Mapping of tank silt application using Sentinel-2 images over the Berambadi catchment (India)

Cécile Gomez, S. Dharumarajan, Philippe Lagacherie, Jean Riotte, Sylvain Ferrant, M. Sekhar, Laurent Ruiz

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6   **(India).**

7   Gomez[1,2,*] C., Dharumarajan[3] S., Lagacherie[1] P., Riotte[2,4] J., Ferrant[5] S., Sekhar[2,6] M., Ruiz[2,4,7] L.

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9   [1] LISAH, Univ. Montpellier, IRD, INRAE, Institut Agro, Montpellier, France

10   [2] Indo-French Cell for Water Sciences, IRD, Indian Institute of Science, Bangalore, India

11   [3] ICAR-National Bureau of Soil Survey and Land Use Planning, Hebbal, Bangalore, India

12   [4] GET, Université Paul-Sabatier, IRD, CNRS, Toulouse, France

13   [5] CESBIO, Université Paul-Sabatier, CNRS, CNES, IRD, INRAE, Toulouse, France

14   [6] Indian Institute of Science, Civil Engineering Department, Bangalore, India

15   [7] SAS, INRAE, Institut Agro, Rennes, France

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17   [*] Corresponding author. cecile.gomez@ird.fr

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19   **Highlights**

20   • We studied an Indian age-old practice: a black-colored tank silt application over red-colored

21   soils

22   • Soil color maps were produced by supervised classification method using Sentinel-2

23   images

24   • Soil color changes between two S2 images were used as proxy to identify tank silt

25   applications

26   • The proposed approach allows mapping soil colors with correct accuracy

27   • This anthropogenic soil modification was identified over 202 fields

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Abstract

Mapping soil properties is becoming more and more challenging due to the increase in anthropogenic modification of the landscape, calling for new methods to identify these changes. A striking example of anthropogenic modifications of soil properties is the widespread practice in South India of applying large quantities of silt from dry river dams (or "tanks") to agricultural fields. Whereas several studies have demonstrated the interest of tank silt for soil fertility, no assessment of the actual extent of this age-old traditional practice exists. Over South-Indian pedological context, this practice is characterized by an application of black-colored tank silt to red-colored soils such as Ferralsols. The objective of this work was to evaluate the usefulness of Sentinel-2 images for mapping tank silt applications, hypothesizing that observed changes in soil surface color can be a proxy for tank silt application. We used data collected in a cultivated watershed in South India including 217 soil surface samples characterized in terms of Munsell color. We used two Sentinel-2 images acquired on February and April 2017. The surface soil color over each Sentinel-2 image was classified into two soil types ("Black" and "Red" soils). A change of soil color from "Red" in February 2017 to "Black" in April 2017 was attributed to tank silt application. Soil color changes were analyzed accounting for possible surface soil moisture changes. The proposed methodology was based on a well-balanced Calibration data created from the initial imbalanced Calibration dataset thanks to the Synthetic Minority Over-sampling Technique (SMOTE) methodology, coupled to the Cost-Sensitive Classification And Regression Trees (Cost-Sensitive CART) algorithm. To estimate the uncertainties of *i)* the two-class classification at each date and *ii)* the change of soil color from "Red" to "Black", a bootstrap procedure was used providing fifty two-class classifications for each Sentinel-2 image. The results showed that 1) the CART method allowed to classify the "Red" and "Black" soil with correct overall accuracy from both Sentinel-2 images, 2) the tank silt application was identified over 202 fields and 3) the soil color changes were not related to a surface soil moisture change between both dates. With the actual availability of the Sentinel-2 and the past availability of the LANDSAT satellite imageries, this study may open a way toward a simple and accurate method for delivering tank silt application mapping and so to study and possibly quantify retroactively this farmer practice.

1. Introduction

The soil has an integral part to play in the global environmental sustainability challenges of food security, water security, climate stability, biodiversity, and ecosystem service delivery (McBratney et al, 2014) and accurate mapping of soil properties is crucial for adequate management both at global and very local levels. For many years, digital soil mapping represents an alternative to conventional soil survey, to produce soil predictions maps and associated uncertainties, exploiting large sets of spatial data (e.g., Digital Elevation Model, optic satellite data) combined to recent or ancillary data (McBratney et al., 2003).

To face an increasing demand of food, water scarcity and soil health degradation, farmers adapt their crop types, crop rotations, water supplies and practices (Hardaker, 2004) and these land use practices linked to soil management may determine frequently changes in soil class (Dazzi and Lo Papa, 2015), as the Solonchaks developed from Cambisols in arid environments because of irrigation with saline water, or Regosols derived from the truncation of Cambisols due to soil erosion.

India is highlighted as one of the most risk-prone countries for water scarcity, declining soil fertility through land degradation and climate change impacts (Roberts, 2001). A traditional "tank system", composed of cascades of reservoirs along valleys, has been used for centuries not only to harvest water for irrigation but also to trap sediments to limit erosion losses at the catchment scale by restoring tank-trapped sediments to agricultural fields (Gunnell and Krishnamurthy, 2003). While this latter practice used to be mostly limited to fields in the vicinity of tanks, the recent development of motorization (excavators and tractors) and of governments-implemented vast programs of tanks desilting (DHAN Foundation) have given this age-old practice a new momentum. However, to our knowledge, no estimate of the temporal and spatial evolutions of this is available.

87   While the primary objective of tank desilting is to increase the water storage capacity of

88   these tanks, several studies have demonstrated the interest of restoring tank silt to agricultural

89   fields in India, as it improves soil fertility (DHAN Foundation; Karanam et al., 2008; Osman et al.,

90   2009; Obi Reddy et al., 2017), specifically increasing soil water holding capacity (Deshmukh et al.,

91   2019), organic carbon and available nutrient status (Patil et al., 2017). Moreover, these benefits of

92   tank sediments for the soil quality has been also demonstrated in others parts of the word such as

93   in Peru (Walter et al., 2012) and Poland (Baran et al., 2019).

94   The potential of this technique is large in India: The number of irrigation tanks is estimated

95   around 0.3 million all over India (Reddy et al., 2018), with 35% located in south India (Tamil Nadu,

96   Karnataka and Andhra Pradesh) (Narayanamoorthy A., 2007). From the 1990s, tank irrigation

97   declined sharply at the expense of groundwater irrigation, which accounted for almost 60% of the

98   irrigated area after only 10 years (Shah et al., 2003), thanks to the development of submersible

99   pump technology. However, tank irrigation is still one of the major strategies for adapting to rainfall

100   variability (CWC, 2010; Reddy et al., 2018), and has a great potential provided sustainable solution

101   are found to resolve the problem of silting. In three of the southern Indian states (Andhra Pradesh,

102   Telangana, Karnataka and Tamil Nadu), about 140 000 tanks are silted up and their rehabilitation

103   could both increase irrigation potential and improve soil health (DHAN Foundation).

104   Over pedological contexts characterized by Vertisols, Ferralsols and Chromic Luvisols like

105   over the Deccan Plateau, tank silt is characterized by a black color and is applied to red-colored

106   soils such as Ferralsols and Chromic Luvisols. Therefore, tank silt applications are easily

107   recognizable over landscapes as they change topsoil color. On the field, soil color is commonly

108   and widely measured using a Munsell soil color chart (Munsell Color Company, 1975) which is a

109   system for categorical qualifications of soil color. This chart was designed to reflect our perception

110   of color and its variations, and is widely used by pedologist as a determinant of soil type. The

111   topsoil color can also be studied by Visible-Near Infrared and Short Wave Infrared (VNIR-SWIR,

112   400 to 2500 nm) remote sensing as various soil components exhibit spectral response in the visible

113   range of the electromagnetic spectrum, between wavelengths 400 and 700 nm. The topsoil color

114   study by VNIR-SWIR remote sensing may allow to discriminate eroded and non-eroded soils (e.g.,

Pickup and Nelson, 1984), identify surface efflorescence and salt crust (e.g., De Jong, 1992; Mougenot et al., 1993) and estimate soil organic carbon (e.g., Viscarra Rossel et al., 2006).

With the successful launch of the Sentinel-2 satellites, the Copernicus program has provided global coverage of terrestrial surfaces with multispectral images, with a revisit time of ten days from 2015 to 2017 and five days since 2017 (European Space Agency, 2015; https://sentinel.esa.int/web/sentinel/missions/sentinel-2). Sentinel-2 images are acquired with a spatial resolution of 10 m to 60 m on 13 spectral bands in the VNIR-SWIR spectral domain. Several studies have proven the relevance of individual Sentinel-2 images for soil studies, including primary soil properties mapping such as soil organic mapping (e.g., Gholizadeh et al., 2018; Vaudour et al., 2019) and soil texture (e.g., Gomez et al., 2019), and soil salinity retrieval based on an Electrical Conductivity mapping (e.g., Taghadosi et al., 2019; Wang et al., 2019). Some studies have studied the multitemporal dimension of Sentinel-2 images for soil studies, and showed that it may allow to i) increase the probability of image acquisition in clear sky conditions during periods with consistent bare soil coverage over cultivated areas (e.g., Vaudour et al., 2019), ii) elaborate mosaic images of bare soil area (e.g., Loiseau et al., 2019) and iii) estimate uncertainties of permanent soil properties predictions (Gomez et al., 2019).

The objective of this work is to evaluate the utility of Sentinel-2 images for mapping tank silt application over red soils. This work is based on a changes analysis of soil color from a Sentinel-2 image to another one and was carried out in an Indian cultivated region (Berambadi catchment, Karnataka state). It used two Sentinel-2 images acquired on February and April 2017 and 217 soil surface samples, collected over the study area and characterized in terms of Munsell color.

