Chapitre 4

Evolution des états de surface sur sols nus et travaillés

Sommaire

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Article accepté par *Soil and Tillage Research* (publication à venir)

Predicting the spatio-temporal dynamic of soil surface characteristics after tillage

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4.1 Introduction

Soil surface characteristics (SSC), namely soil cover, topsoil structure and soil crusting (Casenave and Valentin, 1992 ; Leonard and Andrieux, 1998 ; Le Bissonnais et al., 2005) are known to influence the partition of rainfall between infiltration and overland flow (e.g., Auzet and Boiffin, 1995 ; Moussa et al. 2002).

They vary largely in time and space due to many factors, among which soil variation and farming practices are the most effective (Bresson and Boiffin, 1990 ; Earl, 1997 ; Leonard and Andrieux, 1998 ; Sillon, 1999 ; Martin et al., 2004 ; Armand et al., 2009). Knowledge of SSC is therefore essential for predicting hydrological processes at both the field and catchment levels.

Several authors have proposed runoff risk classification schemes based on SSC classification. For example, Casenave and Valentin (1992) related soil runoff capability variation in Western Africa to SSC classes defined by the soil surface vesicular porosity and crusting and the amount of worm casts, whereas Cerdan et al. (2002) related potential values of infiltration capacity to SSC classes corresponding to combinations of soil surface roughness, crop cover and soil crusting stage. These classifications are useful for facilitating the parameterization of topsoil infiltration properties in distributed rainfall/runoff modelling approach (Cerdan et al., 2002). Indeed recognizing SSC variation in space and time at the catchment scale is much faster than measuring the variation of soil infiltration capacities. Nevertheless, field surveys of SSC still remain labor-intensive and costly. An alternative is to use remote sensing techniques. Numerous applications have attempted to map single soil surface attributes, like soil surface crusting (Ben-Dor et al., 2003 ; Goldshleger et al., 2004) or soil surface roughness (Baghdadi et al., 2002). Some have also attempted to map synthetic SSC classes, defined as combinations of soil surface attributes like crust development, topsoil structure, vegetation cover, etc. (Wassenaar et al., 2005 ; Corbane et al., 2008). This approach is promising but is still under development, and it requires fine temporal and spatial image resolutions given the characteristic scales of SSC variation. Another alternative is to develop prediction models of SSC from easily-accessed environmental variables, which would also allow for exploration of prospective scenarios regarding, for example, the effect of changes in agricultural practices on catchment runoff. This is what this paper is concerned with in the specific case of the prediction of SSC changes due to tillage practices.

Tillage is the agricultural management practice that has the greatest effect on soil structure. Many studies in the literature have observed and quantified the impact of tillage on soil surface conditions (e.g. Boiffin, 1984 ; Xu and Mermoud, 2001) and on soil physical properties (e.g. Ndiaye et al., 2005 ; Chahinian et al., 2006 ; Strudley et al., 2008). These studies have clearly shown that tillage initially increases soil porosity, removes existing soil crusts and thereby increases soil infiltration properties. They have also shown that subsequent rainfalls and wetting-drying cycles favor soil reconsolidation and soil-surface sealing or crusting (Boiffin, 1984). However, only a few studies have attempted to develop prediction models of the effects of tillage and subsequent reconsolidation. Green et al. (2003) provided an overview of the advances in prediction approaches. They concluded that quantitative algorithms for computer simulations are scarce and typically limited to the short-term effects of tillage. To our knowledge, the situation has not improved since Green et al.'s review. Moreover, the rare predictive equations that are available concern only single soil properties, like bulk density, surface roughness or hydraulic conductivity (e.g. Boiffin, 1986 ; Risse et al., 1995) and, therefore, do not allow to predict the simultaneous change of several SSC that occur after tillage.

In this paper, we present and evaluate a prediction approach of the changes in time and space of SSC classes after tillage at the catchment scale. A SSC classification scheme developed by Andrieux et al. (2001) and based on several criteria such as topsoil structure as related to tillage practices or type of soil crust, was used. Given the influence of rainfall and general soil characteristics on the dynamic of soil consolidation after tillage (see Boiffin and Sebillotte, 1976 ; Dexter, 1977 ; Martin, 1999), we assume that the variation of SSC can be empirically predicted by a linear combination of (i) rainfall parameters, being the main drivers of the temporal changes in SSC in a given field, and (ii) basic soil and tillage characteristics, determining the between-field variations in the rates of change. The prediction method we chose is a logistic regression that allows us to estimate the probability of the occurrence of ordered events, which is here the sequence of SSC classes, and can make use of several numeric and categorical predictors. The fit and evaluation of the prediction approach was performed on a data set of SSC observations taken from 2004 to 2007 in a 91-ha catchment in the south of France planted mainly with vineyards.

4.2 Materials and methods

4.2.1 Study site

The study site was the 91-ha Roujan catchment (43°30'N and 3°19'E) about 60 km to the west of Montpellier in the south of France. The climate is of a sub-humid Mediterranean type characterized by a long dry season and high-intensity and short-duration storms that cause Hortonian overland flow ; it has a mean annual rainfall of 650 mm and a mean Penman reference evapotranspiration of 1090 mm (Andrieux et al., 1993). The catchment consists of four distinct geomorphological units (Fig. 4.1a) : a slightly undulating plateau, terraces hillslopes, a colluvial glacis and a central depression. The elevation ranges from 75 m above sea level in the depression to 125 m at the top of the plateau, and the slope from 2% in the depression to about 15-20% on the terraces. The main soils from the top down the slope are, according to local soil classifications (and to WRB 1998) : (i) stony brown calcareous soils (calcaric leptosol) and

