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# Automated high resolution mapping of coffee in Rwanda using an expert Bayesian network



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#### ABSTRACT

African highland agro-ecosystems are dominated by small-scale agricultural fields that often contain a mix of annual and perennial crops. This makes such systems difficult to map by remote sensing. We developed an expert Bayesian network model to extract the small-scale coffee fields of Rwanda from very high resolution data. The model was subsequently applied to aerial orthophotos covering more than 99% of Rwanda and on one QuickBird image for the remaining part. The method consists of a stepwise adjustment of pixel probabilities, which incorporates expert knowledge on size of coffee trees and fields, and on their location. The initial naive Bayesian network, which is a spectral-based classification, yielded a coffee map with an overall accuracy of around 50%. This confirms that standard spectral variables alone cannot accurately identify coffee fields from high resolution images. The combination of spectral and ancillary data (DEM and a forest map) allowed mapping of coffee fields and associated uncertainties with an overall accuracy of 87%. Aggregated to district units, the mapped coffee areas demonstrated a high correlation with the coffee areas reported in the detailed national coffee census of 2009 ( $R^2 = 0.92$ ). Unlike the census data our map provides high spatial resolution of coffee area patterns of Rwanda. The proposed method has potential for mapping other perennial small scale cropping systems in the East African Highlands and elsewhere.

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#### Introduction

Coffee farming delivers strong economic, social and ecological benefits to many tropical countries. Despite the relevance of coffee cultivation, reliable spatially explicit coffee system inventories are lacking. Such data are needed to gain better understanding of the spatial differences in coffee quality and quantity and to allow further monitoring of the long-term coffee sector performance (Loveridge et al., 2003). In most countries, the only spatial information available is collected during national agricultural censuses, and is reported by administrative unit. Systematic attempts to map coffee from remote sensing data are very limited (Cordero-Sancho and Sader, 2007; Ortega-Huerta et al., 2012; Trabaquini

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et al., 2011; Gomez et al., 2010; Moreira et al., 2004, 2010), and to our knowledge non-existing for the African highlands. Existing mapping studies concentrate on large-scale coffee plantations in Latin America (e.g. Cordero-Sancho and Sader, 2007; Ortega-Huerta et al., 2012; Trabaquini et al., 2011; Gomez et al., 2010; Moreira et al., 2004, 2010). Despite their importance for rural livelihoods as well as for the national economy of African highland countries, maps that depict the spatial distribution of coffee are lacking. This is because only high resolution images (0.25 m) can reveal enough detail for identification of individual mature coffee trees. Another complication is that hedgerow and scattered trees are common features in the coffee farming systems of the East African highlands, often impeding direct observation of coffee trees by direct coverage or through the shadows that the larger trees cast on the coffee.

Remotely sensed high-resolution imagery including high quality orthorectified aerial photos (orthophotos) have increasingly become available for Africa. However, automated extraction of small-scale coffee fields from such data is a challenge. In Costa Rica shade-grown coffee was mapped using supervised classification on a single Landsat Enhanced Thematic Mapper (ETM +) image with red, near-infrared, and mid-infrared bands (Cordero-Sancho and Sader, 2007). This study yielded a lower accuracy (56%) as compared to other studies that included more spectral bands and ancillary data (e.g. Langford and Bell, 1997). Better classification results (83%) were obtained for a case study in New Caledonia when high spatial resolution satellite sensors (QuickBird) were used and coffee tree crown sizes were considered in the classification (Gomez et al., 2010). Moreira et al. (2004) demonstrated that coffee fields have a high spectral variability due to differences in age, plant spacing and cultivars. In addition, topographical effects and spectral confusion between coffee and other tree crops may lead to poor classification accuracies (Cordero-Sancho and Sader, 2007; Ortega-Huerta et al., 2012; Gomez et al., 2010). Therefore, two recent attempts for mapping coffee systems rely on visual image interpretation (Trabaquini et al., 2011) or classification improved by visual interpretation (Moreira et al., 2010). However, visual image interpretation requires manpower and is time demanding, especially when dealing with small-scale coffee farming systems in mountainous areas. Hence an automated method is needed.

Object-based classification provides an alternative approach to per-pixel image analysis. It allows developing site-specific models that cater the main (local) features of coffee cultivation, such as field size (Chubey et al., 2006; Johansen et al., 2007). Most object-based classification methods use segmentation to generate meaningful image objects (Doxani et al., 2012; Brandtberg, 2007; Gougeon and Leckie, 2006). Several algorithms, membership functions and thresholds are used for image segmentation (e.g. Brandtberg and Walter, 1998; Pouliot et al., 2002; Wang et al., 2004; Wulder et al., 2000; Gong et al., 2002; Chen et al., 2006; Kim et al., 2010; Johansen et al., 2009). However, all of them reported the problem of overestimation or underestimation of surface areas due to the gap area in between trees. This has an effect on the delineation of field boundaries. A potential solution was suggested by Forster et al. (2009) by the use of "growth factors" such as number of trees per hectare, or distance between trees in order to accurately delineate tree crown areas. Recently, Bayesian networks have been proposed as an alternative to image segmentation. Instead of segmentation, Bayesian network techniques use probability functions to discretize image pixels into image objects (Mello et al., 2010).