2. Materials

2.1 Study area

The Berambadi catchment is a subcatchment of the South Gundal located in the Deccan Plateau of Southern India (Figure 1a) and covers 84 km^2. Our study area is located in the eastern part of the Berambadi catchment, which is covered by crop fields and corresponds to 60 % of the catchment, while the western part is covered by forest (Figure 1). The Berambadi catchment

144 belongs to the Kabini Critical Zone Observatory (AMBHAS, BVET, Sekhar et al., 2016; Tomer et

145 al., 2015), which is part of the OZCAR network (Gaillardet et al., 2018). The climate is tropical

146 subhumid with an average rainfall of 800 mm/year and a PET of 1100 mm (aridity index P/PET of

147 0.7). The monsoon dynamics drive three main seasons: dry season (winter in January and

148 February, summer from March to May), Kharif (southwest monsoon season, from June to

149 September) and Rabi (north-east monsoon season, from October to December). Red soils

150 (Ferralsols and Chromic Luvisols, Figure 2a) cover the uplands and hillslopes, while black soils

151 (Vertisols and Vertic intergrades, Figure 2b) are found mostly in the valley bottoms (Barbiero et al.,

152 2010). Uplands and hillslopes are mainly characterized by coarse soil texture (sandy loam) due to

153 erosion processes, whereas valleys bottoms are mainly characterized by finer soil texture (clay)

154 due to deposition processes (Gomez et al., 2019). Finally, every year some farmers apply tank silt

155 over the Berambadi subcatchment during the summer season (Figure 2c).
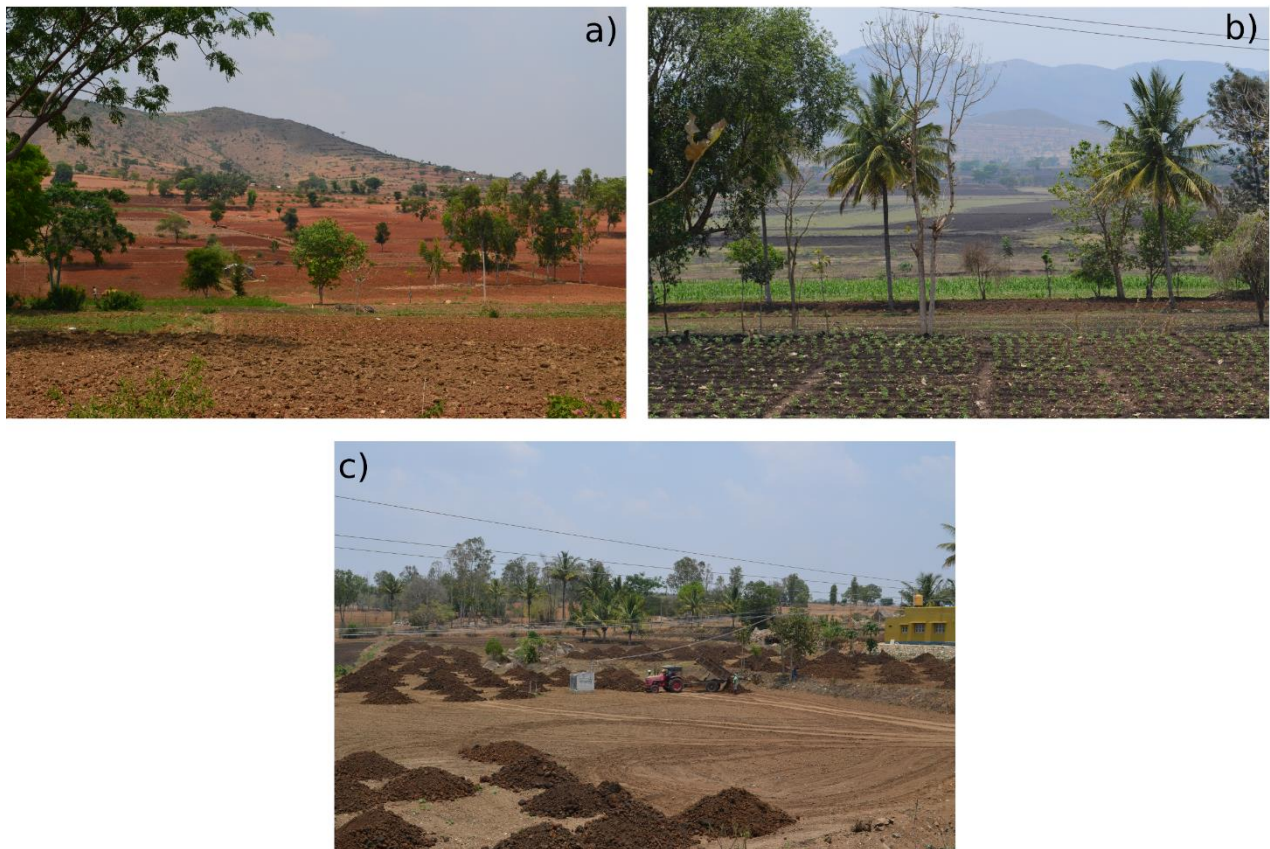
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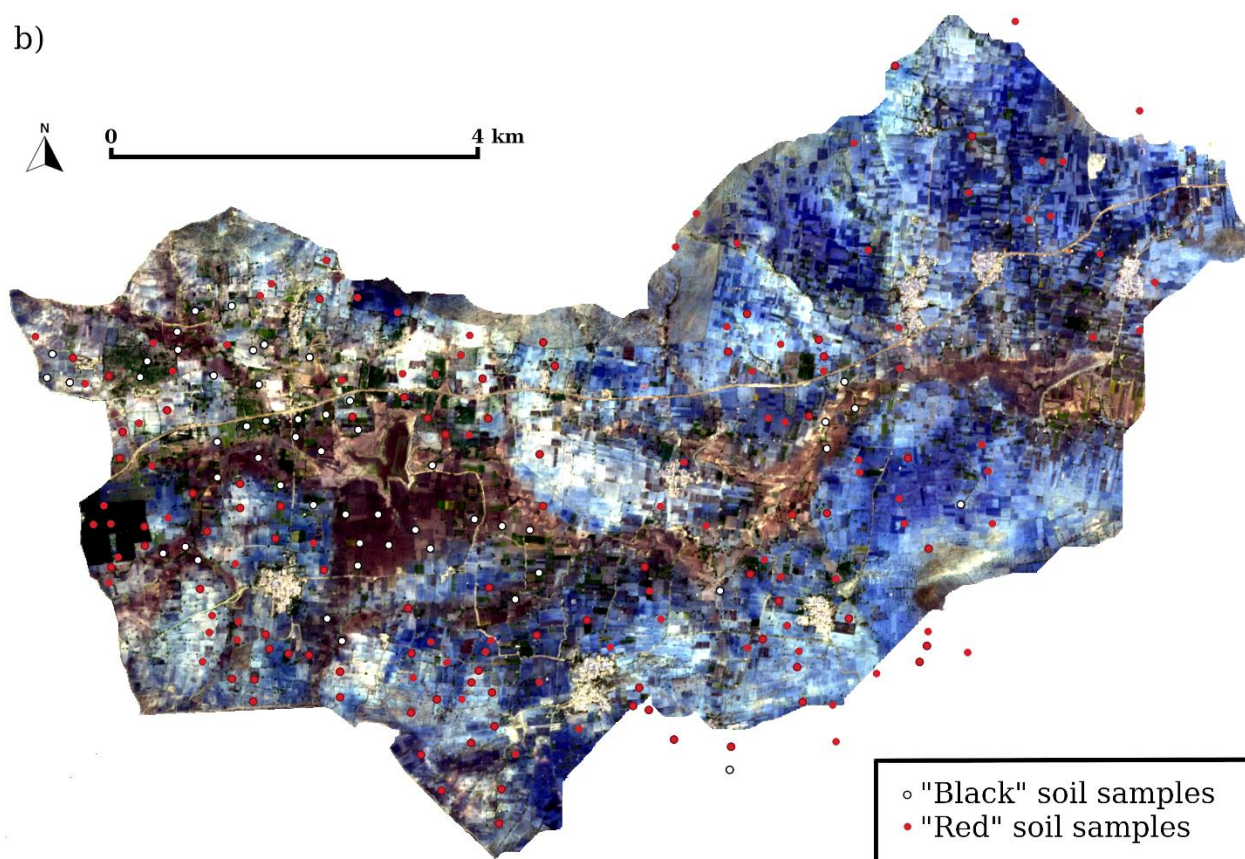
Figure 1: a) Location of the Berambadi catchment in India (Karnataka State) and b) 217 soil surface samples collected on the field and plotted on the Sentinel 2 image (in false color) acquired on 24th of April 2017.

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Figure 2: Example a) "Red" soils, b) "Black" soils and c) Tank silt application over "Red" soils**.**

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167   **2.2 Sentinel-2 images**

168   Sentinel-2A was launched in 2015, followed by the Sentinel-2B launch in 2017. The combination

169   of both satellites delivers a revisit period of up to five days under cloud-free conditions. The images

170   include thirteen spectral bands in the VNIR-SWIR spectral domain, from 10 to 60 m of spatial

171   resolution   (Table   1)   (European   Space   Agency,   2015;

172   https://sentinel.esa.int/web/sentinel/missions/sentinel-2). Only ten bands remain after atmospheric

173   correction, as the three bands acquired at 60 m spatial resolution (coastal at 443 nm, water vapor

174   at 1375 nm and cirrus at 1376 nm) are directly used to perform atmospheric corrections and cloud

175   detection (Table 1). Here, atmospheric and topographic corrections were performed with Sen2Cor

176   software (Louis et al., 2016), and the level-2A images (bottom of atmosphere terrain corrected

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reflectance) were used to perform soil color classification and new anthroposol identification. The six spectral bands initially acquired with 20 m spatial resolution were resampled to 10 m.

