Modeling of (R) USLE C-factor for pasture as a function of Normalized Difference Vegetation Index

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Abstract

In soil erosion prediction, the soil cover and management factor (C-factor) of (R) USLE represents the effects of land use. C-factor values based on experimental studies of different classes of soil use and management are available, and although they are used to produce soil erosion maps, they can hide the effects of spatial variability on erosive processes. Therefore, C-factor maps should represent soil cover heterogeneity. Thus, methods that estimate C-factor on the basis of the Normalized Difference Vegetation Index (NDVI) obtained by remote sensing have been developed, and their applicability must be evaluated by contrasting model outputs with C-factor values obtained experimentally in field plots. The use of a rainfall simulator is a feasible alternative to carry out these tests. The present study evaluated 3 models for C-factor estimation based on NDVI, in order to determine which one estimates better in pasture areas, the predominant soil cover in the study area.

Keywords: Soil use and management, soil erosion, remote sensing, NDVI.

1. Introduction

Soil cover and management are key factors for soil erosion development. In general, the denser the vegetation cover, the lower the rates of soil loss. Plant cover protects soil against the erosive action of rainfall, increases the levels of water infiltration, slows runoff, preserves soil roughness and improves its physical, chemical and biological features (de Asis & Omasa, 2007).

Both the Universal Soil Loss Equation (USLE) and the Revised USLE (RUSLE) use the soil cover and management factor (C-factor) to predict the effects of land use and soil management on the volume of soil loss. The C-factor is often used to compare alternative management systems in terms of impacts on soil conservation, indicating on a 0 to 1 scale the rates of annual soil loss and the distribution pattern of potential erosion rate over the period for which soil is managed (Renard et al., 1997; Wischmeier&Smith, 1978).

In erosion models based on (R)USLE, C-factor values are assigned by adjusting experimental data available in the literature to the soil classes described on land use and occupancy maps of the study area (Beskow et al., 2009; Jebari et al., 2012; Oliveira et al., 2010). However, the attribution of a mean C value for each land use and occupancy class may underestimate soil loss and mask spatial variability and heterogeneity of erosive processes, misrepresenting variations in the vegetation of large areas such as watersheds (de Asis&Omasa, 2007; Wang et al., 2002)

To remedy this situation, different methods have been developed to improve C-factor mapping using remote sensing data. Several models using linear and non-linear regression were developed on the basis of the correlation between C-factor and vegetation indexes, which, in turn, were obtained from satellite images to apply in soil erosion models (Corrêa&Pinto, 2011; de Asis&Omasa, 2007; Lin et al., 2002; Van der Knijff et al., 1999).

The procedure for C-factor determination from the Normalized Difference Vegetation Index (NDVI) has been used in erosion models for watersheds (Chou, 2009; Prasannakumar et al., 2011; Prasannakumar et al., 2012; Wu et al., 2011; Zhou&Wu, 2008). These models do not accurately estimate C-factor values; however, they are suitable for qualitatively predicting distributed soil loss throughout watersheds (de Asis&Omasa, 2007).

In Brazil, studies on modeling of distributed soil erosion in watersheds associated to the use of C-factor values obtained from vegetation maps such as NDVI are scarce, since the models available are developed for other countries. Hence, different models must be studied to select the most adequate and consistent for a watershed in Brazil.

The coherence of models that predict C-factor values based on NDVI can be verified by comparing their outputs to field observations. However, C-factor determination in experimental plots is costly and time-consuming. Accordingly, the use of a portable rainfall simulator is a good alternative to make field assays feasible since it allows a large number of repetitions and a systematic approach to characterize the factors that affect soil erosion in difficult-to-access outlying areas with irregular rainfall distribution (Iserloh et al., 2013).

In the present study we evaluated 3 models that associate (R) USLE C-factor and remote sensing-based NDVI (Corrêa&Pinto, 2011; Lin et al., 2002; Van der Knijff et al., 1999) in an environmental protection area bounded by the Guariroba stream subwatershed (Figure 1). The area contains evidence of erosion and varied cover classes such as pasture at different conservation levels, native vegetation (*Cerrado*, *Cerradão*, riparian forest, rangeland, prairie and shrubs), bare soil, wetlands, artificial reservoirs and eucalyptus crops. We present the best fit model to estimate the C-factor in pasture, the main soil cover in the area (over 70% of the area), comparing it to field data obtained with a rainfall simulator.