This paper presents and implements an expert Bayesian network as a novel object-based classification technique to extract coffee fields from very high resolution (VHR) imagery. The method is developed and tested for ten agricultural zones of Rwanda using aerial orthophotos. By subsequently applying the automated method on 198 orthophotos and one QuickBird image, we produced a high resolution coffee map of Rwanda. We first assessed the spectral separability between coffee and other major land cover classes. Then, the expert Bayesian network model is developed for one site and tested in other nine sites. Finally, the model parameters are implemented to all aerial orthophotos at national level and assessed using field and census validation data sets.

#### Study area

Rwanda is located in the Central and Eastern Albertine Rift of Sub-Saharan Africa  $(1^{\circ}-3^{\circ}S, 29^{\circ}-31^{\circ}E)$  and covers 26,338 km<sup>2</sup>. The country consists of mountains, rounded hills and valleys that have been formed by fault and uplifting of Pre-Cambrian rocks followed by erosion since the Miocene and by volcanic activity that initiated during the Plio–Pleistocene (Huhndorf et al., 2007). The main topographic features (Fig. 1) are a mountain chain from volcanoes in the north (VHP) to mountains in the south west, which makes up the Congo-Nile watershed divide (CND) at the altitude between 2000 and 4500 m a.s.l. Lake Kivu shore (KS), Impala (IMP) in the

south west; central plateaus and ridges (CP, ERP) at altitudes of 1500–2000 m. Mayaga, Bugesera and Umutara lowlands (MBP, EL) in East at altitudes of 1000–1500 m, and Imbo plain (IMB) in the South West at altitude below 1000 m a.s.l. The abbreviations mentioned above refer to the tenagro-ecological zones of Rwanda and are also shown in Fig. 1.

Rwandan agriculture is characterized by small-scale farming consisting of mixed seasonal, annual and perennial crops. The total agricultural land (coffee included) is estimated to 57% of the country area. The rest of the country territory is covered by natural and planted forest (26%), water bodies (5%), wetlands (6%) and urban areas (6%).

Coffea Arabica is the dominant coffee species cultivated in Rwanda, with a share of more than 99% of the national coffee area. Coffea Robusta occupies less than 1% of the total production area. The most cultivated Arabica variety is Bourbon Mayaguez (BM 71, BM 139), followed by Jackson 2/1257, Harrar, and POP 3302/21. Coffee plantations in Rwanda are generally found in hilly terrain and largely consist of small monoculture systems. Very few plantations are shaded with selected leguminous trees, and sometimes in association with other perennial crops like banana. Coffee is grown on a range of different soil types, some more fertile than others. The age of coffee trees ranges from months to more than 30 years. Coffee field sizes depend on the available land of individual households. Loveridge et al. (2003) demonstrated that individual coffee fields in Rwanda are typically small consisting of about 155 to 200 coffee trees. In fact, the recent national coffee census (2009) reported relatively small coffee field sizes consisting of 320 trees in East, 161 trees in West, 150 trees in North, 168 trees in South, and 183 trees in the rural part of Kigali city (Nsengiyumva, 2009). These individual fields are generally located on steep slopes, and near forests and bushes. Farm management practices (mulching, fertiliser application, pruning, etc.) also differ depending on socioeconomic status of coffee farmers. The plant spacing varies from 1.5 to 2.5 m depending on agricultural zones.

#### Data and variables

#### Remote sensing data

We used very high spatial resolution imagery covering the entire extent of Rwanda. Aerial orthophotos covered 99% of the country and a QuickBird image of June 2004 covered the remaining part in the south-west of Rwanda. Orthophotos were obtained from an aerial photography mission over Rwanda during the summer time (July-August) in 2008 and 2009. The images were acquired using a Vexcel Ultra Cam-X aerial digital photography camera at 3000 m altitude above ground level, with a mean ground resolution of 0.22 m (Swedesurvey, 2010). The orthophotos were processed by the image provider to a nominal 0.25 m pixel size and contain three visible bands (blue, green, and red). The QuickBird image has four multispectral bands recording radiation in the visible and near infrared domain that have a 2.44 m spatial resolution and a panchromatic band with a spatial resolution of 0.61 m at nadir. Using the panchromatic band, pan-sharpening was performed on the multispectral QuickBird bands. A total of 198 orthophotos and one QuickBird image were processed to map coffee at the national level.

Two additional spatial data sources were used in our study as an input to the classification. The first is a high-resolution digital terrain model (DTM) that was produced from the aerial photographs using stereoscopy (Swedesurvey, 2010). The second is an existing national forest cover map of 2007 (of over 90% overall accuracy), which was made based on image classification using ASTER, SPOT, and Landsat TM images (Schilling et al., 2007).



Fig. 1. Main topographic features of Rwanda with Agro-Ecological Zones: KS = Kivu lake Shore, IMP = Impala, IMB = Imbo, CND = Congo Nile watershed Divide, MPB = Mayaga plateau & Central Bugesera; CP = Central Plateau, ERP = Eastern Ridge and Plateau, EL = Eastern Lowland, BH = Buberuka Highlands, VHP = Virunga Summit and High plains. The black dashed outline delineates national parks i.e. Birunga (NW), Nyungwe (SW) and Akagera (E). The elevation map is derived from a 10-m resolution digital terrain model.