Table 1: Specifications of the Sentinel-2 images. In italic characters are highlighted the spectral bands used in this work.

| Spectral band	Central wavelength (nm)	Band width (nm)	Original spatial resolution (m)
B1	443	20	60
B2	*490*	*65*	*10*
B3	*560*	*35*	*10*
B4	*665*	*30*	*10*
B5	*705*	*15*	*20*
B6	*740*	*15*	*20*
B7	*783*	*20*	*20*
B8	*842*	*115*	*10*
B8A	*865*	*20*	*20*
B9	945	20	60
B10	1380	30	60
B11	*1610*	*90*	*20*
B12	*2190*	*180*	*20*

Two Sentinel-2 images covering the Berambadi catchment during the dry season of 2017 were selected. The study year, 2017, was selected because the tanks were dry over the study area during the dry season, so the period was suitable for tank silt applications. Both Sentinel-2 data were acquired under clear sky conditions. A first image was acquired on the 3rd of February 2017 after 6 days without any rainfall (purple vertical line, Figure 3) and a second image on the 24th of April 2017 after 3 days without any rainfall (red vertical line, Figure 3). Both images were previously described and used in Gomez et al. (2019).

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191　　　　　Once atmospherically and topographically corrected, the images were filtered to select only

192　　　pixels corresponding to bare soil and to mask pixels corresponding to urban areas, bodies of water,

193　　　crops and natural vegetation. Crops and natural vegetation were masked using the normalized

194　　　difference vegetation index (NDVI) calculated using spectral bands at 865 nm and 665 nm (Rouse

195　　　et al. 1973; Frampton et al., 2013). In April 2017, a field campaign was conducted over the

196　　　Berambadi catchment, allowing to localize some cultivated fields (covered by green vegetation)

197　　　and ploughed fields (covered by bare soil). Based on these observations and linked to the NDVI

198　　　calculated over the S2 image acquired on 24th of April 2017, a threshold of NDVI has been

199　　　determined to separate the bare soil pixels to the vegetated pixels. This threshold of NDVI was

200　　　fixed at 0.3 and used for both images. Urban areas and lakes were also masked using a land use

201　　　map available for the study area (e.g., AMBHAS Team, 2015). We selected the pixels which were

202　　　both common to the two images and in bare soil condition (65 % of the total) to analyze the changes

203　　　of soil color from a date to another one.

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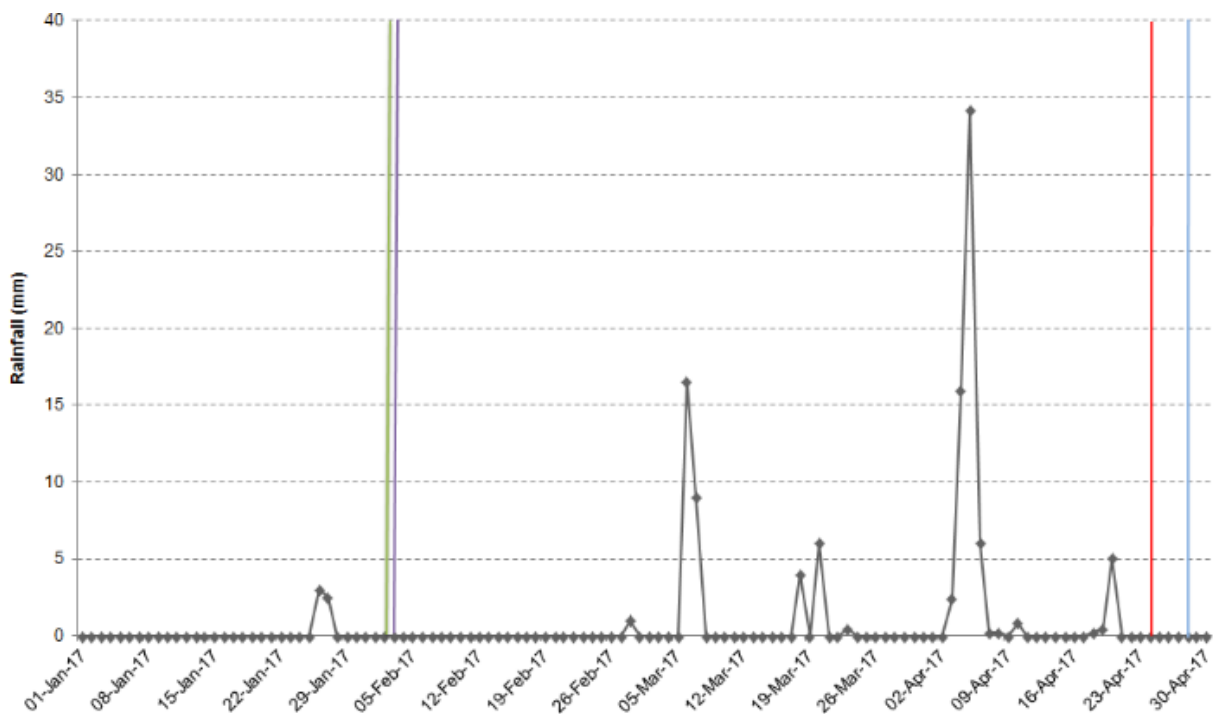
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206　　**Figure 3:** Rainfall (in mm) measured every day at 6 am, over Maddur village (Berambadi). The

207　　green, purple, red and blue vertical lines localize in time the acquisition date of the first SMAP

208　　image (2nd of February 2017), both first Sentinel-2 and Sentinel-1 images (3rd of February 2017),

209   the second Sentinel-2 (24th of April 2017) and the second Sentinel-1 image (28th of April 2017),

210   respectively.

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213   **2.3 Soil data**

214   217 soil profiles were studied over the Berambadi catchment (Figure 1b), comprising 177 soil

215   profiles studied from March to July 2015, and 40 soil profiles studied from the 25th March to the 7th

216   April 2017. The profiles sampling was based on the soil physiographic relationship (relationship

217   between soil and landform) over the study area. First, several transects from ridge to valley were

218   selected over the Berambadi catchment. Secondly, the soil profiles locations were selected along

219   each transect, taking into account that these soil profiles are located at closely spaced intervals

220   and represent the changes in land use, slope, erosion features, stones and gravels along the

221   transect.

222   This study was based on 217 soil surface samples where each soil surface sample

223   corresponds to the surface layer of a soil profile. As the surface layers had a depth from 10-30 cm

224   (plough layer or top horizon), our soil surface samples had a depth from 10-30 cm. Each soil profile

225   was located with a GPS and the soil surface sample was associated to a Munsell soil color,

226   following the Munsell Chart. From the Munsell soil colors determined on the field, the 217 soil

227   samples were firstly post-classified in four soil color classes (Table 2): Yellow, Brown, Red and

228   Black soils. As Yellow and Brown are shades of Red color developed from granitic parent material,

229   these three classes were then grouped as "Red" soil in this paper, and the following work was

230   based only on two soil types: "Red" and "Black" soil (Table 2, Figures 2a and b).

231   Among the 217 soil surface samples associated with Munsell soil color, 130 were located

232   over the common bare soil pixels between both Sentinel-2 images. Among these 130 soil surface

233   samples, 25 correspond to "Black" soils and 105 correspond to "Red" soils, and so were used in

234   this work to analyze the changes of soil color from a date to another one. As the number of "Black"

235   soil samples is much less important than the number of "Red" soil samples, the dataset is

236   imbalanced, which reflects the imbalanced repartition of soils types over the study area, as Black

237   soils cover a minority of the area (mostly in the valley bottoms) (Barbiero et al., 2010).

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Table 2: Correspondence between the observed Munsell soil color, the soil color classes and the

soil type.

Munsell soil color	Soil Color Class	Soil type
10YR4/3, 10YR4/4, 10YR4/6, 10YR4/1, 10YR4/2, 10YR5/3, 10YR5/4, 10YR6/4	**Yellow soil**	**"Red" soil**
2.5YR3/2, 2.5YR3/3, 2.5YR3/4, 2.5YR3/6, 2.5YR4/4, 2.5YR4/6, 2.5YR5/4, 5YR3/2, 5YR3/3,5YR3/4, 5YR4/3, 5YR4/4, 5YR4/6, 5YR5/4, 5YR5/6	**Red soil**	
all the 7.5YR	**Brown soil**	
10YR3/1, 10YR3/2, 10YR3/4, 10YR4/1, 10YR4/2	**Black soil**	**"Black" soil**

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2.4 Agricultural Parcel boundaries

A parcel delineation map was created by Sharma et al. (2018) based on the following methodology. First, individual parcels have been identified using a 2 m spatial resolution google earth image acquired in 2012. Secondly, all individual parcels were re-examined using successively three LISS IV satellite images acquired in 2013, 2014 and 2015 with 5 m of spatial resolution and one SPOT-6 satellite image acquired in 2016 with 1.5 m of spatial resolution. This parcel delineation work allowed identifying a total of 18178 polygons over the Berambadi catchment, with an average size of fields of 0.27 ha (Sharma et al., 2018).