2. Materialandmethods

2.1. Studyarea

The experimental field is inside the Guariroba stream subwatershed, which covers 362 km², located between south latitude 20°28' and 20°43' and west longitude 54°29' and 54°11' (Figure 1). The climate according to Köppen's classification is Cfa, subtropical with a hot summer. The subwatershed, located in the *Cerrado* (Brazilian Savannah) biome, is mostly covered by pasture and smaller patches of native vegetation, riparian forests and eucalyptus.

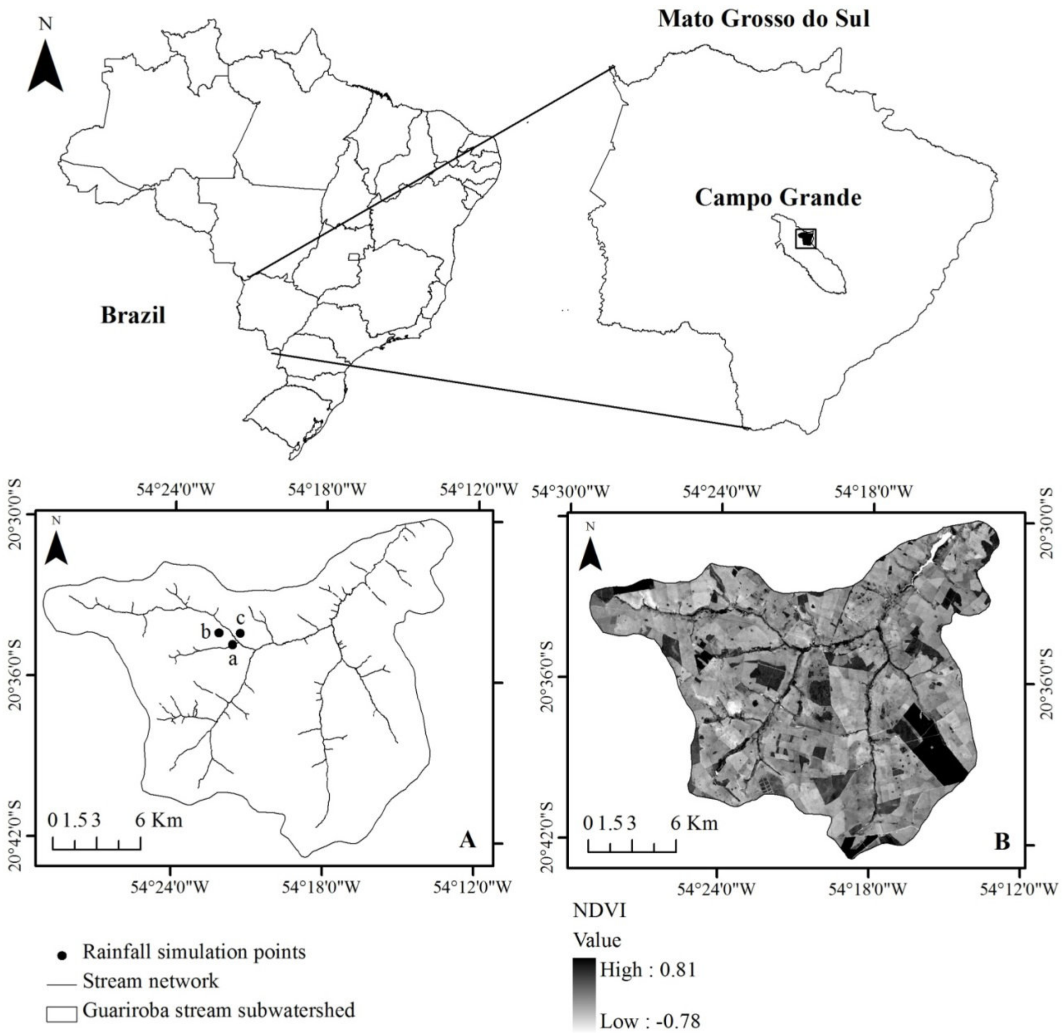

Figure 1.Location of the Guariroba stream subwatershed (upper frame), rainfall simulation points (A) used for C-factor determination and NDVI distribution (B).

