 1520 mm, with an average of 1070 mm received in two distinct rainy seasons; the long rains from mid-March to June, and the short rains from mid-October to December. The average long-term (1992–1997) daily temperature ranged between 12.6°C and 25.0°C, with a mean of 18.1°C. Annual evapotranspiration was 1135 mm, ranging from 1100 to 1170 mm.

Muranga station is located in central Kenya, in an undulating terrain within a medium to high potential agro-ecological zone. During 2002, it received 820 mm of rain and total evapotranspiration was 1470 mm. Average mean temperature was 19.6°C, with the coolest day 14.6°C and the warmest day 23.6°C.

Ahero is located in western Kenya, about 30 km from the shores of Lake Victoria, and has a subhumid climate. This flat terrain received an annual rainfall of 1265 mm in 1986 and the potential evapotranspiration was 1730 mm. According to Njogu (2002), annual rainfall pattern shows no distinct dry season, and it is weakly trimodal with peaks during the long rains (March–May) and short rains (October–December). The third peak occurs in August. The rainfall is controlled by the northward and southward movement of the Intertropical Convergence Zone. However, altitude, proximity to the highlands, and nearness to the lakeshore causes considerable spatial and temporal variations in rainfall (19). Daily mean temperature

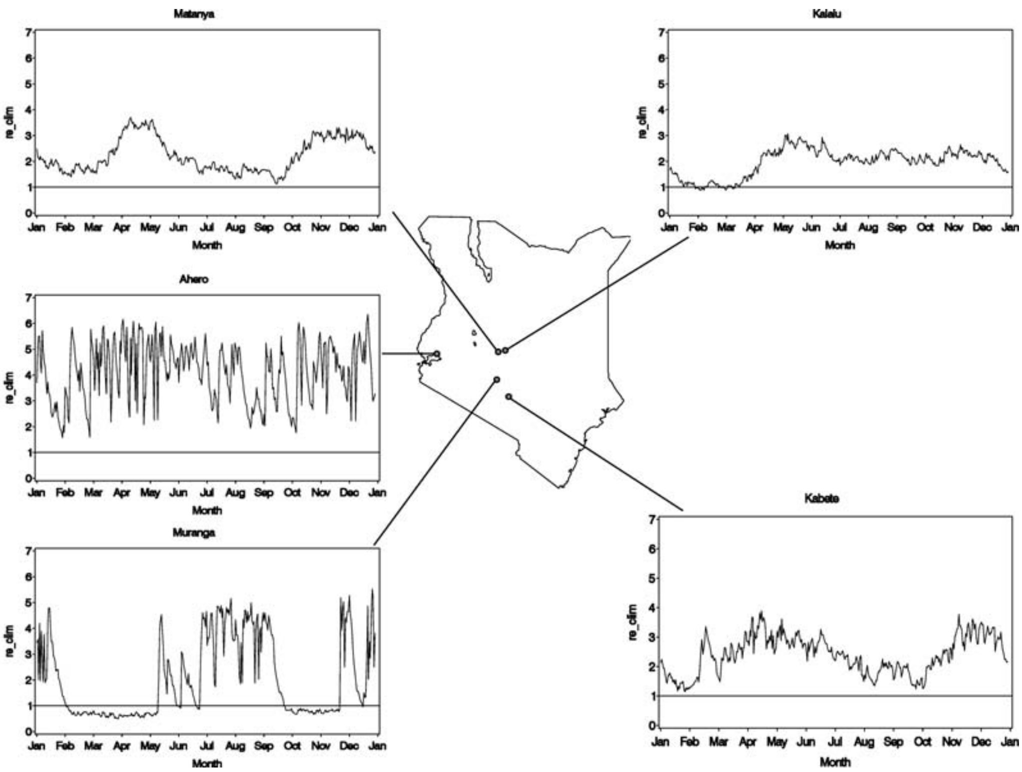

Figure 4. Mean within-year dynamics of r_{e_clim} in Kenyan sites. See Table 1 for more information.

during 1986 ranged from 20.3°C to 25.6°C, with an annual average of 22.5°C.