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2.5 Surface soil moisture map

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253 Two soil moisture maps were created following the procedure presented in Tomer et al. (2016)

254 based on Sentinel-1 and Soil Moisture Active Passive (SMAP) data, with a 20 m spatial resolution.

255 This process used the closest Sentinel-1 and SMAP data from Sentinel-2 data to estimate surface

256 soil moisture. A first surface soil moisture map was created based on a Sentinel-1 data acquired

257 on 3rd of February, so simultaneously with our first Sentinel-2 data and after 6 days without any

258 rainfall (red vertical line, Figure 3), and a SMAP data acquired on 2nd of February, so one day

259 before our first Sentinel-2 data (green vertical line, Figure 3). A second surface soil moisture map

260 was created based a Sentinel-1 data and a SMAP data both acquired on 28th of April, so four days

261 after our second Sentinel-2 data and after 7 days without any rainfall (blue vertical line, Figure 3).

262 As no rainfall have been recorded during 6 and 7 days before the Sentinel-1 data acquired on 3rd

263 of February and 28th of April, respectively, variations in surface soil moisture can be supposed to

264 be due only to irrigation. The estimated soil moisture content varies from 0 to 1, where a value of

265 0 correspond to the lowest soil moisture content and a value of 1 corresponds to the highest soil

266 moisture content.

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3. Methods

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270 To map the tank silt application from February to April 2017, the proposed approach followed 3

271 main steps. In a first step, N Calibration and Validation databases were built with a bootstrap

272 approach from both Sentinel-2 image and the corresponding observed Munsell soil colors (Figure

273 4b). A classification model was built from each of the N Calibrations dataset and then validated

274 from the associated Validation dataset (Figure 4b). So N maps of "Black" soils and "Red" soils were

275 provided (Figure 4a) from both selected Sentinel-2 image. The classification of "Black" and "Red"

276 soils using the S2 image acquired on the 3rd of February 2017 and the nth Calibration and Validation

277 database, was called *Map_1_n*. The classification of '"Black" soils and "Red" soils using the

278 Sentinel-2 image acquired on the 24th of April 2017 and the nth Calibration and Validation database,

279 was called *Map_2_n*. In a second step, N maps of changes between beginning (3rd of February

280   2017) and end (24th of April 2017) of the period were provided based on differences between

281   *Map_1_n* and *Map_2_n* (Figure 4c). In a third and last step, a map of the frequency of changes

282   was provided (Figure 4d), based on the *N* maps of changes (Figure 4c).
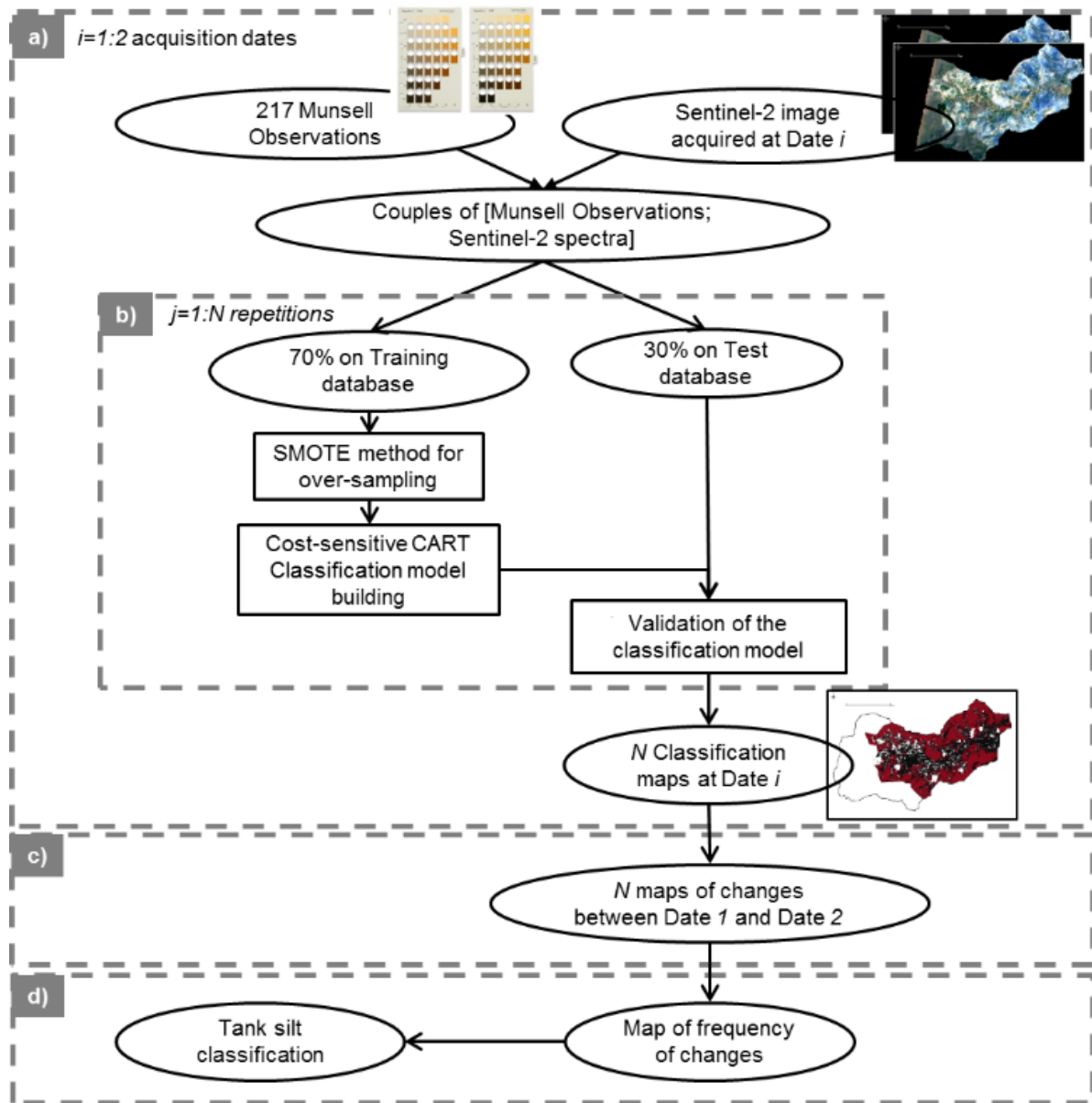
284   **Figure 4:** Workflow of the tank silt application mapping.

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287   ### 3.1. Classification Models

288   A standard normal variate (SNV) was applied to the sentinel-2 spectra consisting of substracting

289   the mean of this spectrum and dividing the standard deviation of this spectrum to every spectral

290 value along the spectrum. The SNV is an effective pretreatment method for baseline correction of

291 diffuse reflection Vis-NIR spectra (Barnes et al.,1989).

292   Class-imbalanced datasets occur in many real-world applications. With imbalanced data

293 sets, data mining learning algorithms produce degenerated models that do not take into account

294 the minority class as most data mining algorithms assume balanced data set (e.g., Sun et al., 2009;

295 Ali et al., 2015, Taghizadeh-Mehrjar et al., 2019). To deal with the class-imbalance problem, some

296 solutions were proposed at the algorithmic level (Chawla et al. 2004) which include adjusting the

297 costs of the various classes so as to counter the class imbalance, adjusting the probabilistic

298 estimate at the tree leaf (when working with decision trees) or adjusting the decision threshold.

299 Cost-sensitive learning, which takes the misclassification costs (and possibly other types of cost)

300 into consideration, is often used to deal with datasets with very imbalanced class distribution

301 (Japkowicz and Stephen, 2002).

302   Here, we used the Cost-Sensitive Classification And Regression Trees (CART) algorithm,

303 initially proposed by Breiman et al. (1984), a nonparametric prediction method based on a binary

304 decision tree algorithm dealing with imbalanced Calibration data. It processes continuous and

305 categorical attributes and target, using the Gini splitting rule to search the best possible variable to

306 split the node into two child nodes and grow the trees to their maximum size until no splits are

307 possible. The Cost-Sensitive CART algorithm is the adaptation of the CART algorithm where the

308 misclassification cost plays an important role in the learning process. The algorithm targets the

309 cases where the cost of incorrectly classifying a minority (positive) class will have a higher cost

310 than the cost of incorrectly classifying a majority (negative) class (Breiman et al., 1984). Details

311 about the cost-sensitive CART algorithm can be found in Steinberg B. (2009). In our classification,

312 the validation accuracy was performed using 10-fold cross-validation, selecting the model with the

313 lowest cost-complexity metric. A value of 1 was affected to pixels classified as "Black" soil (so

314 considered as the positive class) and a value of -1 was affected to pixels classified as "Red" soil

315 (so considered as the negative class). The classification models were built using the *train* function

316 provided in caret package (Kuhn et al., 2016).

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3.2. Calibration and Validation Database preparation

The spectral information from the 130 pixels for which soil color observations are available was extracted for each Sentinel-2 image (Figure 4a). For each classification, these couples of spectral information and corresponding soil color were split into Calibration (70%) and Validation (30%) datasets using a stratified random sampling for Calibration and Validation data to follow a similar distribution of soil color classes (Figure 4b).