#### Evidence variables for coffee

We characterized the spatial pattern of coffee across the country based on spectral and spatial variables derived from the orthophotos and QuickBird image? Spectral variables considered in this study are homogeneity and dissimilarity within and between coffee fields. As these are relative spectral variables, further radiometric calibration was not justified as it would have minor effects on these variables. Therefore we derived these variables directly from the digital number (DN) values provided. Homogeneity is measured by the minimum and maximum DN within a window around a pixel, and dissimilarity is assessed from the standard deviation (DN) within that window. Spatial variables used for mapping coffee fields are the average diameter of the tree crown and the minimum size of the field. The diameter of the coffee tree crown is set to 2 m based on our knowledge of the coffee trees and their spacing across Rwanda whereas the size of the field is set to a minimum of 200 coffee trees following Nsengiyumva (2009) giving it the same minimum criterion as used in the national coffee census. Land use and topography variables were also considered to optimize the location of coffee within the landscape. The existing national forest map and DTM-derived flow accumulation data were added in the process to exclude forest and channel/gully locations, therefore reducing possible errors related to location, the shape and the size of coffee fields.

#### Training and validation dataset

Two datasets were used for model development at small test site, and evaluation of the model performance in the rest of the country as follow: (1) 80 GPS sample points were randomly collected in coffee fields to train the model in the 0.4 km<sup>2</sup> test site in

the South plateau (Huye district). (2) 137 GPS points were collected in the test site based on random sampling of which 79 were taken in coffee fields and 58 in no-coffee fields. These points were for validation of the model at the test site. (3) 469 GPS coffee locations were collected following random sampling during our field work to validate the model transferability in the ten agro-ecological zones that exist in Rwanda. (4) 640 GPS locations of coffee plantations where soil samples were taken by the National coffee authority (OCIR-CAFÉ) for lime and fertiliser recommendation (Cordingley, 2009). (5) 253 GPS locations of soil profiles for which only 2 profiles were located in coffee plantations and 251 in no-coffee fields (Verdoodt and Van Ranst, 2006). A total of 1362 sample locations were used for validation. (6) Reported coffee areas by the national coffee census of 2009. The census was conducted in all 30 districts of Rwanda by OCIR-CAFÉ together with Statistics Officers at the district and sector level (Nsengiyumva, 2009).

#### Preliminary spectral analysis

Before setting up our classification model, we first examined to what extent coffee can spectrally be distinguished from other crops on high resolution images. Pixel samples of coffee and no-coffee fields were randomly selected through visual interpretation of the aerial photographs from ten training subsets representing different agro-ecological zones of Rwanda. Transformed Divergence (TD) values were calculated to evaluate the separability between coffee, forest, banana, and mixed seasonal crops. TD values range between 0 and 2000, with higher values ( $\geq$ 1900) indicating good separability of class pairs. TD values below 1700 imply that classes are poorly separable, and therefore spectral classification techniques are not expected to produce accurate classification results (Kumar and Silva, 1974). This initial analysis (Fig. 2) showed that coffee can



Fig. 2. Transformed Divergence (TD) index values (-) show the spectral separability between coffee and other crops of Rwandan agro-ecosystems (mixed seasonal crops, banana and forest). The Agro-Ecological Zones are ordered in west-east direction. KS=Kivu lake Shore, IMP=Impala, IMB=Imbo, CND=Congo Nile watershed Divide, SP=South Plateau, MP=Mayaga plateau; CP=Central Plateau, CB=Central Bugesera, ERP=Eastern Ridge and Plateau, EL=Eastern Lowland.

hardly be separated from banana, mixed crops and forest based on their spectral signatures only. Particularly low TD values were obtained for the plateau area where coffee fields are small and surrounded by mixed crops, banana and forest. This indicates that we cannot obtain a good accuracy if we try to map these coffee fields using merely spectral classification techniques on orthophotos.

#### Coffee classification with a Bayesian network

#### Principles and definitions

A Bayesian network can be considered as a graphical model of interactions among a set of data variables (Gambelli and Bruschi, 2010). It is used for knowledge representation and reasoning about a data domain (Cheng and Wang, 2010; Bressan et al., 2009). Bayesian networks are based on the Bayes theorem on conditional probability between two events *A* and *B*. The probability of *A* given that *B* occurs p(A/B) is given by:

$$p(A/B) = \frac{p(B/A) \times p(A)}{p(B)} \tag{1}$$

A Bayesian network structures a set of data (usually a finite set of random samples containing various variables) and analyses their relationships (Aguilera et al., 2011). Building a Bayesian network model requires two important steps. The first step is the analysis of causal relations between different variables for random samples (Gambelli and Bruschi, 2010) in the form of a network structure known as "Directed Acyclic Graph (DAG)". In a DAG, each variable is represented by a node N, and connected to other nodes by an arc A (Park and Stenstrom, 2006). The arcs represent the relationship between nodes. Once the DAG is formed, the second step consists of quantifying the relations between the connected nodes using conditional probability (Gambelli and Bruschi, 2010). A Bayesian network is consequently a function of *N*, *A*, and  $\theta$ , where the components N and A  $\langle N, A \rangle$  denotes the DAG graph with children nodes  $\{X_i, i=1...n\} \in N$ . N consists of n variables referred as nodes in the DAG, and  $a \in N$  representing probabilistic dependency between nnodes. The component  $\langle \theta \rangle$  represents the conditional probability distribution of the sample value  $x_i$  of homogenous samples  $X_i$  in the attribute table. The conditional probability  $\theta_{X_i}/Pa_{X_i}$  at each pixel is given by  $p(X_i/Pa_{X_i})$  following Eq. (2).

$$p(X_1, X_2, \dots, X_n) \prod_{i=1}^n p(X_i / Pa_{X_i}) = \prod_{i=1}^n (\theta_{X_i} / Pa_{X_i})$$
(2)

where n = |N| parents. Thus a Bayesian network can infer the spatial distribution of the parent *Pa* given *X* representative and

homogenous samples. A Bayesian network can also be used as a classifier because it produces the posterior probability distribution of a class node, given their corresponding values (Cheng and Wang, 2010; Bressan et al., 2009; Aguilera et al., 2010; Qu et al., 2008).