2.2. C-factordetermination

The (R) USLE C-factor was obtained from the relationship between soil loss in areas with and without vegetation cover. In a complete factorial design, soil loss was determined experimentally at 3 pasture sampling points, with and without vegetation cover. Four replicates were carried out in each point (Figure 1) in different plots using artificial rainfall produced by a portable rainfall simulator (Figure2) developed by Alves-Sobrinho et al. (2008).

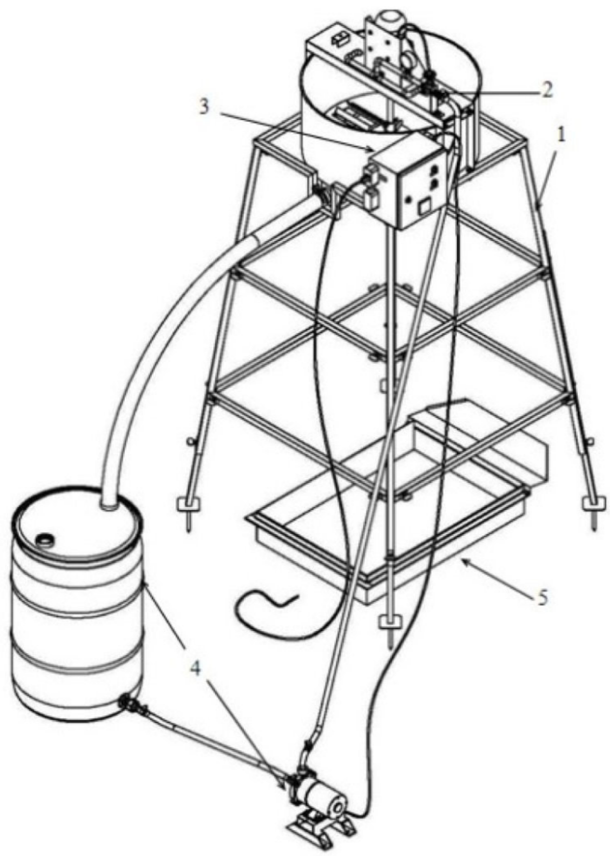

Figure 2.Rainfall simulator InfiAsper. (1) structure; (2) water application unit; (3) electric system; (4) water pump; (5) runoff collector (Alves-Sobrinho et al., 2008).

The equipment produces artificial raindrops, approximately 2.0mm in size, using two Veejet 80.150 nozzles positioned 2.30m above the ground. The correspondence between the kinetic energy of natural rain and that of the artificial rain generated by this simulator is above 90%. The experimental plot receiving artificial rain was demarcated by a rectangular frame (0.70m x 1.00m) aligned lengthwise on the slope. This structure allowed the capture of water and disaggregated soil carried by surface runoff.

The experimental plots were pre-wetted before rainfall simulation tests to ensure uniform humidity conditions. The simulator was adjusted to produce artificial rain with an intensity of 60 $mm.h^{-1}$ for 60 min after runoff onset. Runoff volume was measured every 2 min, and the material drained (water + disaggregated soil) was sampled every 6 min. Soil losses were determined by multiplying the volume of material drained by the solids content in surface runoff samples. Solids content was determined in the laboratory by sample drying at 60° C followed by weighing. The relationship between the weight of soil loss and the plot area (0.70 m^2) corresponded to soil loss values in $kg.(m^2)^{-1}$.