To deal with the class-imbalance problem, some solutions were previously proposed at the data level in addition to the ones proposed at the algorithmic level (Chawla et al. 2002). At the data level, these solutions include many different forms of re-sampling such as random oversampling with replacement, random undersampling, directed oversampling or creation of synthetic data. The simplest method to increase the size of the minority class corresponds to random over-sampling, that is, a non-heuristic method that balances the class distribution through the random replication of positive examples. Nevertheless, since this method replicates existing examples in the minority class, overfitting is more likely to occur. In this work, we used the Synthetic Minority Over-sampling Technique (SMOTE), proposed by Chawla et al. (2002) to create balanced Calibration data from the initial Imbalanced Calibration dataset build by splitting the 130 couples of spectral information and corresponding soil color (Figure 4b). This SMOTE preprocessing algorithm was used as an over-sampling approach in which the minority class is over-sampled by creating synthetic data rather than by over-sampling with replacement and is considered as standard in the framework of learning from imbalanced data (Douzas et al., 2019b). The perc.over value was selected at 100, to guarantee that, after applying SMOTE, the minority class would have the exact same number of training samples as the majority class (50% of samples associated to "Black" color and 50% of samples associated to "Red" color). The k value was set to 5 as the number of minority class samples was larger than 5. The balanced-datasets were built using the *smote* function provided in caret package (Kuhn et al., 2016).

3.3. Classification performance measures

347 The overall accuracy was calculated for each classification model and from each Validation dataset

348 to measure the performance of the classifications (Cohen et al., 1960) (Figure 4b). The overall

349 accuracy is commonly measured as the percentage of pixels correctly classified in the Validation

350 dataset. The kappa coefficient was calculated on observed dataset to compare the observed

351 accuracy with the expected accuracy resulting from randomness. According to Landis and Koch

352 (1977), a value < 0 is indicating no agreement: 0–0.20 as slight, 0.21–0.40 as fair, 0.41–0.60 as

353 moderate, 0.61–0.80 as substantial, and 0.81–1 as almost perfect agreement. The Sensitivity and

354 Specificity were calculated for each classification model and from each Validation dataset.

355 Sensitivity is the metric that evaluates the model's ability to predict true positives, which is the class

356 of "Black" soil in our case, and is calculated as:

357   *Sensitivity = True Positives / (True Positives + False Negatives)*   [1]

358 Where the *True Positives* corresponds to the number of pixels observed as "Black" soil and

359 correctly classified in the "Black" soil class and *False Negatives* corresponds to the number of

360 pixels observed as "Black" soil but misclassified in the "Red" soil class.

361   The Specificity, also called the true negative rate, which is the rate of "Red" soil correctly

362 classified in our case, was calculated as following:

363   Specificity = True Negatives / (True Negatives + False Positives)   [2]

364 Where the *True Negatives* corresponds to the number of pixels observed as "Red" soil and correctly

365 classified in the "Red" soil class and *False Positives* corresponds to the number of pixels observed

366 as "Red" soil but misclassified in the "Black" soil class. These performance measures were

367 calculated using the *confusionMatrix* function provided in caret package (Kuhn et al., 2016).

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370   **3.4.   Bootstrap**

371 A bootstrap procedure was applied to the original dataset to define *N* sets of Calibration and

372 Validation subsets for each Sentinel-2 image, where *N* is equal to 50 (Figure 4b) (Efron et al.,

373 1993). The bootstrapping involved repeated stratified random sampling for Calibration and

374 Validation data to follow a similar distribution of both classes, with replacement of the available

375 data and the SMOTE over-sampling approach. For each bootstrap iteration, a classification model

376 was fitted and applied to generate a soil classification (Figure 4b). So 50 maps of "Black" soils and

377 "Red" soils were provided (Figure 4a) from each selected Sentinel-2 image. This bootstrap

378 procedure follows the common way in soil properties mapping initiated by Brodsky et al. (2013)

379 and pursued by Gomez et al. (2015), Viscarra Rossel and Hicks (2015) and Gomez et al. (2019).

380   The classification performance measures were calculated for the 50 tests. The mean and

381 standard deviation of the classification performance measures were analyzed to evaluate,

382 respectively the models performances and the variabilities from each S2 image.

383   After the bootstrap procedure, a single-date map of the most frequent class obtained for each

384 pixel of each Sentinel-2 image was produced.

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387   **3.5.   Temporal color changes mapping method**

388 The N classifications based on the Sentinel-2 image acquired on the 3rd of February 2017

389 (*Map_1_n*) may reflect the initial mapping of the "Black" and "Red" soils before tank silt applications.

390 The N classifications based on the Sentinel-2 image acquired on the 24th of April 2017 (*Map_2_n*)

391 may reflect the mapping of both "Black", "Red" soils and tank silt applications.

392   To highlight the tank silt application over the study area, N maps of soil color changes

393 between the 3rd of February 2017 and the 24th of April 2017 were provided based on differences

394 between *Map_1_n* and *Map_2_n* (Figure 4c). A value of 0 was affected to pixels where no change

395 of soil color is identified between the *Map_1_n* and the *Map_2_n*. A value of 1 was affected to

396 pixels classified as "Red" soils on *Map_1_n* and then classified as "Black" soils on *Map_2_n*. A

397 value of -1 was affected to pixels classified as "Black" soils on *Map_1_n* and then classified as

398 "Red" soils on *Map_2_n*.

399   Then the mean of frequency of changes over the 50 iterations was calculated at the field

400 scale (Figure 4d) using the agricultural field boundaries (section 2.4), based on the N maps of soil

401 color changes (Figure 4c). Only fields covered by more than 30 % of bare soil pixels were analyzed.

402 Changes over fields covered by less than 30 % of bare soil pixels were not studied and mapped.

403 High and positive values (from 40 to 50) correspond to frequent changes of soil color from "Red"

404 to "Black", which may be considered as tank silt application. Null values correspond to none change

of soil color between both dates along the bootstrap. Low and negative values (from -40 to -50) correspond to frequent changes of soil color from "Black" to "Red".

3.6. Analysis of color changes regarding to surface soil moisture changes

The mean of relative surface soil moisture difference $Diff_{moisture}$ between the 3rd of February and the 28th of April was calculated, for each field *f* using the agricultural field boundaries (section 2.4), following:

$$Diff_{moisture_f} = \frac{1}{p}\sum_{i=1}^{p}(MoistureT1_i - MoistureT2_i) \quad [3]$$

Where $MoistureT1_i$ and $MoistureT2_i$ are the relative surface soil moistures estimated on the 3rd of February and on the 28th of April, respectively, both on pixel *i* over the field *f*. As for creating the map of mean of frequency of changes over the 50 iterations (section 3.5), only fields covered by more than 30 % of bare soil pixels were analyzed. Changes over fields covered by less than 30 % of bare soil pixels were not studied and mapped. When the surface soil moisture contents are higher on the 3rd of February 2017 ($MoistureT1$) than on the 24th of April 2017 ($MoistureT2$), the values of $Diff_{moistude}$ are positive. Inversely, when the surface soil moisture contents are lower on the 3rd of February 2017 ($MoistureT1$) than on the 24th of April 2017 ($MoistureT2$), the values of $Diff_{moistude}$ are negative.

4. Results

4.1 Classifications performances

50 classification models were built from the Sentinel-2 image acquired on the 3rd of February 2017 and using balanced data obtained by the SMOTE method and the cost-sensitive CART classification method. These 50 models provided 50 classifications of "Black" and "Red" soils with accurate overall accuracies (mean overall accuracy = 0.81) and moderate agreement (mean kappa = 0.51) (Figure 5). The standard deviations of overall accuracies and kappa over the 50 models derived from the Sentinel-2 image acquired on the 3rd of February 2017 were low, with values of

433 0.05 and 0.12, respectively. The averaged sensitivity and specificity of these classification models

434 were around 0.75 and 0.83 respectively.

435   50 classification models were built from the Sentinel-2 image acquired on the 24th of April

436 2017 and using balanced data obtained by the SMOTE method and the cost-sensitive CART

437 classification method. These 50 classification models provided 50 classifications of "Black" and

438 "Red" soils with also accurate overall accuracy (mean overall accuracy = 0.76) and moderate

439 agreement (mean kappa = 0.40) (Figure 5). The standard deviations of overall accuracies and

440 kappa over the 50 models derived from the Sentinel-2 image acquired on the 24th of April 2017

441 were low, with values of 0.12 and 0.18, respectively. The averaged sensitivity and specificity of

442 these classification models were around 0.66 and 0.79 respectively.

443   Whatever the Sentinel-2 image, the sensitivity is lower than the specificity (Figure 5). So

444 the proportion of actual positives that are correctly identified as such is lower than the proportion

445 of actual negatives that are correctly identified as such. It means that the proportion of "Black" soils

446 that are correctly identified as such is lower than the proportion of "Red" soils that are correctly

447 identified as such, in spite of the calibration data balanced thanks to the SMOTE method.