#### Building an expert Bayesian network classifier

When building an expert Bayesian network classifier, a number of information about a target features and their corresponding values are needed to estimate probabilities of membership. Such information is structured in the DAG and learning algorithms are used calculate the conditional probability distribution from data (Bressan et al., 2009) according to predefined rules and thresholds by the subject specialist. Fig. 3 shows the DAG structure that is developed to automate the delineation of coffee fields in orthophotos by the Bayesian network classifier.

#### Step 1. Pixel-based classification: a naive Bayesian classifier

Let  $C_{X_i}$  be a set of coffee field and  $N_{X_j}$  a set of no-coffee field parents i.e. fields in which coffee and no-coffee samples are randomly selected. Pixel candidates for coffee and no-coffee samples are given by  $X_i$  and  $X_j$ .  $x_i$ ,  $x_j$  are the DN values of the pixel candidates of the three bands for coffee and no-coffee pixels. The distribution of coffee field pixels is determined by the distribution of coffee pixels candidates { $\theta_{X_i}/C_{X_i} = p(X_i/C_{X_i})$ }, given the distribution of no-coffee pixels candidates { $\theta_{X_j}/N_{X_j} = p(X_j/N_{X_j})$ } used to train the Bayesian model.  $N_{X_j}$  is also called the background class. This no-coffee class may contain banana, forest, mixed crops, bare soils, or buildings.

The dependence relation between pixel samples values ( $x_i$  and  $x_j$ ) allows the calculation of conditional probability  $\langle \theta \rangle$  distribution. This conditional probability is deduced from the spectral characteristics (i.e. DN variability in the three bands) learned from coffee pixel samples. In this first level classification, a classifier assigns the probability of coffee pixel candidates  $X_i = (X_1, X_2, ..., X_n)$  to belong to coffee class *C* as shown in Eq. (2). Higher probability values are assigned to pixels spectrally similar to coffee pixel samples. Lower probability values are assigned to no-coffee pixels or otherwise significantly different from coffee.

The joint probability distribution is a product of the probability distribution of DN values ( $0 \le x_i \le 255$ ) of the coffee pixel candidates given the probability distribution of DN values of the no-coffee (c = 0 - 255), as given by Eq. (3):

$$p(X_i/c) = p(x_1, x_2, ..., x_n)/c) = \prod_i^n p(x_i/c)$$
 (3)



**Fig. 3.** A Directed Acyclic Graph (DAG) used to train the expert Bayesian network model for coffee mapping. DAG 1 represents the naive Bayesian network classifier that distributes the probability of coffee based on the spectral properties of pixel candidates and the pattern of coffee fields used as training samples. DAG 2 and 3 represents the expert knowledge in the Bayesian network model. DAG 2 introduces tree and field rules whereas DAG 3 introduces flow accumulation and forest data to model the location of the coffee field in the toposequence and land use systems.

where  $x_i$  denotes DN values of the pixel candidates  $X_i$ , c representing DN values of coffee field samples  $C_{X_i}$ . The resulting Bayesian classifier is then:

$$f_{nb}(C) = \frac{p(c_i = C)}{p(c_i = N)} = \prod_{i=1}^{n} \frac{p(x_i/c_i = C)}{p(x_i/c_i = N)} \ge 1, x_i = C, \text{ otherwise, } N \quad (4)$$

where  $f_{nb}(C_i)$  is the naive Bayesian network classifier (n-BN). This classifier is referred throughout in this study as a single Pixel Probability Classifier (PPC). The output of  $f_{nb}(C_i)$  is a pixel probability with values  $\{x_i/c_i = 0 - 1\}$ . The value of  $f_{nb} = 1$  corresponds to the probability threshold above which the spectral dependence supports the classification of coffee.

The second stage of the naive Bayesian classifier consists of Object Probability Classification (OPC). In this stage, we used the probability threshold to convert the probability map to a binary coffee/no-coffee map. In order to classify a pixel as coffee or no-coffee, we assume that its direct neighborhood provides significant additional information. Following Bressan et al. (2009), we applied the four neighbor rule to eliminate single pixels of no-coffee within a cluster of coffee pixels. Single coffee pixels of coffee within a cluster of no-coffee are also eliminated accordingly. The four neighbor operation only retains class if its four neighbors have that class. The resulting image objects remain with pixels with only probability greater than the probability threshold (*P* > 0.49).

