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Mapping rice field anopheline breeding habitats in Mali, West Africa, using Landsat ETM+ sensor data

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Abstract

The aim of this study was to determine whether remotely sensed data could be used to identify rice-related malaria vector breeding habitats in an irrigated rice growing area near Niono, Mali. Early stages of rice growth show peak larval production, but Landsat sensor data are often obstructed by clouds during the early part of the cropping cycle (rainy season). In this study, we examined whether a classification based on two Landsat Enhanced Thematic Mapper (ETM)+ scenes acquired in the middle of the season and at harvesting times could be used to map different land uses and rice planted at different times (cohorts), and to infer which rice growth stages were present earlier in the season. We performed a maximum likelihood supervised classification and evaluated the robustness of the classifications with the transformed divergence separability index, the kappa coefficient and confusion matrices. Rice was distinguished from other land uses with 98% accuracy and rice cohorts were discriminated with 84% accuracy (three classes) or 94% (two classes). Our study showed that optical remote sensing can reliably identify potential malaria mosquito breeding habitats from space. In the future, these 'crop landscape maps' could be used to investigate the relationship between cultivation practices and malaria transmission.

1. Introduction

Malaria is one of the most common and devastating diseases in the tropics. The situation is especially acute in sub-Saharan Africa, where 250–450 million clinical cases and over one million deaths occur each year (Lindsay et al. 1998, Greenwood and Mutabingwa 2002). Remote sensing and Geographical Information Systems (GIS) are becoming important tools for the study of diseases involving invertebrates as intermediate hosts (see reviews by Hay et al. 1997, Kitron 1998, Thomson and Connor 2000). Malaria in particular has been the focus of recent efforts to use remote sensing to control and mitigate this disease (see, for example, reviews by Hay et al. 2000, Rogers et al. 2002). The most obvious applications of remote sensing have been to survey areas at risk and to identify potential breeding sites for mosquitoes. However, this technology can be used beyond simply mapping potential habitat to predicting the spatial patterns of mosquito production (Wood et al. 1991, 1992). Our goal in this study was to determine whether remotely sensed data could be used to identify and monitor environmental factors that influence malaria vector populations in our study area, an irrigated rice growing area near Niono, Mali.

A major source of concern for malaria control are irrigation projects in the Niger Delta Region, some of which contain large numbers of rice fields. Rice fields are important breeding sites

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for *Anopheles gambiae* s.l. and *An. funestus*, the main malaria vectors in sub-Saharan Africa (Goonasekera and Amerasingue 1988). There, the population dynamics of malaria mosquitoes is coupled to the growth cycle of the rice plants. *An. gambiae* in particular thrives in the shallow inundated fields during tilling, transplanting, the first weeks of the growing period (until canopy closure) and after harvest (Mather 1984, Dolo et al. 1997, Mutero et al. 2000). Specifically in our study area in Mali, Klinkenberg et al. (2003) found that larval densities of *An. gambiae* s.l.—the most important vector in the area—increased after transplanting, reached peak density, and then decreased after 35–40 days. Larval densities are affected by changes in plant height and biomass, which are associated with certain microhabitat characteristics, such as light conditions, temperature, mechanical obstruction and nutritional state of the water (Surtees et al. 1970, Chandler and Highton 1975, Snow 1983). It is therefore essential to identify those early rice growth stages in any attempt to control mosquito populations.

As in many tropical areas, rice cultivation is not synchronous in Niono, due to variations in water availability, the practice of single or double cropping and other economic factors that affect farmers (Klinkenberg et al. 2003). The existence of rice ‘cohorts’ planted at different times during the cropping season provides continuous availability of breeding habitats for mosquitoes, as the most suitable (early) rice growth stages shift from field to field. We hypothesize that villages that practise more asynchronous or patchy rice cultivation would have a more stable vector population throughout the season. Conversely, more homogeneous or synchronous cultivation may cause a reduction in the numbers of mosquitoes produced as the season progresses. Changes in vector population dynamics will affect malaria transmission patterns, through changes in their vectorial capacity. To study this process, an essential first step is to determine the plausibility of obtaining maps of the different rice cohorts during a season, which can be integrated in the future into disease transmission studies.