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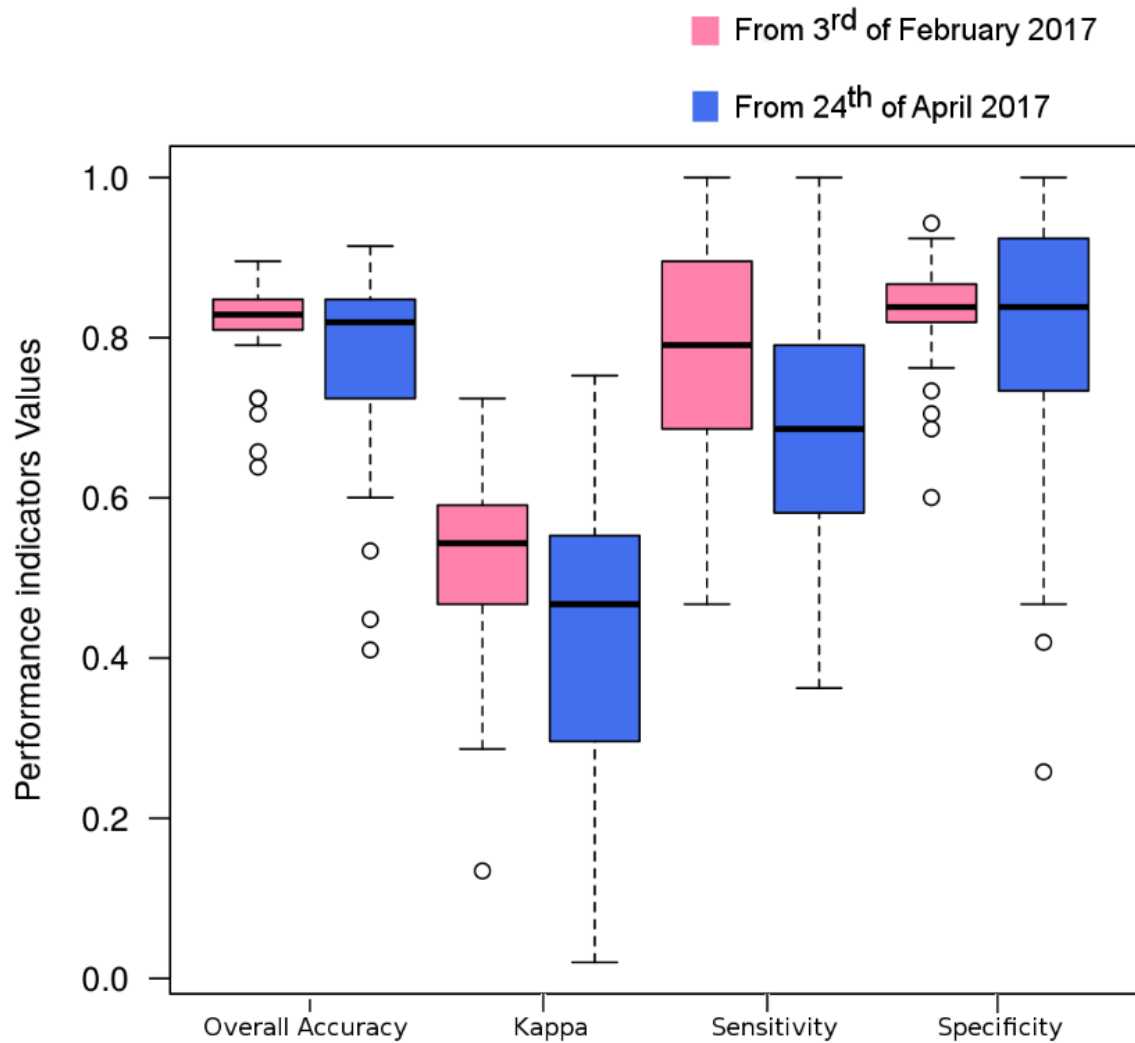
Figure 5. Boxplot of overall accuracy, kappa, sensitivity and specificity calculated from the
Validation datasets and obtained for 50 classification models built using well-balanced data (using
SMOTE method) and the Sentinel-2 image acquired on 3rd of February 2017 (pink) and on the 24th
of April 2017 (blue).

The most frequent soil color classes among the 50 *Map_1_n* after the bootstrap process provided
a classification of soil color for the Sentinel-2 data acquired on 3rd of February 2017 (Figure 6, left).
As well, the most frequent soil color classes among the 50 *Map_2_n* after the bootstrap process
provided a classification of soil color for the Sentinel-2 data acquired on the 24th of April 2017
(Figure 6, right). Whatever the Sentinel-2 data, the soil color over valley bottoms was mainly
classified as "Black", while the soil color over hillslopes was mainly classified as "Red" (Figure 6).

The "Black" soils represent 45.7 % and 44.1 % of the bare soils pixels, from the Sentinel-2 data acquired on 3rd of February 2017 and 24th of April 2017, respectively.
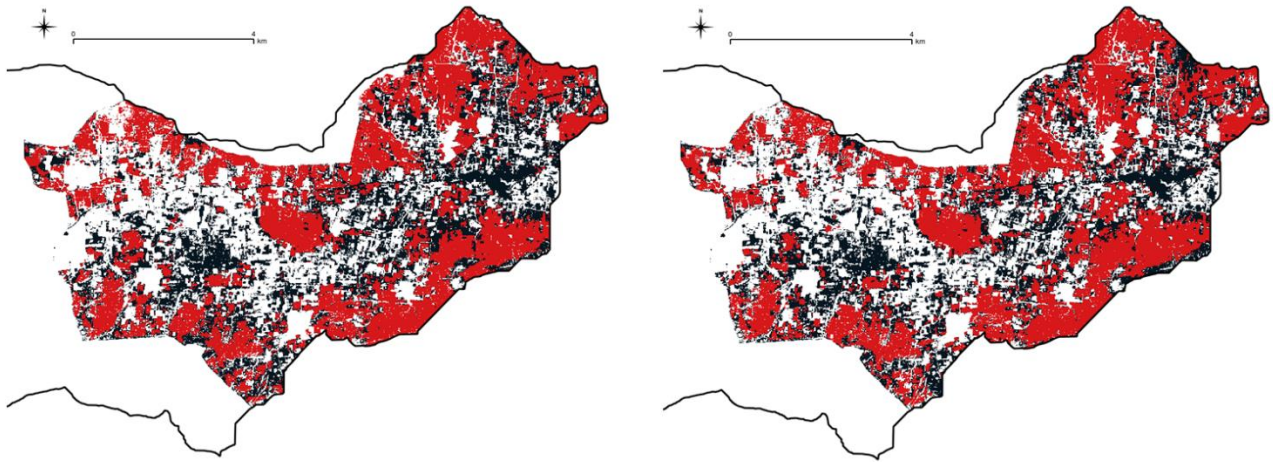
Figure 6. Map of "Black" and "Red" soils obtained from the Sentinel-2 image acquired on 3rd of February 2017 (left) and 24th of April 2017 (right).

### 4.2   Soil color changes analysis

50 maps of changes between the 3rd of February 2017 and the 24th of April 2017 were provided based on differences between the *Map_1_n* and *Map_2_n* (Figure 4c). 79 % of the fields (i.e., 14 474 fields) were covered by more than 30% of bare soil pixels and so were analyzed in term of soil color change. A map of the frequency of changes was provided (Figures 4d and 8) for these 14 474 fields, based on these 50 maps of changes.

Among these 14 474 fields, 100 fields had been classified as "Red" soil on the 3rd of February 2017 and then "Black" soil on the 24th of April 2017, more than 45 times over the 50 iterations (Figures 7 and 8A). So a soil color change from "Red-to-Black" soil between February and April over these 100 fields was detected over more than 90 % of the iterations. So these 100 fields can be considered as affected by tank silt applications (example Figures 8B1, 8B2, 8C1 and 8C2). These 100 fields are characterized by an average size of 0.16 hectares and cover a total of 16.2 hectares. 102 fields had been classified as "Red" soil on the 3rd of February 2017 and then

22

484 "Black" soil on the 24th of April 2017, more than 40 times over the 50 iterations but less than 45

485 times over the 50 iterations (Figures 7 and 8A). So a soil color change from "Red-to-Black" soil

486 between February and April over these 102 fields was detected over more than 80 % of the

487 iterations. These 102 fields are characterized by an average size of 0.25 hectares and cover a total

488 of 25.6 hectares.

489 Among the 14 474 fields, 33 fields had been classified as "Black" soil on the 3rd of February

490 2017 and then "Red" soil on the 24th of April 2017, more than 45 times over the 50 iterations

491 (Figures 7 and 8A). These 33 fields are characterized by an average size of 0.12 hectares and

492 cover a total of 3.99 hectares. 98 fields had been classified as "Black" soil on the 3rd of February

493 2017 and then "Red" soil on the 24th of April 2017, more than 40 times over the 50 iterations but

494 less than 45 times over the 50 iterations (Figures 7 and 8A). These 98 fields are characterized by

495 an average size of 0.17 hectares and cover a total of 17.27 hectares.