2.3. C-factormodeling

2.3.1.NDVI

NDVI determination was based on TM Lands at 5 images (path/row 224/074) on June 27 2011 (INPE, 2013), with spatial resolution of 30m. that matched the period of rainfall simulation tests. The image was georeferenced (less than 20m of error) using Universal Transverse Mercator projection (UTM, zone 21, South American of Datum 69) in a GIS environment and map algebra to calculate NDVI (Eq. 1).

$$NDVI = \frac{NIR-VIS}{NIR+VIS} \quad (1)$$

where VIS corresponds to the near-infrared band and NIR to the visible red band. Based on the geographic position, NDVI values were obtained for the soil loss sampling points in experimental plots with and without vegetation cover (**Error! Reference source not found.**).

2.3.2. ***C-factorestimate***

We tested 3C-factor prediction models based on NDVI. The model developed by Van der Knijff et al. (1999) is widely used in Europe (C1; Eq. 2), whereas that proposed by Lin et al. (2002) is applied in Asian countries (C2; Eq. 3).To that end, Corrêa&Pinto (2011) created a simple linear regression model, the only Brazilian model evaluated in the present study (C3; Eq. 4).

$$C1 = \exp\left[-2 \times \left(\frac{NDVI}{1-NDVI}\right)\right] \quad (2)$$
$$C2 = \left(\frac{1-NDVI}{2}\right)^{1+NDVI} \quad (3)$$
$$C3 = 0.5 - (0.5 \times NDVI) \quad (4)$$

2.4. Statistical analysis and model evaluation

C-factor estimates obtained with rainfall simulation violated normality assumptions within a 95% confidence interval. Therefore, the non-parametric Kruskal-Wallis test was applied to compare the null and alternative hypothesis, that is, equality of C-factor distribution functions between sampling points *vs* difference in distribution functions between at least two sampling points.

The evaluation of C-factor estimation models based on NDVI require analysis of residual errors, the difference between predicted and observed values and prediction characterization between over- and underestimates. To that end, we used the statistical parameters described by Loague&Green (1991), such as the following equations:

Root mean square error(RMSE)

$$\mathrm{RMSE} = \left[\sum_{i=1}^{n} \frac{(P_i - O_i)^2}{n}\right]^{0.5} \quad (5)$$

Coefficient of determination (CD)

$$\mathrm{CD} = \sum_{i=1}^{n}(O_i - O)^2 / \sum_{i=1}^{n}(P_i - O)^2 \quad (6)$$

Model efficiency (EF)

$$\mathrm{EF} = \left[\sum_{i=1}^{n}(O_i - O)^2 - \sum_{i=1}^{n}(P_i - O)^2\right] / \sum_{i=1}^{n}(O_i - O)^2 \quad (7)$$

Coefficient of residual mass (CRM)

$$\mathrm{CRM} = \left(\sum_{i=1}^{n} O_i - \sum_{i=1}^{n} P_i\right) / \sum_{i=1}^{n} O_i \quad (8)$$

Maximum error (ME)

$$\mathrm{ME} = \mathrm{Max}\,|P_i - O_i| \quad (9)$$

Mean difference (MD)

$$MD = \sum_{i=1}^{n} {(P_i - O_i)}/{n} \quad (10)$$

Where P_i is the predicted value; O_i is the observed value; i is the sample index; O is the mean of the values observed; and n is the number of samples. The lower limit for parameters ME, RMSE and CD is zero. The highest EF value is 1. CD determines the variance of observed values in relation to predicted values. Data were not pooled to run the tests, and RMSE, CD, EF, CRM and ME values were expected to be as close as possible to 0.0, 1.0, 1.0, 0.0 and 0.0, respectively.

3. Results and discussion

According to results obtained applying the Kruskal-Wallis test, the null hypothesis of similarity between the distribution functions of observed and modeled soil loss and factor C values (Table 1) was accepted ($P<0.05$). One noteworthy aspect is that predicted C-factor values were equal between replicates of a same sampling point. This occurred because they were concentrated in a same area with spatial resolution of 30m and therefore shared a same NDVI value in the model.

Table 1. Soil loss kg.(m²)$^{-1}$ in areas with vegetation cover (VC) and without vegetation cover (NV), observed and predicted C-factor and NDVI based on remote sensing.