The use of low-spatial, high-temporal resolution optical sensors (especially the National Oceanic and Atmospheric Administration Advanced Very High Resolution Radiometer (NOAA AVHRR)) for land use/land cover mapping is well established (see review by Cihlar 2000). However, the small size of most rice fields in our study area requires the use of higher spatial resolution sensors (e.g. Landsat Enhanced Thematic Mapper (ETM)+ and Système Probatoire de l'Observation de la Terre (SPOT) high resolution visible (HRV)) to map and model rice parameters. Previous work shows that such sensors are potentially able to discriminate several factors important to mosquito production, including estimation of rice planted area (Panigrahy and Parihar 1992, Tennakoon and Murty 1992, Okamoto and Fukuhara 1996, Singh and Singh 1996, Fang et al. 1998, Okamoto et al. 1998, Xiao et al. 2002), different rice cultural practices and planting dates (Singh and Singh 1996, Turner and Congalton 1998) and plant developmental rates and condition (Wood et al. 1992, Singh and Singh 1996, Turner and Congalton 1998). Other researchers have described the seasonal spectra of rice canopies in relation to different rice growth parameters (e.g. biomass, leaf area index (LAI), chlorophyll a) using multi-temporal optical remote sensing (Shibayama and Akiyama 1989, Wood et al. 1991, Xiao et al. 2002) or hand-held radiometers (Casanova et al. 1998, Choubey and Choubey 1999, Yang and Su 1999). In this paper, we built on these findings using Landsat ETM+ data to identify and map the area cultivated with rice and to distinguish between different rice growth stages that relate to mosquito larval production.

Multi-temporal datasets give best classification accuracy by overcoming the ambiguity that exists in defining the spectral signature in single-date data (Hill and Megier 1988). Multiseasonal imagery (within a given year) has proved highly effective to map different crops (Ehrlich et al. 1994, Brisco and Brown 1995, Panigrahy and Sharma 1997, Brewster et al. 1999, Oetter et al. 2001), including rice (Tennakoon and Murty 1992, Okamoto et al. 1998, Turner and Congalton 1998, Xiao et al. 2002). In the case of rice, agronomic management practices such as localized flood control, ploughing and harvesting of rice fields may produce

distinctive signatures during certain periods of the cropping season, that may help in the discrimination of rice from other crops. The use of multi-temporal imagery data acquired across a cropping cycle has a high potential for exploiting such contrasts in classification (Turner and Congalton 1998). In our study area, images acquired at flooding/ploughing are usually obstructed by clouds. We therefore examined whether Landsat ETM+ data acquired in the middle of the season and around harvesting time can be used, individually or combined, to map the different land uses and rice cohorts. A map of rice cohorts could be used in the future to compare malaria transmission in villages that tend to have 'early' versus 'late' cultivation calendars, with different degrees of patchiness.

2. Study area

The study area is located around the town of Niono, in the Northern Sudan region of Mali, at 14°18' N and 5°59' W, about 330 km north-east of Bamako. This encompasses the largest rice irrigation project in Mali. The 'Office du Niger' in the Niono District of Mali oversees irrigation in the area from a dam on the Niger River. The facility was first built in 1932, and now irrigates about 55 000 ha of rice; it is continuously being enlarged. A large reservoir provides water year-round, permitting rice to be double-cropped in some areas.

The climate of Niono is typical of the Sahel, with a wet season of about three months (July–September), a 'cold' dry season (November–February) and a hot dry season (March–May/June). The average annual precipitation is 400 mm. The short rainy season restricts mosquito breeding. The introduction of irrigation schemes and construction of dams provides additional semi-permanent water surfaces, which can serve as mosquito breeding sites. Besides providing suitable habitat for mosquitoes, artificial irrigation can substantially prolong the transmission season for malaria, especially when a second crop is grown during the dry season (Dolo et al. 1997).

3. Rice cultivation

In our study area, the beginning of each cropping cycle is scheduled according to the water distribution scheme and the schedule of rice husbandry differs from a group of fields to another. Most fields are cultivated once a year, though some farmers cultivate a second crop during the dry season. Breeding sites are therefore available throughout most of the year (Dolo et al. 1997, Klinkenberg et al. 2003).

The typical cultivation cycle in the Office du Niger includes a sowing–transplanting period (June–August), a growing period (August–November) and an after-harvest period (November–December). The second crop is cultivated between January and May. The duration of the rice cycle varies between 120–150 days depending on the rice variety, and includes a vegetative period when plants develop and grow, a reproductive phase during which plants stop growing and orient towards the development of the panicles and grains, and a ripening phase, in which plants senesce and their water content drops. Rice plants are usually transplanted when 20–30 days old, and the vegetative phase lasts 45–60 days, including the seedling transplant, tillering and stem elongation stages. Tillering extends from the appearance of the first tiller until maximum tiller number is reached. During stem elongation, the tillers continue to increase in number and height, with increasing ground cover and canopy formation. This stage sometimes overlaps with the tillering stage; its duration depends on rice variety and is highly variable in our study area. The reproductive phase lasts 20–30 days and includes the panicle initiation, booting, heading and flowering stages. We considered that plants were in the reproductive phase when more than 50% of plants had panicles. Finally, the ripening phase lasts 35–65 days, during which the grains fill and turn yellow and the plants senesce.