#### Step 2. Object-based classification: an expert Bayesian classifier

The second step introduces the spatial characteristics of coffee tree crown and the coffee field in the Bayesian network model as spatial evidence. Knowledge about the Rwandan coffee systems is used to build rules into the network structure. These rules are a set of conditions defined by the subject specialist in the DAG to optimize the conditional likelihood for coffee fields given surrounding no-coffee fields. The local dependence i.e. "direct neighbor" probability is derived from the conditional probability pixel outputs  $\{x_i/c_i\}$  of step 1. Eq. (3) is consequently extended to Eq. (5).

$$p(a_i/X_i) = p(a_1, a_2, \dots, a_n)/c = p(c) \prod_{i=i}^n p(a_i/X_i)/c$$
(5)

where  $a_i$  denotes the derivative probability value from the output image pixels probability of the DN value c, and  $a_i$  represent the spatial nodes predefined by the subject specialist. The joint probability distribution  $\langle \theta_{a_i} \rangle$  is determined by the derivative probability  $dp(x_i/c_i)$  translating the local dependence (i.e. local structure) of coffee  $C_{X_i}$  given the structure of no-coffee  $N_{X_i}$  in the Rwandan agroecosystems.

In the Bayesian network structure,  $a_1$  introduces the Tree Crown rule-set Classifier (TCC). The coffee average crown diameter is used to set a threshold in the Bayesian network model in order to calculate the joint probability distribution  $\theta_{a_1}$  as derivative of probability of OPC output. The average coffee tree crown size used in this study is thus 16 pixels corresponding to the average coffee tree crown diameter (2 m in our case) or in other words, the average of coffee plant spacing (2 m × 2 m). The mean derivative probability for each cluster is calculated using 4 × 4 kernel functions. This procedure will discard young coffee trees and pruned coffee trees with smaller tree crowns from the analysis.

After the tree crown classifier, a node  $a_2$  representing the Field Size rule-set Classifier (FSC) is introduced in the Bayesian network structure. Coffee tree probability output is aggregated into a coffee field probability. We set the threshold to 3200 pixels corresponding to the average minimum field size of 200 trees as reported by Nsengiyumva (2009). The field size rule therefore filters out coffee fields that are below the threshold and recomputed the new probability of coffee field object in the conditional probability attribute table. In some cases, pruned coffee trees may be recuperated by the field size classification as long as they are within and direct neighbor coffee trees with larger crowns. The boundary of the coffee field is delineated at this stage. Only if edge-rows contain pruned trees these will remain excluded. Unlike the rule-set classifiers, the location values  $(a_3, a_4)$  are added in the Bayesian network as data-set classifier. In this way the DAG 2 is extended to DAG 3. We used flow accumulation data from the digital terrain model to remove the classified coffee fields in gullies and flood plains. The national forest map of 2007 (Westinga et al., 2013) was finally used to remove classified coffee fields in known large forest areas to reduce errors due to the poor separability between coffee and forest. These data do not only filter but also the final probability of the coffee polygon is accordingly adjusted to the total number of coffee pixels. The expert-based



**Fig. 4.** Intermediate and final coffee classification results after each step of the expert Bayesian network model. The location of the potential coffee ( $P \ge 0.49$ ), is shown by the probability maps (left) and the number of pixels and their likelihood to coffee (C) or no-coffee (N) is shown by the boxplot (right). Top-down: a. Pixel probability result of spectral analysis; b. Object probability result of four-neighbor classification. c. Coffee objects are clustered by the Tree Crown Classifier. d. The Field size classifier aggregates the tree objects into coffee field objects and adjusts probability of coffee field. e. Final coffee probability map after the forest and flow accumulation data are added in the model to filter out coffee within the forest and in the channels. The size of the test sites used to build the model is about 0.4 km<sup>2</sup> located in Huye. <sup>0</sup>\* represent the number of pixels that are deemed to be outliers.

Bayesian network classifier for coffee becomes, after a series of  $a_i$  nodes and on basis of coffee and no-coffee pixel candidates, as follows:

$$f_{eb}(C) = f_{nb}(C) \prod_{i=1}^{n} \frac{dp(a_i/x_i = C)}{dp(a_i/x_i = N)} \ge 1; \quad DF = \prod_{i=1}^{n} dp(a_i/x_i)$$
(6)

where  $x_i$  represents spectral dependence variables,  $a_i$  represents the spatial dependence variables used to build the Bayesian model.

The dependence factor (DF) is determined by the product of the derivative probability of object nodes  $a_i$  given the spectral nodes  $(x_i)$  used to build the model. The DF also reflects how each of the local dependences (local structure) distributes pixels to coffee class C and how all of them worked together to produce a better classification result for coffee. The dependence factor can be used as a measure of the model sensitivity since it quantifies percentage of the pixels changing probability/uncertainty at each stage of the Bayesian network classifier.

#### Country-wide implementation of the expert Bayesian network

The Bayesian network was applied to 198 orthophotos covering almost 99% of the entire country (26,338 km<sup>2</sup>) and one QuickBird image covering the remaining part in Impala region. For the Quick-Bird, the same steps were followed, but tree crown and coffee field threshold values were different due to the different pixel size. The tree crown threshold was set to 9 pixels corresponding to a circle with a diameter of 2 m; the mean probability of the tree object was calculated using  $3 \times 3$  kernel function. For the field classification a field size threshold of 1300 pixels was used, which corresponds to 200 trees. Unlike on orthophotos, we also used the near infrared (NIR) band for classifying the QuickBird image.