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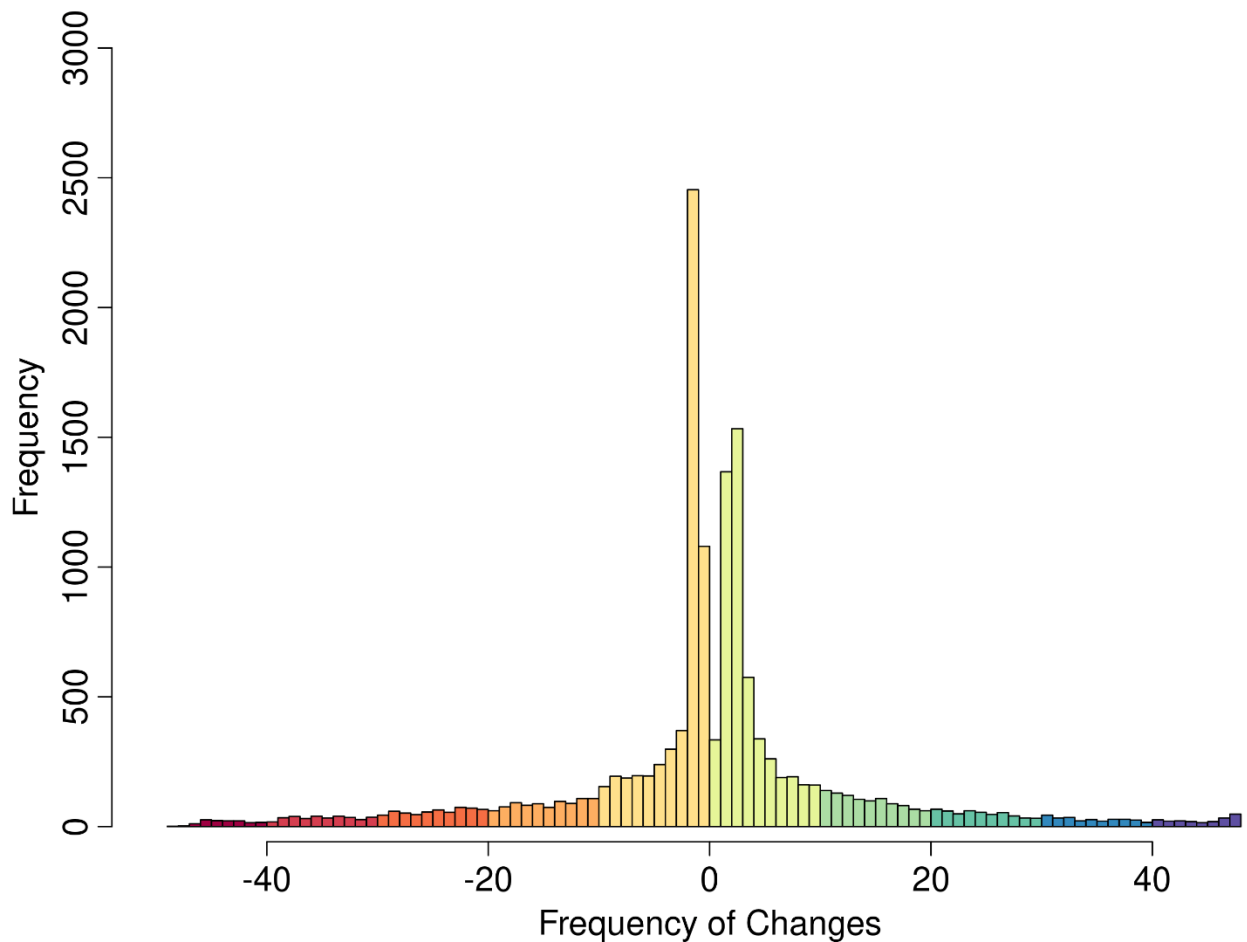
Figure 7. Density of the soil color changes frequency (over the 50 iterations) calculated over fields

499 covered by more than 30 % of bare soil pixels. Positive values correspond to changes from "Red-

500 to-Black" soil. Negative values correspond to changes from "Black-to-Red" soil.

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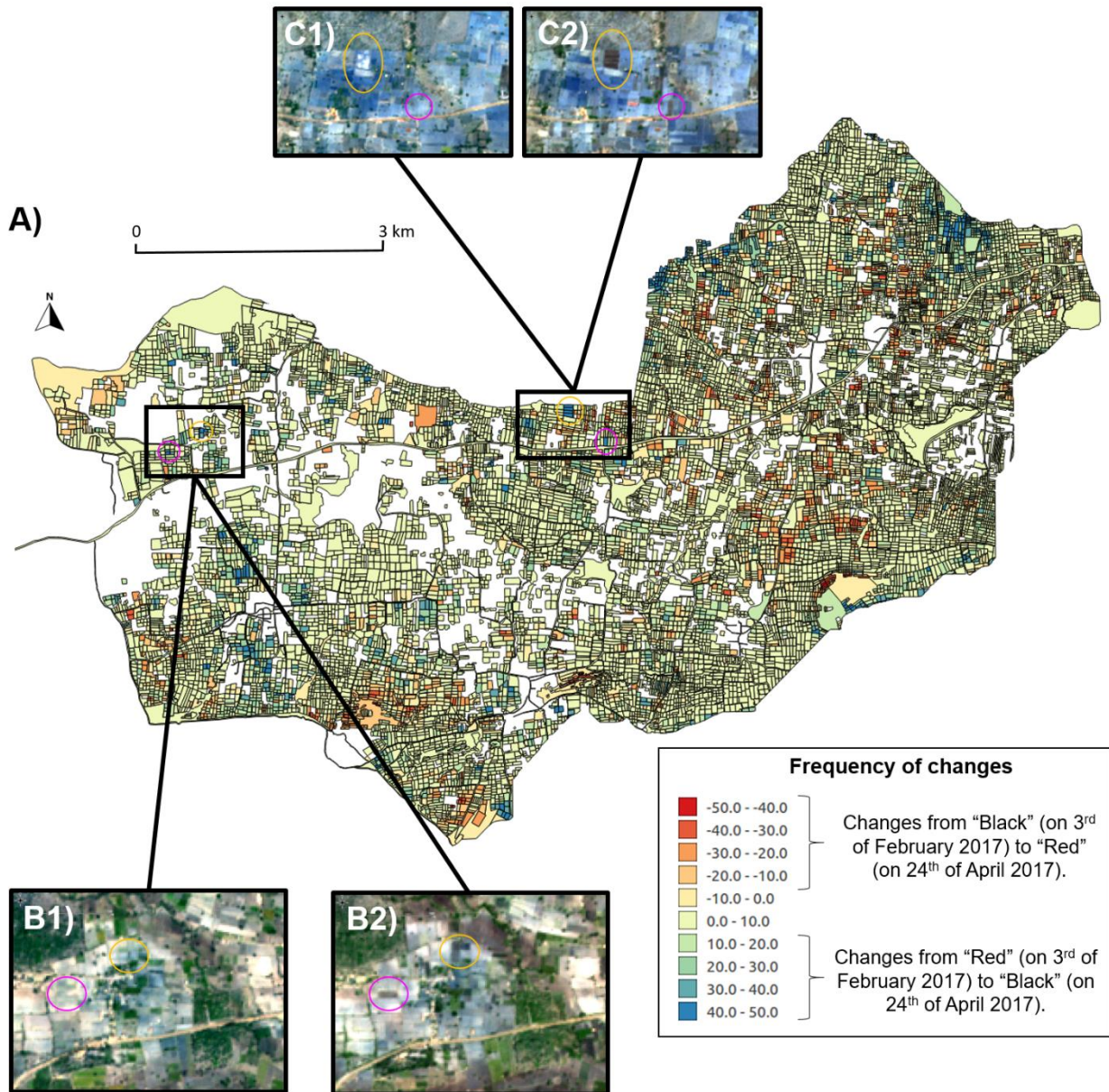
502

503 **Figure 8.** A) Number of changes per parcel from the 3rd of February 2017 to the 24th of April 2017,

504 obtained after 50 classification models built using balanced data obtained by the SMOTE method.

505 B1) and C1) corresponds to zooms on the Sentinel-2 image acquired on 3rd of February 2017. B2)

506 and C2) corresponds to zooms on the Sentinel-2 image acquired on 24th of April 2017.

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509 The surface soil moisture difference between both dates over fields covered by more than 30 % of

510 bare soil pixels, follow a normal distribution centered around -0.5 (Figure 9A). So a majority of fields

511 has a negative moisture difference showing an increase of moisture from the 3rd of February 2017

512 to the 24th of April 2017 (Figure 9A), which can be explained by irrigation after seeding as it is

513 usually time in April.

514   Finally, no relation exists between the soil color changes frequency and the surface soil

515 moisture difference between both dates (Figure 9B). The Pearson correlation coefficient between

516 the changes from "Black-to-Red" soil and the surface soil moisture difference between both dates

517 is around 0.008 with a p-value of 0.9 (Figure 9C). And the Pearson correlation coefficient between

518 the changes from "Red-to-Black" soil and the surface soil moisture difference between both dates

519 is around -0.03 with a p-value of 0.75 (Figure 9D).