4. Materials and methods

4.1. Ground reference

We collected ground reference data between 15–27 October 2000, using Global Positioning System (GPS) units (GeoExplorer® II, Trimble Navigation Ltd). Training areas consisted of 1-ha areas of homogeneous land use near road intersections (41 sites, 1943 pixels) and land use strips on the sides of roads (3 sites, 722 pixels). We excluded areas where adjacent rice fields were at different stages. By doing this, and by starting to record land use 100 m from the road, we attempted to minimize mixed pixels. In the case of urban, rangeland, roads and wetland land uses, training areas were identified and digitized from a colour composite image using ETM+ band combination 5, 4, 3.

We defined the land use classes present at the time of ground data collection as: urban, rangeland, garden, roads, wetland, standing rice (hereafter 'rice') and harvested rice (hereafter 'harvested'). The *urban* class consisted of villages and their surroundings; *rangeland* was the open savannah of the Sahel type with thorny shrubs and few large trees, mainly baobab (*Adansonia digitata*) and balazan or kad (*Faidherbia albida*); *gardens* were areas cultivated with other crops (tomatoes, onions, okra and others), either year-round or after rice was harvested; *wetlands* were areas permanently inundated, mostly around the central irrigation channel.

We subdivided the *rice* class into three rice 'cohorts', namely 'late', 'on time' and 'early' rice (figure 1). We labelled rice as 'late' when it was in vegetative stage, as 'on time' if in reproductive stage and as 'early' if in ripening stage at the time of data collection. Although the rice stages were clearly distinguishable, in case of ambiguity we assigned rice to the vegetative stage when less than 50% of plants had panicles, to the reproductive stage when more than 50% did and to the ripening stage when the grains started to fill and the plants turned yellow. We defined these categories to match the criteria used to describe larval habitats in the area.

4.2. Remotely sensed data and pre-processing

We used two level 1G Landsat ETM+ scenes (path/row: 198/50) in this study (Earth Resource Observation System (EROS) Data Center, Sioux Falls, SD, USA). The dates of the ETM+ scenes were 18 September, during the growing cycle, and 5 November, around harvesting time, 2000. These were the only scenes available with little or no cloud cover during the autumn 2000 cropping season. Outside the United States, Landsat sensor data are not acquired on every pass and acquisition requests are not available. In our study area, acquisition frequency is about two months, which, in addition to cloud cover, limits the availability of cloud-free scenes during the cropping season.

We converted digital numbers to exoatmospheric reflectance (top of the atmosphere (TOA) reflectance) following the procedures described in the Landsat 7 Science Data Users Handbook, chapter 11 (Landsat 2003). During 1G-product rendering image pixels are converted to units of absolute radiance using 32 bit floating point calculations. Pixel values are then scaled to byte values prior to media output. We used equation (1) to convert digital numbers (DN) back to at-satellite spectral radiance units:

$$\text{Radiance} = ((\text{LMAX} - \text{LMIN}) / (\text{QCALMAX} - \text{QCALMIN})) * (\text{QCAL} - \text{QCALMIN}) + \text{LMIN} \quad (1)$$

where QALMIN=1 (Level 1 Product Generation System (LPGS) product), QCALMAX=255, and QCAL=DN. The LMINs and LMAXs were the spectral radiances for each band at DN 1 and 255 (i.e. QCALMIN, QCALMAX), respectively, and obtained from table 11.2 in Landsat (2003).

We computed TOA reflectance (combined surface and atmospheric reflectance of the Earth) with equation (2)

$$\rho_p = \frac{\pi L_\lambda d^2}{ESUN_\lambda \cos \theta_s} \quad (2)$$

where ρ_p =unitless planetary reflectance, L_λ =spectral radiance at the sensor's aperture, d =Earth–Sun distance in astronomical units (interpolated from table 11.4 in Landsat 2003), $ESUN_\lambda$ =mean solar exoatmospheric irradiances (from table 11.3 in Landsat 2003), and θ_s =solar zenith angle in degrees.