The accuracy of our resulting national coffee map was assessed against the 1362 coffee locations using Kappa statistics, Root Mean Square error (*RMSE*) and the coefficient of determination ( $R^2$ ). Moreover, the mapped coffee area was aggregated to district ( $C_m$ ) and compared to the district coffee areas reported by the detailed national coffee census of 2009 ( $C_c$ ) as shown by Eq. (7).

$$RMSE = \sqrt{\frac{1}{N}} \sum_{i=1}^{n} (C_{m(i)} - C_{C(i)})^2$$
(7)

Besides a large  $R^2$  and a low RMSE, the slope of the regression should ideally be close to 1, and the offset close to 0.

#### Results

#### Bayesian network results for a test area

Fig. 4 presents the coffee probability distribution results in the test areas (0.4 km<sup>2</sup> in Huye district, Southern province). In these test areas, coffee is relatively more prevalent as compared to the country average. This is why random sampling of the test areas resulted in a higher proportion of coffee samples as compared to the proportion that would be obtained when randomly sampling for the whole country. The location of the potential coffee ( $P \ge 0.49$ ) is shown by the probability maps (left) and the number of pixels and their likelihood to coffee (C) or no-coffee (N) is shown by the boxplot (right). With the pixel probability classifier (PPC) (Fig. 4a), the mean probability threshold is first determined (PT = 0.49). The probability threshold constitutes a cut-off below which the pixel probability classifier considers pixels as no-coffee pixels. The results showed that only 25% of the total image pixels were likely to be coffee  $(P \ge 0.49)$  with only 0.5% of the pixels having probabilities between 0.49 and 0.75, and 24.6% of the pixels over 0.75.

In Fig. 4b, the object probability is assigned the mean probability to the coffee object produced after the four-neighbor analysis. This operation slightly increased the percentage coffee pixels from 25% to 27% of the total image pixels.

Fig. 4c shows that the likelihood for coffee decreased when tree crown size rule was applied. About 27% of total image pixels previously classified as coffee by the object probability classifier decreased to 22% due to the tree crown size criterion. The probability for coffee also decreased from 0.75 to 0.50 showing that the use of tree crown size as an explanatory variable was an important step to distinguish coffee from other tree crops.

A clear distinction between coffee and no coffee was observed when a minimum field size rule was applied to the tree crown probability output. The resulting coffee probability map demonstrated an increase of coffee fields from 22% to 28% of the total image pixels with only 8% highly confirmed as coffee fields ( $P \ge 0.75$ ). The level of detail however reduced and outliers were removed (Fig. 4d). Forest and flow accumulation data are added in the final step to filter out coffee within known forest areas and in channels and flood plains. Coffee probability is also adjusted to remained coffee pixels. Only



**Fig. 5.** The percentage of pixels that falls within each probability class for different steps of the expert Bayesian network model for the 0.4 km<sup>2</sup> Huye test site.

## 15.5% of total image pixels remained as coffee fields as shown in Fig. 4e.

Step-wise addition of factors to the Bayesian network resulted in a gradual decrease in the percentage of image pixels identified as coffee for the test area (Fig. 5). With the pixel-based classifier, an overall accuracy of only 48% was obtained. After application of the subsequent steps of the expert Bayesian network model, the overall accuracy was 87.6% with a Kappa value of 0.82 for the test area (Table 1). This shows that for the test site the Bayesian network could accurately extract coffee fields from the orthoimages.

#### Accuracy of the Rwanda coffee map

Application of the trained expert Bayesian network to all images resulted in a total coffee area for the whole country of 25,148 ha, corresponding to 1.4% of the total arable land. The maximum coffee area (2979 ha) was found in Nyamasheke district, and the minimum area (5 ha) in Burera district. Fig. 6 shows the coffee coverage map aggregated by  $5 \text{ km} \times 5 \text{ km}$  grid (Fig. 6a) and by district boundary (Fig. 6b). The maximum coffee coverage within a single  $5 \text{ km} \times 5 \text{ km}$ pixel is about 13.5% and was found in Rusizi and Nyamasheke (west), Nyaruguru (south), Ruhango (central) and Gatsibo (east).

Based on the GPS locations, the overall accuracy of the produced map ranges from 56% to 100% on a district basis, with an average accuracy of 83.4% for the whole country (Fig. 6b). We observed agroecological dependent differences in the accuracy results which may be related to the level of separability between coffee and other land use classes. The accuracy was higher in Congo-Nile watershed (97.1% in Rutsiro), Mayaga Plateau (94% in Ruhango) and in the Eastern Ridges and Plateaus (over 97% in Gatsibo and Gicumbi).

#### Table 1

Error matrix of observed coffee fields vs. classified coffee fields by the expert Bayesian network (e-BN) for the test site  $(0.4 \text{ km}^2)$  in Huye, South plateau of Rwanda. The matrix values were calculated on the final coffee polygons. Overall accuracy of the test model were obtained by considering all pixels with *P*>0.49 as coffee and *P*<0.49 as no-coffee. Overall accuracy is 87.6%.

	Reference fields			
	Prob.	Coffee	No-coffee	Total
Coffee probability	≥0.75	24	0	24
	0.5075	38	0	38
	0.25-0.49	14	0	14
	<0.25	0	58	58
	0	3	0	3
Total		79	58	137



**Fig. 6.** Aggregated national coffee cover results following nation-wide application of the e-BN model to aerial orthophotos: (a) percentage of coffee cover within a 5 km  $\times$  5 km grid cell. (b) Coffee areas aggregated per district and overall accuracy for each district calculated based on 1362 GPS locations of coffee and no-coffee in the 30 districts of Rwanda. The graph (c) plots mapped coffee ( $C_m$ ) vs. to reported coffee area ( $C_c$ ) by the national coffee census of 2009. The coffee map explains 92% of the spatial variation of the census data.