Calculations

The calculations were performed in six steps:

i) Daily weather data were obtained from various sites (Table 1). The daily variables necessary for the calculations are date, mean air temperature (°C), precipitation (mm d^{-1}), and reference crop evapotranspiration, ET_0 (mm d^{-1}). In many cases, ET_0 was not directly available but was calculated from other variables, such as wind speed, relative humidity, solar irradiation (or latitude and percentage cloudiness), etc. We adapted a semiempirical model developed for spatial modeling (20) for estimating soil temperature from air temperature records.

ii) For calculations of water balances we used field capacity, Θ_{fc}, and wilting point, Θ_{wp}, of the soil in question. These are not often measured but can be calculated from sand, clay, and organic carbon content using pedotransfer functions, e.g., those developed by Rawls et al. (21) and validated for Swedish soils by Kätterer et al. (22). Since in this application we focus on climatic differences, we use the calibration soil values for the site in Uppsala, Sweden (clay 36.5%, sand 22.5%, organic carbon 1.14%), resulting in $\Theta_{fc} = 35.3\%$ and $\Theta_{wp} = 21.8\%$ by volume. The horizon thickness from the surface down is set to 25 cm (this determines the amount of water that can be stored and evaporated, and rainfall amounts higher than this are considered to percolate down or be lost as runoff). This value can be changed, but this also means that the calibration factor must be changed, i.e., the Uppsala site must be rerun with the new horizon thickness. Values for this are presented in Table 1. With 25-cm soil depth, the water store at Θ_{wp} was 54.6 mm, and at Θ_{fc} 88.4 mm.

iii) The actual water balance model is a simple bucket model that keeps track of precipitation and evapotranspiration for every day using the approach explained in detail by Allen et al. (18). This model, when applied to soil with a plant cover, uses daily green leaf area index (GAI) for calculations of transpiration. Since in the present application for calculating r_{e_clim} we assume that we have a bare soil with no plant cover, we set GAI = 0. This actually means that potential evapotranspiration here is set to 80% of ET_0, the reference crop evapotranspiration defined with GAI = 3, corresponding to a standard grass vegetation.

iv) The influence of temperature on soil biological activity is described by the function presented by Ratkowsky et al. (23), with a zero activity cutoff at −3.78°C and a base temperature (where $r_{e\_temperature} = 1$) of 30°C (see 24). Soil water influence on the activity is calculated using the function described in Andrén et al. (25) using parameter values from Lomander et al. (26). Close to field capacity, the factor r_{e_water} is about 10 times higher than at wilting point.

v) The daily values for the activity factor for water and temperature, respectively, were multiplied to obtain the daily activity factor, $r_e = r_{e\_water} \times r_{e\_temperature}$. This factor was divided by the calibration factor for Uppsala, Sweden, no crop, 250-mm horizon thickness, which is 0.105; thus $r_{e\_clim} = r_e/0.105$. See Table 1 for calibration factors. The calibration site r_{e_clim} was calculated as a mean for two weather stations, representing central Sweden, agricultural production region 5 (25).

vi) Annual means and Julian day means of r_{e_clim} were calculated and plotted in various combinations.

The calculations were performed in a SAS program (27). This program reads a SAS data set prepared for each site, using small input programs unique for every data set, which calculates the necessary variables for the following computations. The main SAS program makes the calculations and plots in steps *iii–vi* above, which takes a few seconds to run for 30 y of daily data (Fig. 1).

To compare the climate indices, linear regressions between mean temperature, precipitation, ET_0, aridity index, or (temperature × precipitation) and r_{e_clim} were calculated.

Model Experiment

A model experiment using the Introductory Carbon Balance Model (ICBM) (16) was performed. ICBM is a five-parameter model that has two state variables, young and old soil carbon. The five parameters are i (carbon input), h (humification coefficient), k_Y (decomposition rate constant for young), k_O (rate constant for old), and r_e (climate factor affecting decomposition of young and old). The model is analytically solved and only has two equations, which means that it can be programmed in a spreadsheet for interactive experimentation. The climate factor r_e is calculated as described here for r_{e_clim}, which is a special case of r_e where there is no vegetation and the soil type is a clay loam.