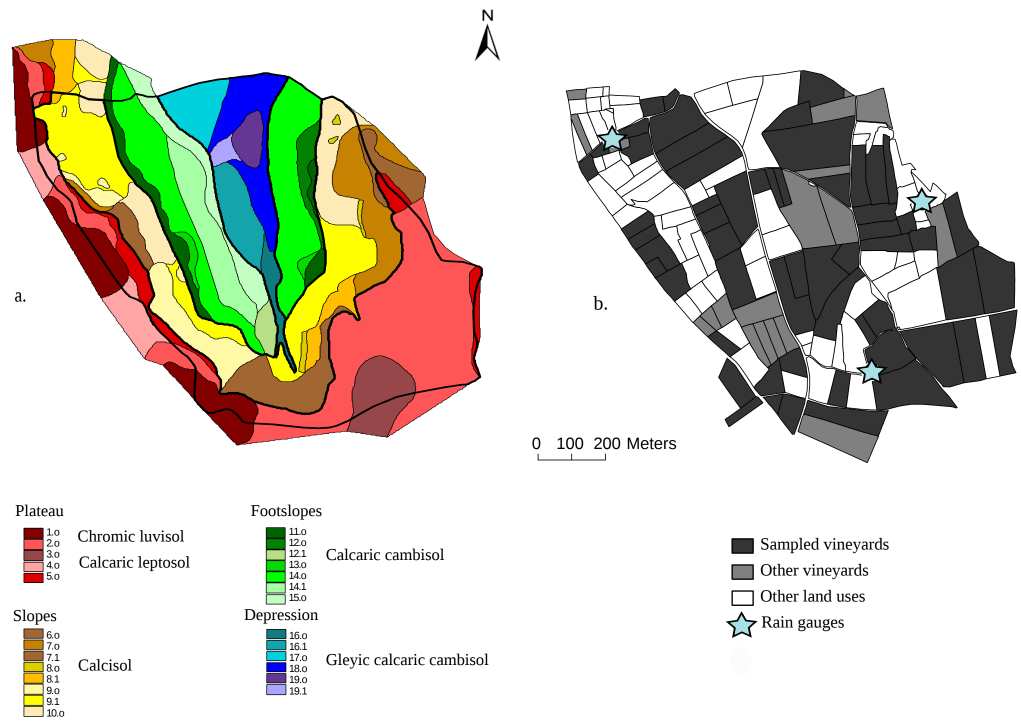

FIGURE 4.1 – Spatial distribution of soil and geomorphological units in the Roujan catchment. b. Sampling design

stony red soils on the plateau (chromic luvisol), (ii) calcareous clay soils (calcisol) on the slopes, (iii) calcareous soils with poorly differentiated profiles and a loamy texture (calcaric cambisol) on the footslopes and (iv) calcareous soils with a medium-to-fine texture with hydromorphic features (gleyic calcaric cambisol) (FAO, 1988) on the depression. Land use in the catchment consists mainly of vineyards. During the monitoring period, vineyards covered 62% of the catchment area on average. The total number of fields in the catchment varied from 153 in 2004 to 147 in 2007, with their area ranging from 0.1 to 2 ha. A dense network of ditches, 11 km long, isolates most fields, collects overland flow, recharges and drains the shallow groundwater and routes water to the catchment outlet. Concerning the agricultural practices, a survey identified three types of soil treatments of the vineyards. In the first one, herbicides are applied over the whole field without any tillage. Consequently, soil surface characteristics remain the same throughout the year. In the other two treatments, herbicides are applied only along the vine rows, whereas the inter-row is tilled one to four times per year or covered permanently with grass. In these last two soil treatments, the soil surface characteristics vary with time due to tillage or changes in the extent of grass cover.

4.2.2 Classification of soil surface characteristics

Here we focus on the description of SSC in the Roujan catchment on the tilled vineyards, which during the study period corresponded to 86% of the vineyards and exhibited a large temporal and spatial variation of SSC. To distinguish between the various SSC that can be observed on the tilled fields, we followed the classification of SSC resulting from a work by Andrieux et al. (2001) on the same site. These authors classified the SSC according to the observed soil cover, topsoil structure and soil crusting and showed that the distinguished classes have different infiltration properties as measured by rainfall simulation. Here we use only the part of the classification describing the SSC in the tilled vineyards. They are represented in Fig. 4.2. They correspond to different stages in the evolution of the soil structure of the vineyard soils due to the effect of tillage and of natural reconsolidation by raindrop impact and redistribution of soil particles by splash and flow (e.g., Robinson and Philips, 2001) :

(i) The first stage, named "recently tilled" and in short "T," corresponds to the stage just after tillage when the soil porosity increased, the topsoil structure loosened and the surface crusts if any were destroyed. In the field, this stage is recognized by a fragmentary structure of the soil surface with clods and particles clearly distinguishable and the absence of any crust.

(ii) The second stage, named "formerly tilled" and in short "TCst," follows the T stage. It still exhibits a loose topsoil structure but a thin structural crust has formed over at least parts of its surface. In the field, this stage is recognized by a still very rough soil surface that is partially to totally closed with a thin and porous structural crust. Soil clods must remain visible even under the crusted part of the soil surface since at this stage the crust that has formed only covers the soil surface but has not altered significantly the underlying soil structure.

(iii) The third stage, named "crusted" and in short "Cst," is the final state of soil reconsolidation after tillage. The topsoil is recompacted and a continuous structural crust with a thickness larger than in the second stage overlays it. In the field, this stage is recognized by a totally closed soil surface with a continuous and consolidated structural crust, a compacted topsoil structure with soil clods that are no longer visible from the surface.

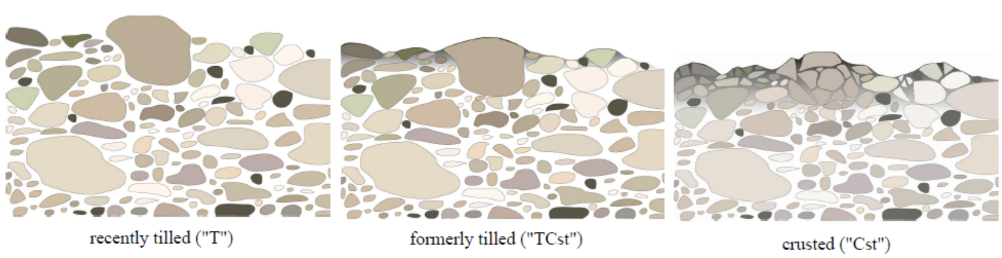

FIGURE 4.2 – The three stages of soil surface evolution after tillage.
The deep-grey shapes portray stones and gravels. Shapes of other colors portray clods. The grey shading that appears between the soil clods indicates the change in extension of the structural crust.