This is likely because in these areas mostly older trees are present with a better developed tree crown. In fact, the Rusizi, Nyamasheke, Karongi and Rutsiro districts in west Rwanda are the first established (in the 1930s) coffee areas and have high production levels (Nsengiyumva, 2009). However, for Rusizi the model performed worse than for other western districts. In Rusizi QuickBird covered more than 50% of the district area. The time of the QuickBird acquisition (April 2004, older than orthophotos) and the lower resolution of QuickBird may explain the lower accuracy for Rusizi. The Bayesian model yielded an accuracy of 76.9% on QuickBird. Other low accuracies (68% and 70%) were observed in newly established (in 2000s) coffee fields of districts of the Eastern province (Nyagatare) and of Kigali (Nyarugenge). According to the national coffee census (Nsengiyumva, 2009), the highest rate of young coffee trees is observed in the Eastern Province (36%), followed by Kigali City (35.5%). Young coffee trees do not satisfy the tree crown rule in our expert Bayesian network. Moreover, in young coffee plantations line spacing i.e. large gaps between trees is common. When these gaps, classified as no-coffee by the tree crown classifier, are relatively small, they are included in coffee field by the field classifier, but for large gaps this is not the case.

The environment in which coffee fields are located also matters. For example, in high mountainous areas, accuracies were higher as compared to lowland areas. Except for coffee fields established in Mayaga, Bugesera and Imbo lowlands due to the coffee intensification policy during the period from 1960s to 1980s (Verwimp, 2003), more coffee fields are located at high altitudes (above 1500 m a.s.l.). These coffee areas experience relatively low temperatures (15–20 °C), high rainfall (>1000 mm per year) during  $\frac{3}{4}$  of the year

and consequently develop very well their branches and leaves (i.e. a good crown development).

Another factor that may explain differences in accuracy is the farming system in place. Larger coffee fields are found in the western mountains and eastern lowlands as compared to the central plateaus and ridges. Very highly fragmented and over-exploited lands of the central plateaus inhibited classification of very small coffee fields as these were ruled out by the field size criterion. The health of coffee trees in such fields is also poor leading to reduced accuracies in the plateau districts as opposed to other agro-ecological zones.

We compared the mapped coffee fields from the orthophotos of 2008/2009 with the national coffee census of 2009 (Fig. 6c). The 2004 QuickBird based inventory was omitted in this comparison because of the large time difference between image acquisition and census. Our spatially aggregated coffee map shows a strong agreement with the census data ( $R^2 = 0.92$ ). This shows that both methods agree in most districts despite the underestimated coffee areas of Rusizi due to the earlier described problems of QuickBird data. The root mean square error (RMSE) revealed a total of that on average 256 ha of coffee areas for each district reported by the census that could not be explained by the mapping results. This difference may be attributed partly by the fact that pruned trees and young trees were not accounted for with our mapping approach to loss of coffee tree by the tree crown classifier due to the pruning of mature trees and stage of development for the younger trees. It can also be a result of average plant spacing used to estimate the area in the census. In fact coffee spacing varies from  $1.5 \text{ m} \times 1.5 \text{ m}$ to  $2.5 \times 2.5$  with an average of  $2 \text{ m} \times 2 \text{ m}$  but for the estimation of the area, OCIR-CAFE used the average  $(2\,m\times 2\,m)$  for the whole country.

#### Discussion

Coffee trees and fields show a large spectral variability on orthophotos and QuickBird imagery. The Bayesian network structure proposed in this paper provided a possibility to handle such complexity through a stepwise object-based classification by modeling the probability of coffee trees and fields based on their surroundings. The conversion of expert knowledge on key spatial characteristics of coffee cultivation in Rwanda into evidence variables is the key to the model. In our case, spectral and spatial evidence of coffee occurrence were combined to gain a better representation of coffee farming systems design in Rwanda.

## Effect of individual Bayesian steps on the scale and the quality of the final coffee map

The sequence of classifiers as a result of the number of evidences for coffee occurrence is an important process in the modeling of coffee distribution. From a single unit (pixel) to an object unit (field) through a subunit (tree), a number of aggregation steps are involved. The hierarchy of the classifiers is carefully defined to reach a desired accuracy. Dropping a step or reversing the order of classifiers will affect the accuracy. For example, when the fourneighbor coffee pixels is ignored, the tree crown classifier will include about 34% of the total image pixels of no-coffee in coffee pixels.

Aggregation is an important component in building the e-BN structure. During the subsequent steps of a Directed Acyclic Graph, the unit size of the resulting probability map increased. For example, scattered coffee pixels in the pixel probability classification output when the minimum Coffee Mapping Unit (CMU) is set to 1 pixel tend to decrease their abundance in the OPC output (i.e. CMU = 4 pixels). When the tree crown rule is set to the average tree crown size (i.e. CMU = 16 pixels), the abundance of coffee is reduced. Yet, when the field size rule is included to allow only the coffee field with 200 coffee trees and above (i.e.  $CMU \ge 3200$  pixels) the number of coffee pixels decreased and the uncertainty also reduced. The CMU is therefore aggregated to a coarser scale (1:3200). The level of detail in field size output is significantly reduced but the outlier pixels are also reduced accordingly. The effect of aggregations depends on the original resolution of the image used and the steps as predefined by the expert in the BN model. It is known that aggregation of spatial data usually obscures internal variability and uncertainty (Kok and Veldkamp, 2011; Veldkamp et al., 2001).