We extracted subsets of 1878×3109 pixels from both scenes. We georegistered the 18 September scene using 80 ground control points (GCPs) obtained during ground data collection, obtaining a RMS error of 0.1. We then registered the 5 November scene to the September scene using 50 GCPs and obtaining an RMS error of 0.26. We performed a first degree polynomial transformation and a nearest neighbour resampling algorithm for both registrations. The panchromatic band (ETM+ band 8) was used to locate the GCPs and the other ETM+ bands were resampled to 15m to match the panchromatic band resolution before transformation. We applied two masks to all scenes for all subsequent analyses. The first excluded the desert area outside the irrigation perimeter, based on a map of the irrigation scheme. The second was a cloud mask generated through a supervised classification of Landsat ETM+ bands 1 and 6 (thermal) into two classes, 'cloud' and 'non-cloud'. The training areas for the 'cloud' category were selected to represent the diversity of cloud types and their shadows. 'Cloud' masks from both scenes were merged with the 'desert' mask and applied to all data.

4.3. Image analysis

We overlaid the class-labelled polygons obtained in the field with the satellite data. For each land use class, we randomly selected 300 and 100 pixels within these polygons to use as regions of interest (ROIs) for training and testing the classification, respectively. We used a maximum likelihood algorithm to classify all bands (except band 6) in each ETM+ scene into the seven main land use classes. We also merged the six bands of both scenes to produce a multi-date, 12-band classification, and we compared the results with those of the single-date classifications.

To classify the rice cohorts within the 'rice' category obtained above, we followed the sequential masking classification approach of Ehrlich et al. (1994). In order to maximize the discriminability among rice growth stages, we generated a 'non-rice' mask from the land use map. For each of the rice categories ('early', 'on time' and 'late'), we randomly selected 100 and 33 pixels from the ground reference data to use in training and testing, respectively. We applied a maximum likelihood classification algorithm to each single-date and the multi-date datasets to classify rice into three categories. A second classification was performed pooling the 'early' and 'on time' classes, resulting in two rice classes.

4.4. Accuracy assessment

We explored the robustness of the classifications (for land use and rice stages, using single- or multi-date datasets) using two approaches. Before the classification, we examined the spectral separability between all pairs of training ROIs using the transformed divergence separability index (Richards and Xiuping 1999). This index value ranges from 0 to 2.0 and indicates how well the selected pairs are statistically separate. Values greater than 1.9 indicate that the ROI pairs have good separability. After the classification, we calculated the kappa coefficient (Lillesand and Kiefer 1994) and we generated confusion (contingency) matrices to determine

the overall percentage accuracy of the classification (number of ground pixels correctly classified/total number of pixels used for testing $\times 100$).

5. Results

5.1. Land use classification

The seven land use categories in our study area were classified with 89.7% accuracy (kappa coefficient=0.88) when the two-date, 12-band classification was used in the analysis (table 1). Rice in particular was classified with 98% accuracy, which is consistent with the high separability index between rice and the other classes (1.99–2.00) (table 2). Figures 2 and 3 illustrate the basis for this high separability, i.e. rice showed higher mean Normalized Difference Vegetation Index (NDVI) and lower mean middle infrared (MIR; ETM+ bands 5 and 7) reflectance than the other classes (except wetland), for both dates. In addition, rice mean spectral trajectory was very different from the other classes, showing a much smaller change in mean NDVI and MIR reflectance between the two acquisitions (figure 3). Figure 4 shows the final classification map for land uses and rice cohorts.

All land use classes, except rice and wetlands, exhibited a large decrease in mean NDVI and an increase in mean MIR reflectance between the two acquisitions. This is consistent with the onset of the dry season, with slowing growth rates, senescence and decrease in water content of the natural vegetation in the 'rangelands' and the harvesting of some rice fields ('harvested') and other crops ('gardens'). In the case of the 'urban' and 'roads' classes, the relatively smaller seasonal decrease in NDVI and increase in MIR is likely to be due to pixels 'mixed' with 'rice' or 'garden' land uses. Overall, the 'urban' and 'rangeland' classes showed the highest reflectance for all bands (figure 2), as expected from the high-albedo bare soil that predominates in these land uses. Wetlands showed the lowest reflectance values for all bands in both seasons. The fact that the wetlands showed only a small change in NDVI (consistent with the presence of some vegetation pixels) and no change in MIR indicates that the radiometric calibration of both scenes was acceptable, which validated the visual interpretation of the observed changes in reflectance values and NDVI.