A typical Swedish soil, in balance with respect to C (7 kg C m^{-2}, 0–25 cm depth), was moved to Ahero, Kenya. It is assumed that annual C input was the same (0.33 kg m^{-2} y^{-1}) and only the climate factor, r_e, was changed from 1 to 4.1 (Table 2). Also, a soil that was in balance under the Ahero climate was moved to Sweden. The model then projected changes in soil carbon over 30 y.

RESULTS

Table 2 summarizes climatic data for the weather stations used. Note that the calibration site r_{e_clim} actually is calculated as a mean for two weather stations, representing central Sweden, agricultural production region 5 (25). The Swedish sites stand out as being much cooler and having a lower r_{e_clim}, but the other standard climatic variables are within the range of the African stations. Aridity index (ET_0/precipitation) showed a wide range, from 0.6 to almost 900, but it should be noted that this index becomes mathematically unstable when precipitation approaches zero (i.e., division by zero).

In spite of the very dry conditions in Faya, r_{e_clim} was close to that in Sweden. See Discussion for further details on the validity of the functions used under very dry conditions.

Figure 2 shows the daily average r_{e_clim} values for the two Swedish weather stations, representing central Swedish plains. Clearly, r_{e_clim} shows a peak in the summer months, which is mainly due to soil temperature, which in the winter often is well below 0°C. Note that in the summer r_{e_clim} can reach about 3, a value well within the range of the African data.

Figure 3 shows the daily average r_{e_clim} values for the West and Central African stations, and the annual means are given in Table 2. The within-year dynamics are mainly dependent on the rainfall patterns, with a unimodal dry period in most places. Faya stands out, with hardly any rain at all; here the annual dynamics are mainly determined by temperature.

Figure 4 shows r_{e_clim} within-year dynamics for the Kenyan sites, and the annual means are given in Table 2. These sites show a lower average (mainly due to lower temperature because of altitude) and a bimodal distribution due to two rainy seasons (and possibly one trimodal with three rainy seasons).

In the calculations of r_{e_clim}, the daily water store in the soil is calculated. This is an important determinant for when to perform agricultural measures, e.g., sowing. Figure 5 shows the

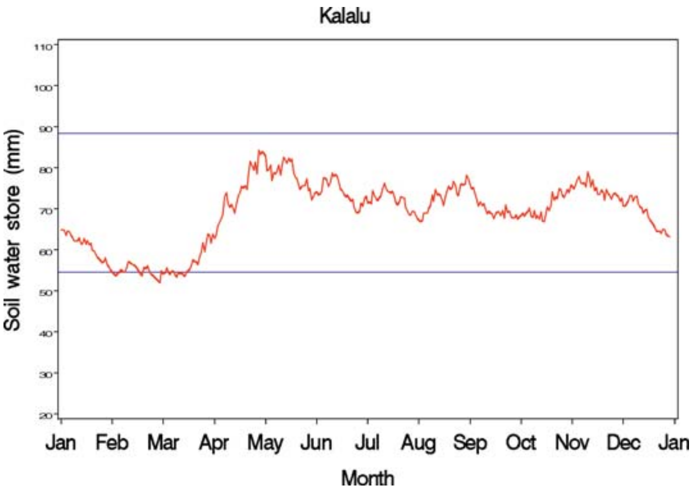

Figure 5. Soil water store dynamics (0–25 cm topsoil, in red) calculated for Kalalu, Kenya climate 1986–2000. Water store at the calibration soil's field capacity, Θ_{fc}, and wilting point, Θ_{wp}, are indicated (blue).

average daily water store for Kalalu in Kenya. Clearly, in late March–April the soil is refilled from wilting point or below, and about 30 mm of water store becomes available for the crop. In other units, useful for calculating irrigation equivalents, 30 mm of water is 30 L m^{-2}.