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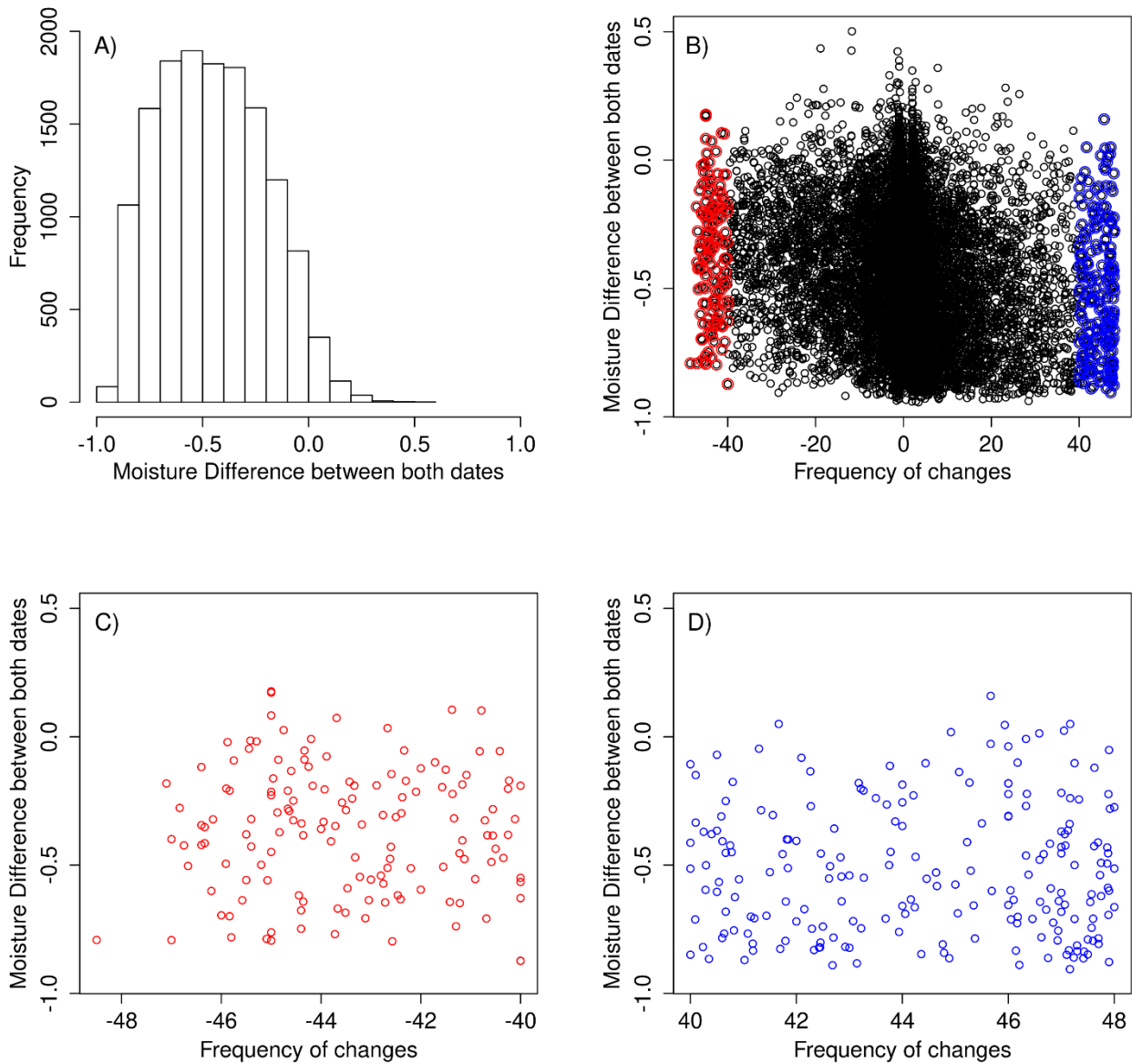
Figure 9. A) Frequency of surface soil moisture difference over the Berambadi catchment. Scatters
plots of soil color changes frequency versus the surface soil moisture difference for B) all fields
covered by more than 30 % of bare soil pixels (red dots correspond to fields identified as changed
from "Black-to-Red" soil; blue dots correspond to fields identified as changed from "Red-to-Black"
soil), C) fields identified as changed from "Black-to-Red" soil with medium to high confident
(between 40 to 50 changes over the 50 iterations), and D) fields identified as changed from "Red-
to-Black" soil with medium to high confident (between 40 to 50 changes over the 50 iterations).

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5. Discussion

Mapping of tank silt applications

Based on the proposed approach, 100 fields corresponding to 16.2 hectares and 102 fields corresponding to 25.6 hectares were associated to a silt tank application with more than 45 changes over 50 iterations and between 40 changes to 45 iterations, respectively. So this approach is able to identify this old-age practice in our context in spite of the small size of fields (0.27 ha in average, Sharma et al., 2018) and allows highlighting that this practice of tank silt application concerns a minority of farmers each year. Moreover this methodology allows highlighting that the fields receiving tank silt are geographically far apart from each other and are distributed throughout the area (Figure 8). So this practice of tank silt application is not restricted to a small part of the catchment.

Mapping of "Red-to-Black" soil

Based on the proposed approach, 33 fields were identified as changed from "Black-to-Red" soil with more than 45 changes over the 50 iterations and 98 fields were identified as changed from "Black-to-Red" soil with between 40 to 45 changes over the 50 iterations. As no relation was highlighted between soil moisture changes and frequencies of color changes between both dates, these changes of "Black-to-Red" soil cannot be attributed to a soil moisture change. Based on our field knowledge, these changes of "Black-to-Red" soil may be attributed to an application of tank silt before the acquisition of our first Sentinel-2 image which may explain the black color identified on our first Sentinel-2 image over these fields and then a ploughing of the tank silt and original red soil between our both Setinel-2 images which may explain the red color identified on our second Sentinel-2 image over these fields. These changes of "Black-to-Red" soil may also be attributed to a bad correspondence between the observed Munsell soil color "5YR5/4" and "10YR3/4" and the soil color class "Red" and "Black", respectively (Table 2). Indeed the observed Munsell soil colors "5YR5/4" and "10YR3/4" correspond both to very dark reddish soils and are associated to different soil color classes (Table 2).

Classifications dealing with imbalanced calibration data

In soil science, Sharififar et al. (2019) highlighted that uncertain maps of soil classes result in imbalanced distribution of class observations, with a loss of minority classes and relatively poor

classification accuracy. As final produced soil classes maps produced using imbalanced classes could be misleading for users or decision makers, a data pre-treatment, with either an over- or under-sampling of the Calibration data, coupled by a decision trees model showed significant improvement in keeping the minority soil classes (Sharififar et al., 2019). Sharififar et al., 2019 also highlighted that, in case of a use of data resampling, decision trees algorithms perform better than random forest and multinomial logistic regression algorithms. Our methodology based on a well-balanced Calibration data created from the initial imbalanced Calibration dataset thanks to the SMOTE methodology, coupled to the CART algorithm, which is a binary decision tree algorithm, follows this line, avoiding uncertain maps, misclassifications, and loss of the minority class (the "black" soil in our case). In a future methodological work dedicated to soil classes mapping, the performance of the SMOTE algorithm could be compared to the Geometric-SMOTE developed by Douzas and Bacao (2019a), as the Geometric-SMOTE algorithm has been recently demonstrated to outperform every other oversampling technique, for land cover classification (Douzas et al., 2019b).

Two-class classifications

Our methodology provided correct accuracies of the two-class classifications with a mean overall accuracy around 0.81 and 0.77 from the Sentinel-2 image acquired on February and April 2017, respectively (Figure 5). These performances are higher than those obtained for a soil texture classification using Landsat-5 TM images (Dematte et al., 2016) and Sentinel-2 images (Gomez et al., 2019), and for soil type discrimination using Landsat-5 TM images (Nanni et al., 2012). Both soil color classification maps showed good discrimination ability for hillslopes and uplands which correspond to red soils and for valleys which correspond to black soils (Figure 6) as previously described over this study area by Barbiero et al. (2010).

Limitation to bare soil pixels

As the number of mapped fields receiving tank silt is low, the success of our proposed approach dealing with two Sentinel-2 images depends on the area covered by bare soil pixels. The larger the bare soil surface area, the more accurate the spatial representation of tank silt will be. An increase in vegetation cover changes completely the shape of soil spectral reflectance (Bartholomeus et al., 2011; Ouerghemmi et al., 2011). So a characterisation of the topsoil color

589 has to be done only over bare soils, which limits the mapped surface. Moreover as the study is

590 based on two images, only the bare soil pixels common to both images can be studied. In our case,

591 after masking the vegetation areas on both images in addition to the urban areas and lakes, only

592 65% of the catchment remained to be map in term of topsoil color.

593 ***Futures studies***

594 As we showed that a couple of Sentinel-2 images encompassing the tank silt applications period

595 allows localizing the tank silt application, an extended study of this farmer practice could be

596 addressed using couples of Sentinel-2 images acquired each year from 2015 (start of the Sentinel-

597 2A satellite) till today. This extended study would provide a multi-year time series of tank silt

598 application maps and so would allow to monitor this practice. Such multi-year time series of tank

599 silt application maps would bring new knowledge about both spatial repartition and frequency of

600 this practice over the Berambadi catchment.

601 These maps of tank silt application might also provide inputs for agronomic modelling as

602 tank silt application brought out an increase in the productivity of different cropping systems

603 (Sharma et al., 2015), and organic carbon and available nutrient status (Patil et al., 2017). It might

604 also provide inputs for hydrological modelling as tank silt application has been demonstrated to

605 increase available water capacity (Deshmukh et al., 2019). Moreover, a field survey could be done

606 to estimate the depth of tank silt applied over fields. This would allow calculating the volume of silt

607 extracted from the tanks each year and so studying the erosion processes on the study area.

608

609

610 **6. Conclusion**

611 The objective of this study was to evaluate the utility of Sentinel-2 images for mapping tank silt

612 application characterized by a black color as they come from Vertisols soils, over red soils using a

613 couple of Sentinel-2 images encompassing the tank silt applications period. In this study a two-

614 class classification at each Sentinel-2 date was produced with correct accuracies and then the

615 changes of soil color from the first image to the second one were produced. This approach took

616 care of having a well-balanced Calibration data to avoid some misclassification of "soil changes

due to over representation of the "Red" soil in the Calibration data. This approach was able to identify this old-age practice in our context in spite of the small size of fields and allows highlighting that i) this practice of tank silt application concerns a minority of farmers each year and ii) the fields receiving tank silt are geographically far apart from each other and are distributed throughout the area. This work was also able to demonstrate the potential of Sentinel-2 images for monitoring farmer practices. Finally, the study of this farmer practice is a large issue that needs to be address and the current multi temporal remote sensing data might help for improving its spatio-temporal characterization.

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