It must be pointed out that variants of the third stage exist. A first variant is related to possible grass growth that partly covers the soil. It was rarely observed during the monitoring periods due to the droughts that limited grass development after tillage. A second one is linked to sedimentary crusts that form, instead or in addition to structural crusts, in downslope topographical depressions where redeposition of eroded material can occur. However, these crusts are of limited spatial extent in our study area and represent at the most a very small part of the fields (Corbane et al., 2008). Given their rarity, the variants were not considered in our analysis.

4.2.3 Data collection

4.2.3.1 Soil surface characteristics

SSC were monitored on 58 fields of the Roujan catchment, corresponding to almost all of the tilled vineyards (95% of the total area of tilled fields) (Fig. 4.1b). All of them were tilled one or several times during the monitoring period, which lasted from February 2004 to February 2007. Thus, different sequences of SSC evolution after tillage, called tillage sequences, could have been observed for the same field. Observations were made once per month, apart from March to July 2007 when they were made every week. Only the observations within three months after tillage were retained for analysis to focus on the periods of soil reconsolidation. They consisted in examining the four main criteria for determining the SSC class : (i) the presence or absence of surface crusts, (ii) the thickness of the crust if present, (iii) the visibility of soil clods, (iv) the degree of compaction of the topsoil structure as estimated with a knife. Several observations were made in each field in order to identify the major SSC of the tilled inter-rows. It is important to emphasize that all of the staff who did the observations were preliminary trained in the field to recognize the SSC to limit variations in judgment between surveyors as much as possible. SSC monitoring produced a sample of 547 observations from 158 tillage sequences and 58 fields which was submitted to statistical analysis.

4.2.3.2 Rainfall characteristics

Rainfall was recorded by three tipping bucket rain gauges spatially distributed over the catchment (Fig. 4.1b). For each observation field, the reference rainfall measurements were those taken by the nearest rain gauge. For each SSC, two rainfall characteristics were estimated from the rainfall measurements : (i) the cumulative rainfall amount since tillage and (ii) the cumulative kinetic energy of the rainfall since tillage. The cumulative rainfall was directly computed from the rainfall measurements, whereas kinetic energy was calculated by using empirical equations relating rainfall kinetic energy to rainfall intensity Salles et al. (2002)(see review by Salles et al., 2002). Because no single equation is generally recognized to be valid, we chose to test three different equations, as described in Table 4.1.

TABLE 4.1 – Equations relating time-specific kinetic energy (KE_{time}) and rainfall intensities (I) (after Salles et al., 2002) N.B. The third equation is composed of two equations, (3a) and (3b), based on the same approach and with two complementary definition domains.

	Reference	$KE_{time}(J\,m^{-2}\,h^{-1})$ - $I(mm\,h^{-1})$ relation	Location	Range of I $(mm\,h^{-1})$
Eq. (1)	Cerro et al., 1998	$38.4\ I\ (1 - 0.538e^{-0.029I})$	Italy	n.a.
Eq. (2)	Zanchi and Torri, 1980	$I(9.81 + 11.25\ log_{10}I)$	Barcelona, Spain	n.a.
Eq. (3a)	Uson and Ramos, 2001	$23.4I$ - 18	NE Spain	$I < 20$
Eq. (3b)	Sempere-Torres et al., 1992	$34I$ - 190	Cévennes, France	$20 \leqslant I \leqslant 100$

They were all derived from measurements in Mediterranean sites. Let us note that the third equation is a combination of two published equations, one for intensities under 20 mm/h and one for intensities larger than 20 mm/h. For the application of the three equations, rainfall intensities were estimated in time steps of 5 min. This time step was chosen to be as small as possible to avoid overly smoothing the actual rainfall intensities while remaining realistic with regard to the inertia of the tipping bucket rain gauges.

4.2.3.3 Tillage dates and features

Because each SSC observation had to be related to the last tillage, the dates and the characteristics of tillage operations were registered. They were determined from the farmer's statements for the monthly observations and from the SSC observations when they were realized weekly. When there was a large uncertainty on the date and feature of the tillage that preceded an SSC observation, this SSC was not included in the sample. The tillage characteristics that were recorded included the kind of tool used for tillage, the size of the clods created by tillage and the perpendicular roughness created by tillage. The latter two characteristics were measured in the field and classified in three classes, as seen in Table 4.2.

TABLE 4.2 – Distribution of observations among SSC classes and predictor candidates

	Number of observations				Number of fields	Number of sequences
	T	TCst	Cst	Total		
Soil type						
Luvisols	81	49	73	203	23	64
Regosols	42	52	38	132	14	39
Cambisols	80	75	57	212	21	55
Clay level						
< 12.5%	33	46	28	107	12	29
[12.5% ; 22.5%[	111	78	81	270	27	84
≥ 22.5%	59	52	59	170	19	45
Stoniness						
[0% ; 25%[	76	79	49	204	23	52
[25% ; 50%[	64	65	71	200	16	56
[50% ; 100%[	63	32	48	143	19	50
Tillage tool						
Spring-tine cultivator	134	102	105	341	-	101
Rotary cultivator	69	74	63	206	-	57
Roughness after tillage						
< 2cm	41	21	32	94	-	33
[2cm ; 5cm[	145	142	130	417	-	112
≥ 5cm	17	13	6	36	-	13
Clod size after tillage						
< 1cm	18	8	10	36	-	15
[1cm ; 5cm[	113	107	96	316	-	96
≥ 5cm	72	61	62	195	-	47
Total	203	176	168	547	58	158

4.2.3.4 Basic soil properties

Each sampled field was also characterized by the values of some of its permanent soil attributes, namely clay content, stoniness and soil type, which were observed during the soil survey of Roujan (Andrieux et al., 1993) and by visual inspection during the SSC monitoring. Table 4.2 indicates the classes that were distinguished for these soil attributes.