Table 3 gives the regression parameters and R^2, coefficient of determination, for the regression between the various annual mean climate characteristics and r_{e_clim}. Regressions including or excluding the dry and hot Faya, Chad, and the Swedish cool and wet stations are given. For most characteristics, R^2 is low, and both the regression parameters and R^2 vary considerably between the data subsets used in the regressions. However, the synthetic variable (temperature × precipitation) that includes the water/temperature interaction at an overall mean level shows a higher R^2, but both the intercept, *a*, and slope parameter, *b*, differ considerably between the data subsets.

The result of the ICBM experiment, where Swedish soil was moved to Ahero, Kenya, and subjected to that climate for 30 y, is shown in Figure 6. With the same annual C input as in Sweden, the carbon mass would decrease from 7 kg m^{-2} (0–25 cm depth) to 4.11 kg m^{-2}, i.e., a 41% reduction in soil C in 30 y. The new balance point will simply be inversely proportional to r_{e_clim} at Ahero, 4.1, so the soil carbon mass will eventually become 7/4.1 = 1.7 kg (see Andrén and Kätterer [8]). However, this process takes time, and the rate is slowing in absolute terms (cf. Fig. 6), so the model projects that after 60 y, 2.9 kg will still be present in the soil (not shown). Moving the soil in the opposite direction, from steady-state C mass in Ahero (1.7 kg) to Sweden would result in an increase in soil C by 64% after 30 y.

DISCUSSION

Naturally, the precision and bias of r_{e_clim} estimates depend on the original meteorological observations. There are a number of refined methods to, e.g., compensate for precipitation due to wind, etc., but we consider that average quality meteorological data are sufficient for the purpose here. However, evapotranspiration, how it is defined and how it is measured, warrants some discussion. The water model uses reference crop evapotranspiration (ET_0) as input, and this is calculated using the FAO Penman-Monteith equation as recommended by Allen et al. (18). This equation requires a number of parameters and variables, such as daily temperature, wind speed, net radiation, etc. Allen et al. (18) also give a number of equations to obtain these parameters and variables from other measured variables, such as relative humidity and/or Penman evaporation. For this application, we have used the simplest possible approach to calculate ET_0 (see Methods). It is probable that refining the methods here would improve the quality of r_{e_clim}, but this is outside the scope of this paper.

Actually, in many cases r_{e_clim} is not very sensitive even to fairly large systematic errors in input data. Let us assume that we have used a severely biased estimate of ET_0 and that this is 70% of the true value, every day of the year. If we apply this to the Muranga data set, mean annual r_{e_clim} will increase from 2.2 to 2.4, which is not very dramatic. The storage of water in soil and interaction between temperature and moisture both contribute to dampening the effect of a single variable, but the sensitivity to a change in, e.g., ET_0 is dependent on the weather pattern. For example, regions with long drought periods (ET_0 will only affect the rate of drying at the beginning

Table 3. Parameters for the regression function $r_{e\_clim} = a + bx$ for all stations (n = 12). The variable *x* denotes annual mean temperature, annual precipitation sum, annual reference crop evaporation sum (ET_0), aridity index (ET_0/precipitation), and a new variable, obtained by multiplying annual mean temperature by annual precipitation sum. R^2 denotes coefficient of determination, i.e., the fraction of variance explained by the regression. The same regressions were calculated excluding the driest station, Faya (n = 11), and excluding also the Swedish sites (n = 9). All values used for the regressions can be found in Table 2.

x	*a*	*b*	R^2
Temperature	0.408	0.111	0.380
Precipitation	0.634	0.0024	0.557
ET_0	2.9718	−0.0002	0.0479
Aridity	2.7784	−0.0018	0.1251
Temp. × Precip.	−4610.1	8057.8	0.8697
Without Faya			
Temperature	−0.1786	0.1532	0.7182
Precipitation	0.2543	0.0028	0.5172
ET_0	1.8187	0.0008	0.1025
Aridity	2.9205	−0.0777	0.0156
Temp. × Precip.	−3090.5	7651.3	0.8568
Without Faya and Swedish sites			
Temperature	−1.1803	0.1966	0.5311
Precipitation	1.1646	0.0021	0.4062
ET_0	3.6205	−0.0003	0.0205
Aridity	3.5337	−0.175	0.1348
Temp. × Precip.	−1893.6	7325	0.7565