Point/Repetition		a/1	a/2	a/3	b/1	b/2	b/3	c/1	c/2	c/3	Means
Soil loss (VC)		12.31	6.13	3.71	22.01	6.14	6.68	43.75	135.17	18.79	28.30
Soilloss (NC)		87.90	50.96	59.35	164.91	65.36	37.98	99.18	196.28	171.35	103.69
observed C-factor		0.14	0.12	0.06	0.13	0.09	0.18	0.44	0.69	0.11	0.23
NDVI		0.26	0.26	0.26	0.20	0.20	0.20	0.22	0.22	0.22	0.23
	C1	0.49	0.49	0.49	0.61	0.61	0.61	0.56	0.56	0.56	0.55
predicted C-factor	C2	0.28	0.28	0.28	0.33	0.33	0.33	0.31	0.31	0.31	0.31
	C3	0.37	0.37	0.37	0.40	0.40	0.40	0.39	0.39	0.39	0.38

(C1) Van der Knijff et al. (1999); (C2) Lin et al. (2002); (C3) Corrêa & Pinto (2011).

The performance of the 3 models was assessed by comparing them to the values obtained with rainfall simulation, using the statistical parameters calculated (**Error! Reference source not found.**).

Table 1. Statistical fitting of C-factor prediction models.

Identification	Model	RMSE	CD	EF	CRM	ME	MD
C1	Van der Knijff et al. (1999)	0.39	-2.94	-1.94	-1.53	0.51	0.36
C2	Lin et al. (2002)	0.21	0.23	0.77	-0.42	0.37	0.20
C3	Corrêa&Pinto (2011)	0.26	0.73	0.27	-0.76	0.31	0.25

(C1) Van der Knijff et al. (1999); (C2) Lin et al. (2002); (C3) Corrêa & Pinto (2011).

The statistical parameter RMSE indicates that the most accurate method for C-factor prediction was C2 (Lin et al., 2002). Based on the CD value, also called R^2,C3 (Corrêa&Pinto, 2011) was the model that best fit the sample set. However, C2 (Lin et al., 2002) was the most efficient model for estimating the C-factor according to the parameter EF. In an analysis of the CRM coefficient, all the models evaluated overestimated C-factor values. Model C1 (Van der Knijff et al., 1999) shows the highest mean error (ME) and mean difference (MD).The model that best fits C-factor estimates based on NDVI is the equation proposed by Lin et al. (2002).

Although the Van der Knijff et al. (1999) model did not fitlocal conditions, it has beenapplied to study watersheds with similar conditions to those of the study area(Prasannakumar et al., 2011). The model that showed the best fit (C2) was developed for scientific purposes (Lim et al., 2005), and aimed at developing a soil loss model capable of predicting sediment production in a watershed scale, as shown in Chou's study (2009).

The C3 model (Corrêa&Pinto, 2011), which exhibited the worst fit, was not calibrated by experimental plots such as those performed for models C1 (Van der Knijff et al., 1999) and C2 (Lin et al., 2002). Model C3 assumed that the C value was 0 for an NDVI of 1, and 1 for an NDVI of -1, which explains its unsatisfactory performance.

The Guariroba stream sub-watershed exhibits soil cover and management classes that are different from pasture, such as native vegetation (*Cerrado*, *Cerradão*, riparian forest, rangeland, prairie and shrubs), bare soil, wetlands, artificial reservoirs and eucalyptus crops. Thus, Chou (2009), Gertner et al. (2002) and Wang et al. (2002) recommend statistical model fitting according to the data observed and considering the different types of soil cover in order to improve and increase the accuracy of (R) USLE C-factor prediction models.

4. Conclusions

The model that best fits soil cover and management factor (C-factor) prediction, in our local conditions, based on its relationship with NDVI is that proposed by Lin et al. (2002).

The use of rainfall simulator was shown to be a feasible alternative for C-factor determination in field conditions, allowing soil loss assessment in areas with and without vegetation cover. With statistical treatment of simulation outputs, rainfall simulation enable sevaluation of the suitability of models that associate the C-factor and NDVI under different environmental conditions.

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