4.2.4 Statistical analyses

An ordinal logistic regression approach was used to analyze the factors controlling the change in SSC and to build a prediction model of the SSC variation within the Roujan catchment. Logistic regression was chosen because it enabled fitting the logarithm of the probability of an event as a linear regression to a set of predictor variables that may be either continuous or categorical. Compared to the standard binary logistic regression, which estimates the probability of one event only, ordinal logistic regression predicts the probability of a given event and of all events that are ordered before it occurs. This corresponds well to the present case, where we sought a model to predict the probability of the occurrence of SSC categories that follow each other in time.

4.2.4.1 The ordinal logistic regression approach

Several ordinal logistic regression models are available, depending on the exact nature of the response and the predictor variables and of their relationships (see the review of Ananth and Kleinbaum, 1997). Here we used the unconstrained partial-proportional odds model, which is presented in detail by Peterson and Harrell (1990). All statistical calculations were made with the R software (Ihaka and Gentleman, 1996), and its VGAM package (Yee, 2008) was used for applying logistic regression.

To describe the principles of the model, let us first start with the proportional odds model of which the model is an extension. Consider a response variable Y with k ordered categories and x, a vector of n predictor variables. The proportional odds model relates the logarithm of the ratio between the probability of the response variable being larger or equal to a given category ($Y \geq j$ with $j = 2, ..., k$) and the probability of a response smaller than this category to a linear combination of a set of independent predictor variables

$$ln(\frac{P(Y \geqslant j)}{P(Y < j)}) = \alpha_j + x'\beta \quad j = 2, ..., k \tag{4.1}$$

with α_j being the unknown intercept and β being the vector of n unknown regression coefficients corresponding to x. Because $P(Y > j) + P(Y \leqslant j) = 1$, Eq (4.1) can be rewritten as

$$\frac{P(Y \geqslant j)}{1 - P(Y \geqslant j)} = exp(\alpha_j + x'\beta) \quad j = 2, ..., k \tag{4.2}$$

The quotient on the left hand side of Eq. (4.2) is referred to as the odds. Rearranging Eq. (4.2) leads to

$$P(Y \geqslant j) = \frac{exp(\alpha_j + x'\beta)}{1 + exp(\alpha_j + x'\beta)} \tag{4.3}$$

The whole model is composed of $k-1$ linear equations corresponding to the $k-1$ probabilities to be predicted and exhibits $(k-1+n)$ coefficients. The intercepts α_j vary for each equation and satisfy the condition $\alpha_2 \leqslant \alpha_3 \leqslant ... \leqslant \alpha_k$. In the proportional odds model, the n β coefficients do not vary between the equations, meaning that the relationship between x and the log-odds ratio for Y is assumed to be independent of the category predicted. This assumption applies to all predictor variables and corresponds to what is called the proportional odds property, which gave its name to the method. If it is not satisfied, which is true in our case study (as will be seen later), one can apply the unconstrained partial-proportional odds model, which permits non-proportional odds for a subset q of the n predictors. The partial-proportional odds model is as follows :

$$P(Y \geqslant j) = \frac{exp(\alpha_j + x'\beta + t'\gamma_j)}{1 + exp(\alpha_j + x'\beta + t'\gamma_j)} \tag{4.4}$$

with t, the vector of q variables out of the n predictor variables for which the proportional odds assumption is not met, and γ_j, the vector of coefficients associated with the q predictor variables. Notice that the γ_j vectors differ following j and that γ_1 coefficients are simply fixed at 0. Consequently, in this model there are still $k-1$ linear equations, but the number of coefficients to estimate amounts now to $(k-1)+(k-2)q+(n-q)$. The unconstrained partial-proportional odds model is therefore much less parsimonious in terms of coefficients to be fitted than the proportional odds model. In the VGAM package of the R software, the coefficients of the model are estimated by maximum likelihood.

In this case study, because the response variable, the SSC, has three classes, the number $k-1$ of equations to fit was two.

4.2.4.2 Checking collinearity among predictor candidates

To control the absence of multicollinearity between the predictor variables, two measures were carried out. One is the Cramer's V coefficient, which estimates the degree of dependence between two categorical variables (Cramer, 1999) :

$$V = \sqrt{\frac{\chi^2}{l(c-1)}} \tag{4.5}$$

with χ^2being the chi-square statistic, l being the total sample size and c being the minimum number of categories of the two categorical variables. The statistic V ranges from 0 (no dependence) to 1 (perfect association). It was preferred to the chi-square measure because it is not sensitive to the sample size. It does not, however, allow us to test whether the estimated collinearity is statistically significant.

Another measure was the Kruskal-Wallis non-parametric test statistic (Kruskal and Wallis, 1952) that estimates the degree of association between a categorical variable and a continuous variable. This statistic follows an approximate χ^2 distribution, which therefore allows estimation of the probability of the null hypothesis, i.e., the absence of association between a couple of categorical and continuous predictors.

4.2.4.3 Selection of model type and predictor candidates

To decide which model type should be used, an unconstrained partial-proportional or proportional odds model and which predictor variables may be assumed to respect the proportional odds property, we used a likelihood ratio test (Peterson and Harrell, 1990). This test is based on the calculation of the deviance statistic, which estimates the goodness of fit of the logistic model and is defined by :

$$D = -2ln(\frac{Likelihood\, fitted\, model}{Likelihood\, saturated\, model}) \tag{4.6}$$

The smaller the deviance, the better the fit of the model compared to the saturated model that contains all main effects and all possible interactions between factors. The test, then, compares the difference in D between the partial-proportional and the proportional odds models, applied with the predictor candidate as the sole predictor, for each predictor candidate. The difference in deviance is chi-square distributed with $(k-2)$ degrees of freedom under the null hypothesis that there is no difference in the coefficients between the two models, which enables us to estimate its statistical significance.