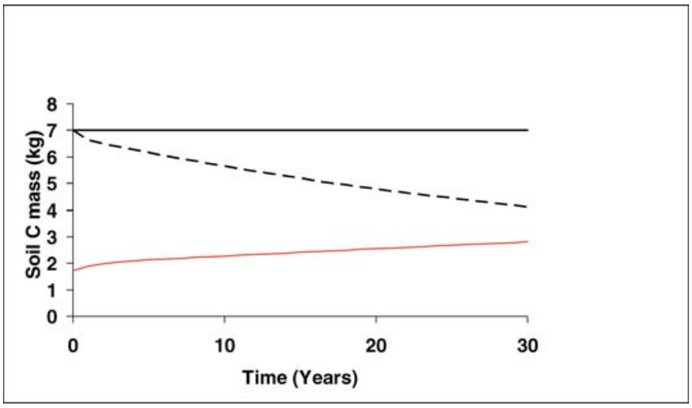

Figure 6. Soil carbon (kg m^{-2}, 0–25 cm depth) in balance (steady-state) in Swedish climate (annual C input 0.33 kg m^{-2} y^{-1}, $r_{e\_clim} = 1$), as projected using ICBM (solid line). The soil, assuming the same annual input, was "moved" (in the model) to the soil climate of Ahero, Kenya ($r_{e\_clim} = 4.1$), and the C mass was projected for 30 y (stippled line). Soil at steady-state under Kenyan climate was "moved" to Swedish climate (red line).

of the drought) will be less sensitive than regions with a more even rainfall distribution.

The activity under very dry conditions, e.g., at Faya (Fig. 3), possibly is somewhat overestimated. The functions for drying out the Uppsala soil used in these calculations yield a minimum value of 15% volumetric water content, i.e., the soil can never become drier. In the model this corresponds to a r_{e_water} that is 12.4% of that at optimum water conditions, which may be too high. However, since we lack high-precision field data from very dry conditions, this is our best estimate for now.

It is clear from Table 2 and Figures 2–4 that r_{e_clim} can give an integrated picture of soil climate, either as one value (Table 2) or as a graph showing within-year variation. Alternatively, annual means for different years can be plotted (not shown), indicating, e.g., consequences of climate change. Daily values for several years can also be plotted, e.g., to compare consequences for soil climate of the low rainfall during late 2005/early 2006 in Kenya compared with similar events during earlier years. This is also true for the water store dynamics (Fig. 5), where the consequences of a drought for the growing conditions of a crop will be obvious.

The thought experiment (Fig. 6) illustrates that 4.1 times the carbon input in Sweden would be necessary to maintain balance and that if the climate in Sweden changed this drastically, the soil would lose much of its carbon. This also illustrates the asymmetry of soil C changes. Moving the soil from Sweden to Ahero resulted in a 41% C loss after 30 y, while the opposite move resulted in an increase by 64%. Expressed in absolute mass change and not as a percentage, the asymmetry remains, but in the opposite direction. The move from Sweden to Ahero resulted in a loss of 2.89 kg C m^{-2}, and moving from Ahero to Sweden resulted in an increase by 1.10 kg C m^{-2} after 30 y (see Andrén and Kätterer (8) for explanation).

However, the real value of the modeling approach lies in thought experiments that are less drastic. For example, it is quite easy to calculate r_{e_clim} for a year (or mean of years) that has a different rainfall pattern and apply this to the soil carbon model.