In this work we did not consider the possibility of polyculture systems in model training. Coffee grown in polyculture fields (if any) may have been mapped with low probability (i.e. high uncertainty) because of generalization. To better account for differences in field types and field sizes within the country, thresholds could be adapted across the country. Due to the choice of the minimum field size, very small plots of less than 8 acres were lost. Field observation indicated that such small plots are rare and associated with abandoned fields. Depending on the purpose and scale, for highly fragmented zones, one could consider changing thresholds for adapting the method for local context. However, for nation-wide coffee mapping, we considered the average thresholds sufficient to capture more than 90% of the coffee plantations, and this has been proven by a strong agreement (92%) between our mapping and the National census results of the same year. In fact the census counted the number of trees regardless the size of the field (Nsengiyumva, 2009).

#### *Performance of the expert Bayesian network*

Firstly, our results confirmed that spectral variables alone are not sufficient to accurately identify coffee fields from high resolution images. With pixel probability classification, each coffee pixel is considered to be independent. However, this assumption is unrealistic given that we deal with coffee farms that are spread over a large area (more than 17,000 km<sup>2</sup> of arable land) across different environments. Information on the key characteristics of farming systems in place is an important step to the design an automated approach to classification of coffee. For a small area of 1200 km<sup>2</sup>, Gomez et al. (2010) obtained a good accuracy when predictive variables were used together with object oriented image analysis using Artificial Neural Network (ANN). In general, the accuracy of the results of Bayesian network models (and of other objectoriented models) likely increases when more relevant variables can be provided. Another observation in our study is that the spatial resolution (i.e. pixel size) seems more important than the spectral resolution (i.e. the number of bands) in separating coffee from other land covers. Although QuickBird contained the additional NIR band, we obtained a relatively low accuracy (76%). An additional cause of this might however be that the QuickBird imagery are acquired five years before the 2009 census. Given the poor spectral separability between low-density woodlands and coffee fields (Cordero-Sancho and Sader, 2007), we improved coffee field identification in mountain forest areas (in west) and in the plateaus and ridges of the east (in Gatsibo) by the use of an existing forest map. The use topographic data in the Bayesian network model was also relevant to exclude coffee from clear flow accumulation areas (streams and gullies).

Although we obtained an overall high classification accuracy with our approach, several factors may cause sub-optimal performance. (1) Topographical effects may have contributed to the spectral confusion between east-facing and west-facing coffee trees that are differently illuminated due the sun's position during the time of image acquisition. This effect also caused a reduction of accuracy in other studies; (2) The Bayesian network model classification was not corrected for shadow of coffee trees; (3) Differences in coffee age and health also account for a loss in accuracy.

In the last decade remotely sensed data is often combined or compared with census data to study environmental dynamics. The main challenge of this integration is the different temporal and spatial scales involved. This is often solved by aggregating the two data sources to the coarsest resolution of the two sources. This has as main disadvantage that some of the detail and variability is lost but it allows to convert typical land cover information into more in land use characterization. So the integration and/or combination of census and remotely sensed data always come with a quality trade-off. The strength of rigorously collected census data is that they are based on on-site inventories and farmer interviews. Nonetheless, spatial detail and verification of all farmer-reported coffee trees is lacking in the census outcomes. Remote sensing, i.e. our high-resolution national coffee map, can therefore offer an important complement to the census data. However, as discussed above, it has its own limitations in terms of accuracy. Despite existing limitations for both sources, in our view they offer important complementary information.

The contribution of our method to existing object oriented classification techniques is the stepwise analysis that allows the creation of intermediate classification outputs. This means the flexibility of the method in shortening or extending rules and data towards improving quality of the map. Potentially more use could be made of the probability value that was derived for each coffee field, for example as an indicator of the health and productivity of the coffee field.

#### **Conclusions and outlook**

In this study we developed a stepwise probabilistic approach for coffee systems classification using an expert Bayesian network. Using the case of Rwandan coffee, the methodology proved to be effective in extracting small-scale coffee fields from very high resolution images. We are convinced that the presented method can be extended (1) to other perennial small scale cropping systems (e.g. banana, cassava systems) that are difficult to map with spectral-based pixel classification techniques. As such the method has great potential to be applied for coffee and other perennial crops (like banana, cacao) across the East African highlands, but also for mapping of perennial crops in small-scale farming systems elsewhere for which the detailed spatial distribution is currently largely unknown.

The method provided an accurate representation of the spatial distribution of coffee cultivation areas of Rwanda despite the spectral diversity of coffee trees and the field sizes. We produced the first nation-wide coffee map for Rwanda. This automated high resolution coffee map contains the producing coffee fields at an overall accuracy of 87%. However, some districts have a lower accuracy, which could potentially be improved with local adaptation of decision rules in the Bayesian network and interactive phase especially for the young or regenerated plantations after cuttings. The produced high spatial resolution coffee map is an important input for further environmental and socio-economic studies regarding the productivity and quality of Rwandan coffee.

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