For upward selection of variables in the ordinal regression models, we used the deviance information criterion (DIC) proposed by Spiegelhalter et al. (2002), which is a Bayesian measure of fit, penalized by an additional term representing model complexity :

$$DIC = \bar{D} + p_D \tag{4.7}$$

with $\bar{D}$ being the mean Bayesian deviance and p_D the effective number of parameters of the model (see Eq. (37) in Spiegelhalter et al. (2002)). Because increasing the number of predictors in the regression model is known to be accompanied by a better fit, the DIC allows us to make a trade-off between improvement of fit and model complexity, represented by the number of free parameters in the model. Thus, at each step of inclusion of an additional predictor, the change in DIC between the (p-1)-predictor model and the p-predictor model was calculated. The additional predictor was retained in the final model if the computed DIC of the model including this predictor was smaller. The significance of a predictor coefficient within each fitted model was assessed with the Wald statistic, W (Hosmer and Lemeshow, 1989),

$$W = \hat{\beta}/s_e(\hat{\beta}) \tag{4.8}$$

which compares the estimated coefficient, $\hat{\beta}$, to an estimate of its standard error, $s_e(\hat{\beta})$. The Wald statistic follows a standard normal distribution under the null assumption that the model coefficient is zero. Lastly, notice that the variables whose distribution exhibited large skewness were square-root transformed, because asymmetric distribution and extreme values caused instability during the parameter estimation. Accordingly, all rainfall variables had to be transformed.

4.2.4.4 Validation

To evaluate the prediction error of the fitted logistic regression models, a cross-validation was applied. The initial data set was randomly divided into two subsets, one corresponding to 90% of the observations and the other corresponding to the remaining 10%. The largest subset was used for fitting the logistic regression models provided by the selection step, and the smallest was used for independent evaluation. This procedure was repeated ten times to estimate the average and standard deviation values of the well-classified rates of SSC. A Wilcoxon signed-rank test (Wilcoxon, 1945) was performed to test the significance of the differences in the performance of the models. As the samples are related and small, we used this non-parametric test to compare averages of well-classified rates. Indeed, the cross-validation data sets are the same for all models, and there are only 10 values to compute the average rate. With the assumption that the differences between matched-pair values are independent observations from a symmetric distribution, the null hypothesis is that this distribution has a median of zero. The Wilcoxon signed-rank statistics W_+ is defined as :

$$W_+ = \sum_{i=1}^{n} \Phi_i R_i \tag{4.9}$$

considering n well-classified rates computed with a model, for $i = 1, \ldots, n, X_i$ and Y_i are two rates computed on the same data set i and $Z_i = Y_i - X_i$. R_i is the rank of the absolute value $|Z_i|$ and ϕ_i is the sign of Z_i.

4.3 Results and discussion

4.3.1 Characteristics of the data set

4.3.1.1 Distribution of observations among variable classes

The distribution is well-balanced between the SSC classes, which reflects that the majority of the observed tillage-reconsolidation periods included all of the stages of soil surface characteristics (Table 4.2). The distribution is well-balanced between the SSC classes, which reflects that the majority of the observed tillage-reconsolidation periods included all of the stages of soil surface characteristics. In contrast, the soil and tillage variables, with the exception of stoniness and soil type, showed a strongly unbalanced distribution of observations between their classes. Concerning clay content, this is linked to the textural characteristics of the soils of the study zone, which mostly exhibit a medium clay content. Concerning the tillage-related variables, the dominance of one class is due to similar choices of tillage practices made by a majority of the farmers of the study site ; they tilled their fields with the same kind of tool and in similar soil wetness conditions.

TABLE 4.3 – Distribution of two rainfall variables among the three soil surface characteristics stages

		T	TCst	Cst
Cumulative rainfall amount since tillage (mm)	Minimum	0	8	32
	Lower quartile	0	37	75
	Median	1	54	92
	Upper quartile	2	60	123
	Maximum	30	121	256
Cumulative kinetic energy since tillage as computed by Eq. (2) (J m^{-2})	Minimum	0	165	1116
	Lower quartile	0	1003	2048
	Median	7	1150	2968
	Upper quartile	32	1288	4025
	Maximum	807	3922	7348

Table 4.3 shows that the median and the range of values of cumulative rainfall and kinetic

energy since tillage is very different between the SSC classes, which confirms the major influence of rainfall on the evolution of soil surface characteristics after tillage. As expected, SSC T was observed when the cumulative rainfall since tillage remained small, whereas SSC Cst was observed with much larger rainfalls and SSC TCst with intermediate values.

4.3.1.2 Collinearity between predictor candidates

When applying logistic regression analysis, the absence of multicollinearity between variables is desirable. Collinearities between rainfall and soil and tillage variables were shown to be insignificant by the Kruskall-Wallis test. This was expected because the observed latter variables are intrinsic soil and tillage properties. In contrast, the associations between pairs of soil and tillage parameters appear variable, as seen in Table 4.4, which presents the Cramer's coefficients. It is possible to distinguish roughly two degrees of associations.

Table 4.4 – Cramer coefficients of the associations between the categorical predictor candidates

	Soil type	Clay level	Stoniness	Tillage tool	Roughness	Clod size
Soil type	-	-	-	-	-	-
Clay level	0.29	-	-	-	-	-
Stoniness	0.62	0.29	-	-	-	-
Tillage tool	0.30	0.37	0.27	-	-	-
Roughness	0.21	0.16	0.25	0.52	-	-
Clod size	0.27	0.25	0.21	0.45	0.36	-

Three pairs of variables (tillage tool-perpendicular roughness, tillage tool-clod size and stoniness-soil type) have coefficients close to or larger than 0.5, which indicates a strong association. The existence of an association between the tillage tool and the perpendicular roughness and clod size is logical because the type of tillage tool determines the latter two soil characteristics. Furthermore, the strong association between stoniness and soil type can be explained by the fact that there is a large variation in stoniness between the soil types, with stoniness being large for the chromic luvisols that occur on the plateau of the Roujan catchment and almost negligible for the other soil types (Andrieux et al., 1993).