As mentioned in the Introduction, the use of daily data should give more exact predictions than calculations based on, e.g., monthly mean weather data. However, in most cases monthly or 10-d averages will not give major differences. One can imagine any of the curves in Figures 2–4 with monthly average "stair steps"—and then an annual mean calculated from these. This value would not be drastically different from that obtained by daily calculations. The timing within a year will be slightly off and considerably so in some cases—a rainfall that comes on the 1st or 31st will be applied to the whole month, so in dry conditions a whole month can be calculated as moist due to a rain on the 31st. This will affect mean annual r_{e_clim} to some extent, but perhaps the strongest argument for using daily values in calculations is that the raw meteorological observations are made at least on a daily basis, and current computing power and data storage transfer capacities can easily handle more than 30-y daily data sets.

Strict validation of all assumptions used to calculate r_{e_clim} would require long-term field measurements of soil temperature, water content, and biological activity in the Swedish soil, relocated to the various stations, and comparisons of these data sets with those calculated. Ideally, the same type of organic matter should be buried at each site, and their relative decomposition rates compared to the relative r_{e_clim} values. This is not possible for the moment. However, the calculations of soil water and temperature are based on well-validated functions (18), and the bucket model concept is generally accepted. Comparisons between soil carbon models reveal considerable differences in formulations and parameter values used for the step from temperature and soil water content to an activity factor (28), but the actual results are in most cases fairly similar.

Since r_{e_clim} is inversely related to soil carbon mass at steady-state (8, 16), we should expect soil carbon to be high in Sweden, lower in Kenya, and even lower in West Africa. Naturally, the annual input and quality of organic matter also influence the topsoil carbon mass (probably inputs and soil C contents are low in Faya, Chad), but let us just make some rough estimates.

In a typical Swedish agricultural mineral soil the average carbon mass in topsoil 0–25 cm can be about 7 kg m^{-2} (25), corresponding to about 2% C if a bulk density of 1.4 is assumed (22). For Nigerian agricultural land in West Africa, values between 0.25% C and 0.45% C are reported (29), and for West African savannas about 0.6–0.9% C were measured (30). The annual crop production in the Swedish arable land is high, but most is exported from the field, so the annual input is on the order of 300 g C m^{-2} y^{-1}. Corresponding inputs for West African cropping systems have been estimated to be 240 to 480 g C m^{-2} y^{-1} , fairly similar to the Swedish inputs (31). Thus, based on differences in r_{e_clim}, one could expect the West African agricultural soil C contents to be 4 to 5 times lower than in Sweden. This corresponds to 0.2–0.25%, which is close to the observed values.

The same approach as used here has been used for comprehensive data sets from Canada (32), comprising long-term meteorological data from a large number of weather stations. In short, r_{e_clim} for western Canada was around 0.8 as a result of summer drought, and r_{e_clim} for eastern Canada was around 1.2 as a result of warm and moist summers. The Canadian data sets also contain large amounts of carbon input and soil carbon mass data, which will help us to fine tune the calibration of ICBM and validate the r_{e_clim} approach for another cold-temperate region, geographically and climatically different from the original Swedish sites.

A partial validation of r_{e_clim} can be made using comparisons between decomposition rates of the same substrate placed in different climates. Jenkinson and Ayanaba (33) compared decomposition rates of ryegrass litter placed in soil in England (mean annual temperature 8.9°C) and Nigeria (26.1°C). As reported and discussed by Ladd et al. (34), the rate in Nigeria was about four times as high as that in England. Inspection of Table 2 reveals that a rough estimate of r_{e_clim} will be slightly above 1 in England, and the Nigerian r_{e_clim} will be around 4.5, judging from the other stations in similar climate (Congo, Togo). The ratio of r_{e_clim} values thus roughly coincides with the ratios between the measured decomposition rates.

In a following paper, we will compile results from African agricultural experiments, where weather and soil climate, crop yields, soil carbon dynamics, etc., are recorded for different treatments. This will provide improved validation for the procedure used to obtain r_{e_clim}—we will model the soil C dynamics using r_{e_clim}, annual C input, etc., and compare the modeled soil C dynamics with the measured values. Clearly, if this is successful, we will have a simple general tool for projecting the effects of different agricultural measures on soil C balances. This can and will be used for selecting optimal means of increasing soil carbon levels within an African context.

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