All of the other pairs show small or very moderate association, with their Cramer's coefficients ranging from 0.16 to 0.37. Soil characteristics, namely stoniness, soil type and clay content seem to have little influence on the choice of the tillage tool and thereby on the resulting soil roughness and clod size.

Eventually, it must be noticed that in the prediction models presented hereafter, we avoided the presence of too strongly associated variables among the set of predictors to avoid undesired effects due to multicollinearity. If one variable of each of the three pairs exhibiting strong association was included in the model, the other was not.

4.3.2 Selection of the predictor variables

The results of the test of proportional odds properties are given in Table 4.5. For the sake of parsimony in the number of model parameters, we considered that the proportional odds property was rejected for a predictor only when the probability of the null hypothesis was smaller than 0.01. Consequently, stoniness and soil type were assumed to require different coefficients for predicting different classes of SSC. Thus, the fit of a fully proportional odds model was inappropriate, and an unconstrained partial-proportional model was used in the following analysis.

TABLE 4.5 – Values (D) of the likelihood ratio test of the proportional odds property of each predictor candidate

	D
Cumulative rainfall amount since tillage	0.512
Cumulative kinetic energy since tillage as computed by	
Eq. (1)	1.000
Eq. (2)	5.525*
Eq. (3)	1.585
Soil type	6.677**
Clay level	0.334
Stoniness	10.833***
Tillage tool	1.955
Perpendicular roughness	4.977*
Clod size	0.100

Table 4.6 presents the results of the upward selection of predictors. The restriction mentioned in the previous section about the associated predictor candidates was taken into account. Moreover, as can be seen, four competing ordinal logistic regression models were fitted in order to analyze which of the four rainfall variables (cumulative rainfall and the three estimates of cumulative kinetic energy) was the best predictor of the influence of rainfall on SSC changes. Indeed, all of the four rainfall-related variables are closely correlated and thus cannot be introduced simultaneously as predictors in the regression. In all four models, the order of inclusion of predictors was the same. Starting from the most significant predictor, we had first the rainfall variable, then successively stoniness, perpendicular roughness, clay content and, finally, clod size. Only the introduction of the first three led to an improved DIC. This decrease in the value of the DIC was large for the rainfall and stoniness predictors but very small for perpendicular roughness. We discuss hereafter the result of the selection for each predictor variable.

TABLE 4.6 – Deviance Information Criterion at each step of the upward selection of variables
N.B. Model A used cumulative rainfall amount since tillage and Models B used cumulative kinetic energy since tillage as computed by Eq. (1) for Model B1, Eq. (2) for model B2 and Eq. (3) for Model B3

Variables added at each step with upward selection	Step 1 : rainfall variable	Step 2 : stoniness	Step 3 : roughness	Step 4 : clay level	Step 5 : clod size
Model A	357.1	335.0	334.8	335.6	337.6
Model B1	338.4	321.0	321.0	322.1	323.9
Model B2	363.7	347.9	347.7	349.2	350.4
Model B3	339.7	321.7	321.1	322.6	324.2

Rainfall is indeed known as the main driving factor of soil surface changes after tillage. Processes like aggregate slaking and dispersion upon wetting and particle displacement due to raindrop impact and surface runoff favor the formation of soil crusts and decrease soil roughness (e.g., Boiffin and Sebillotte, 1976 ; Dexter, 1977 ; Boiffin, 1984 ; Martin, 1999).

The influence of stoniness on soil crusting and topsoil structure dynamics has been less studied, but several authors (e.g., van Wesemael et al., 1996 ; Robinson and Woodun, 2008) showed that stones modify the dynamic of soil surface changes. As in our study, when site stoniness is highly variable between fields, it appears as a significant variable for predicting the variation of SSC in time and space.

Soil roughness was shown to slow down the soil crusting process. As explained by Govers et al. (2000), increasing roughness leads to a decrease in the impact of the kinetic energy of rainfall because the impact is distributed on a larger surface and reduced in the direction normal to the soil surface by local slope. However, the two predictor candidates related to soil roughness, perpendicular roughness and clod size, showed very little or no decrease in DIC. This may be for two reasons. First, the first two selected predictors already explain a large part of the variation in SSC ; second, the variability of roughness is rather small, because almost 80% of the perpendicular roughness and 60% of clod sizes belonged to one class (Table 4.2).

Clay content was also not considered to be a useful predictor. This is in contrast to different studies that showed its role in the stability of soil aggregates : for high clay contents, soils exhibit stable aggregates and limited crusting (Kemper and Koch, 1966 ; Moldenhauer and Kemper, 1969). Ben Hur et al. (1985) have proposed 20% as a threshold of clay content. Because the clay content of our study site varied from values well below to well above this threshold, it was a relevant predictor candidate for predicting SSC changes. However, on our study site, the fields with high clay content are also stony. Consequently, because stoniness was selected before clay content in the upward selection approach, the latter variable did not bring enough additional information.

To conclude, given the results obtained, the same set of predictor variables was kept for all models, with the first two variables producing a significant decrease of the DIC : cumulative rainfall or kinetic energy and soil stoniness.

4.3.3 Evaluation and comparison of models

The statistics of the well-classified SSC classes, i.e. average value and standard deviation of the proportion of predicted SSC belonging to the correct SSC class, by each of the four competing models are given in Table 4.7, as obtained by cross-validation. No matter which model was used, the performance of the predictions was high and similar among the models : the average well-classified proportion varied from 0.89 to 0.90 and its standard deviation was always small. To test whether the differences of proportions were statistically significant, we computed a Wilcoxon-Mann-Whitney statistic between all of the pairs of well-classified rates. They were all larger than 0.1 , which suggests that the differences were not significant at a 10% probability level.

Consequently, it follows that using only cumulated rainfall as a predictor performs as well as using cumulative rainfall kinetic energy. From a theoretical point of view, this was unexpected, because rainfall intensity is generally assumed to better explain the change in SSC than just the rainfall amount. However, in our case study, there was a good linear relationship between the cumulative kinetic energy and the cumulative rainfall, which indicates that the relationship between the rainfall amount and the rainfall intensity did not vary much among all observed rainfalls, regardless of their heights. Thus, in this instance, it was practically impossible to discriminate

TABLE 4.7 – Average rates and standard deviations of SSC well-classified computed from the 10 cross-validation data sets for the four models

	Well-classified rate	
	Average	Std. Dev.
Model A	0.9035	0.0407
Model B1	0.9053	0.0343
Model B2	0.8980	0.0342
Model B3	0.9035	0.0347

between the prediction performance of the rainfall amount and the rainfall kinetic energy. We can also point out that the choice of an equation for computing kinetic energy from rainfall energy was not essential with respect to the prediction performance.

In the following, a more detailed analysis of model fit and model performance is provided for only one of the four competing models, namely model B2 in Table 4.7, because no significant difference was found between them. Although the rainfall kinetic energy did not allow a significantly better prediction than the rainfall amount in our particular case study, model B2 was preferred in the following analysis because it should theoretically be more predictive if rainfall amount and rainfall intensity are not related. According to the test of the proportional odds property, non-proportional odds for stoniness and proportional odds for kinetic energy were used.

TABLE 4.8 – Coefficient estimates and their standard deviations for the Model B2

	Coefficient estimates	Std. Dev.	Wald Chi-square	p-value
Intercept for logit(P[Y ≥ TCst])	-4.68683	0.684879	46.8306	<0.0001
Intercept for logit(P[Y ≥ Cst])	-11.98542	0.912595	172.4846	<0.0001
Cumulative kinetic energy since tillage	0.24060	0.016454	213.8093	<0.0001
Stoniness for logit(P[Y ≥ TCst])	0.12464	0.286040	0.1899	0.6629
Stoniness for logit(P[Y ≥ Cst])	1.02480	0.238396	18.4791	<0.0001

The estimated coefficients of model B2 and their statistical significance are given in Table 4.8. As expected, cumulative kinetic energy is a highly significant predictor and, according to the value of its coefficient in the fitted logistic regression equation, the larger its value, the larger the probability of the occurrence of TCst and Cst. It must also be pointed out that its standard error of estimation is very small. Besides, stoniness is a significant predictor for Cst, the last stage of change in SSC after tillage. Moreover, the coefficient of stoniness is positive, indicating that the evolution of SSC is faster with increasing stoniness. This is consistent with the observation of Robinson and Woodun (2008) who have indicated that, although stones protect a significant proportion of the soil surface from rainfall impact (see also van Wesemael et al., 1996), stones tend to accentuate the development of surface crusts on the areas of soil between them. However, this mechanism seems not to be effective on the early changes in SSC after tillage, because stoniness is not a significant predictor for TCst, the first stage of soil reconsolidation after tillage.

TABLE 4.9 – Average proportions and standard deviations of SSC well-classified computed from the ten cross-validation data sets for the three soil types of the study zone for the Model B2

	Average	Std.Dev.
Cambisols	0.8888	0.07
Regosols	0.9355	0.06
Luvisols	0.8812	0.07

To further evaluate the performance characteristics of the logistic regression fitted model, we also examined from the cross-validation results of Model B2 how the prediction errors varied between the SSC and between the soil types. Table 4.9 shows the differences between the rates of well-classified SSC between the soil types. The differences are minor, and a Wilcoxon signed-rank test indicated that they were not statistically significant. This confirms that the fitted logistic regression model is quite robust among different soil types.

4.3.4 Examples of SSC predictions over the Roujan catchment

To show an application of the fitted ordinal logistic regression of SSC, we used it to predict the spatial variation of SSC over the vineyard fields of the Roujan catchment at two dates within the period where the farmers usually till their soil, namely from March to June. Figures 4.3a and b shows the dates of tillage and the rainfall distribution during this period, whereas Figures 4.3c and e shows the maps for the distribution of SSC having the largest probabilities of occurrence on two dates. On May 30th there is a large variation of the SSC due to the difference in tillage dates between the fields. As a result, a large variability of the runoff-infiltration processes can be expected at the catchment scale. On the contrary, on June 19th the SSC are uniform over the catchment because the rainfall amounts since tillage were sufficient on all of the fields to lead them to the last stage of soil surface reconsolidation, a fully crusted soil surface. Given a classification of SSC according to their infiltration properties, the predicted maps allow us to simulate the influence of the temporal variation of SSC due to tillage and subsequent reconsolidation on the hydrological behavior of the catchment. Because logistic regression predicts probabilities of occurrence, it is also possible to create uncertainty maps of the SSC, as shown in Figures 4.3d and f. These uncertainty maps can be used in a Monte-Carlo approach to estimate the uncertainty of the hydrological model predictions based on the predicted SSC maps.

4.4 Conclusion

The logistic regression approach developed in this work clearly shows that it is possible to accurately predict the rate of change in SSC after tillage at a given field from the knowledge of a limited number of easily accessed climatic and soil variables. It also provides indications of the variables that are the most significant predictors of SSC changes. Rainfall, represented either by its height or by its cumulated kinetic energy, appears to be the main predicting factor of soil reconsolidation. Moreover, it is the sole significant predictor of the first change that occurs after tillage, from the fresh tillage stage to the first stage of crusting. Only during the second change, consisting of a thickening of the structural surface crust from "TCst" to "Cst," do other environmental variables become significant predictors. Here, stoniness is the main predictor, as it accelerates the crusting process. Next is the perpendicular roughness of the soil surface, whose influence is small.

The logistic regression approach as an unconstrained partial-proportional odds model proves to be a very flexible prediction model of SSC change because it can make simultaneous use of numeric and categorical predictors and allows the fitting of different coefficients for the different subsequent SSC stages. Consequently, we believe it can be used successfully in other study zones with different climates and soils. To implement it will certainly require in part a re-examination of the most relevant predicting variables. Obviously, rainfall should remain as the main predictor, but the soil and agricultural practice factors may change according to the specific soil variation and the kind of tillage tools used in the study area.

Finally, it must be noticed that this study focused on the spring and summer periods during which the fields are regularly tilled and SSC changes are mainly due to soil reconsolidation and crusting. During the autumn and winter periods, the processes of crusting and weed development occur simultaneously. Thus, to be able to predict the SSC evolution at an annual scale, it will be necessary to consider weed growth variables as additional predictors.

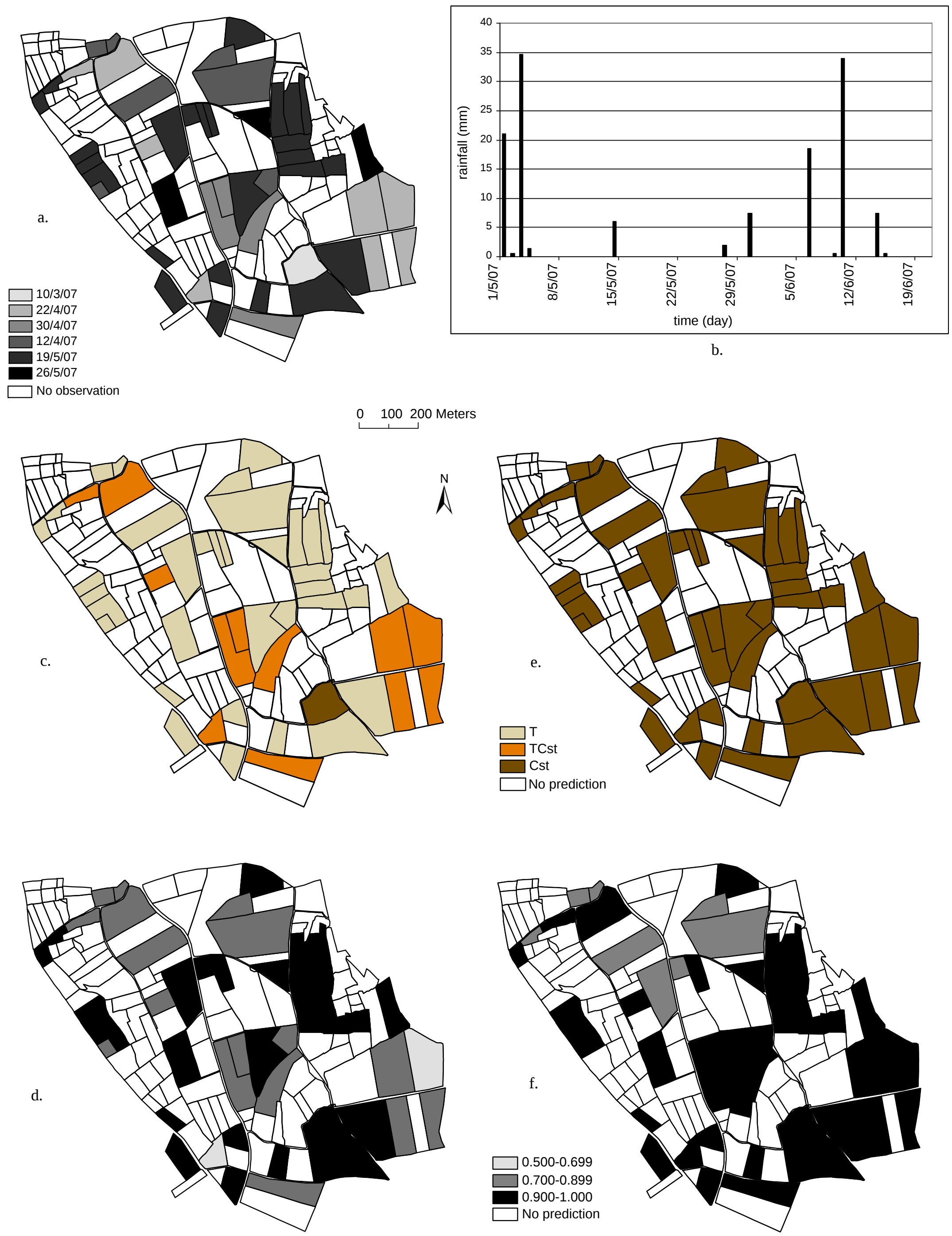

FIGURE 4.3 – Results of the model at two dates : May, 30^{th} 2007 and June, 19^{th} 2007. a. Dates of tillages for each plot. b. Rainfall between June, 1^{st} and June, 19^{th} . c. Soil surface characteristics predicted by the model on May, 30^{th} . d. Probabilities associated to the prediction on May, 30^{th} . e. Soil surface characteristics predicted by the model on June, 19^{th}. f. Probabilities associated to the prediction on June, 19^{th}.

Remerciements

Merci à tous ceux qui ont participé aux relevés d'états de surface utilisés dans ce travail : Jean-Luc Belotti, François Garnier, Gwenn Trotoux, Olivier Huttel, Goulvena Hello et Emmanuel Latge. Merci à Jean-Pierre Vila, Matthieu Hanf, Philippe Besse, Stéphane Robin, Jean-Jacques Daudin et Jean-Stéphane Bailly pour leur appui statistique à différentes étapes de ce travail. Merci à Christian Salles pour ses conseils sur les équations de calcul de l'énergie cinétique. Merci à Yves Blanca pour la réalisation de la figure 4.2. Merci à Nicolas Devaux pour l'aide à la réalisation des cartes. Merci aux co-auteurs de l'article et particulièrement à Patrick Andrieux qui a encadré ce travail et à Marc Voltz pour l'appui rédactionnel.

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