The use of multi-date classification produced the maximum separability between rice and all other land use classes (table 2), as well as the maximum classification accuracy (table 1). However, the single-date classification using the November scene showed very similar separability and accuracy to the two-date classification. The September-only classification, however, performed poorly in discriminating standing and harvested rice. This is to be expected since, even though rice labelled as 'harvested' in October (when ground data were collected) could potentially be discriminated before harvest by its more advanced growth stage, the spectral contrast with standing rice greatly increased after this cohort was actually harvested. Rice was also misclassified as wetland when only the September scene was used in the classification. This was likely to be due to the low plant cover of rice at early growth stages, which would cause the water surface to dominate the pixel's spectral signature and be confounded with open water.

5.2. Rice stage classification

The overall accuracy for the rice stage classification was 84.00% and the kappa coefficient was 0.76 (table 3). Given the relatively lower classification accuracy and separability (table 4) between the 'on time' and 'early' cohorts, we performed a second classification, pooling the training pixels for these two cohorts. The overall accuracy for this classification was 94.00% and the kappa coefficient was 0.87.

The mean reflectance values of the three rice cohorts were not very different in absolute values (figure 5), with the ‘on time’ and ‘early’ cohorts showing higher reflectance than the ‘late’ one for most bands, except for ETM+ bands 1–3 in September. The differences appeared more clearly when we plotted the results in the NDVI–MIR reflectance feature space (figure 6). Mean NDVI increased for the ‘late’ cohorts (figure 6), due to the active growth and increase in biomass characteristic of the vegetative (growing) (figure 1). Plants in the ‘on time’ and ‘early’ cohorts showed a decrease in NDVI, with the ‘on time’ class showing higher absolute values than the ripening stage, the latter undergoing a process of senescence. These changes in NDVI are coupled with an increase in mean MIR reflectance for all stages (figure 6). MIR reflectance is inversely related to soil and plant water content. Background water is highly exposed during the initial stages of the cycle and probably dominates reflectance patterns, producing low MIR reflectance values. MIR reflectance would increase due to the combination of two factors, i.e. the decrease in background water exposure as plants grow and the decrease in plant water content as plants senesce as the cycle progresses.

The use of the two-date classification improved accuracy for the ‘late’ and ‘on time’ cohorts but not for the ‘early’ cohort, for which the classification using only the September scene had higher accuracy. ‘Early’ rice was at very advanced stages in the November scene and many of these fields had actually been harvested. They were not actually labelled as ‘harvested’ because rice was still standing in the plot when ground data were collected on 15–27 October, and labels assigned. The informational value of the November scene for this cohort was therefore low and may even have confounded the information provided by the September scene in the two-date classification.

6. Discussion

Two-date Landsat ETM+ data obtained during the periods of rice vegetative growth and reproduction/ripening discriminated very efficiently among different land uses in our study area. Rice in particular was discriminated with 98% accuracy. Within the rice class, rice cohorts were discriminated with 84% accuracy (three classes) or 94% (two classes, ‘on time’ and ‘early’ cohorts pooled). Although all bands were used in the classification, ETM+ 3 and 4 (and NDVI), 5 and 7 (MIR) seem to be providing the most spectral information for discrimination of these categories. Several authors have addressed the importance of bands 3 and 4 (and NDVI) for rice crop mapping and discrimination from other land uses (references listed in §1). Our results coincide with previous findings, since we were able to obtain a very accurate classification and, as seen in figure 3, NDVI in rice fields was clearly higher than in all other land uses, increasing separability and classification accuracy.

As regards rice growth stage discrimination, of particular interest are those studies that describe the progression of red and infrared reflectance (and NDVI), throughout the rice cycle (Shibayama and Akiyama 1989, Wood et al. 1991, Xiao et al. 2002). In all cases, NDVI was shown to increase in the early stages of growth, reach a peak at the reproductive stage and then decrease. Although only two dates were used, the changes in NDVI observed in our study were consistent with this signature. Figure 6 shows that ‘on time’ rice had the highest NDVI values on 18 September when, according to figure 1, it would have been in the reproductive stage, while ‘late’ rice had the highest NDVI value in November, when it reached the late vegetative/reproductive stage. ‘Late’ fields, which were actively growing and increasing in biomass between acquisitions, showed increasing NDVI, while ‘on time’ and ‘early’ crops showed decreasing NDVI, consistent with a process of senescence. We showed here that the two scenes acquired during the growing and ripening/harvesting periods of the crop calendar capture enough spectral variability to discriminate stages important to larval production.

Several studies have addressed the potential of MIR bands in crop classification (Townshend 1984, Baret et al. 1988, Thenkabail et al. 1994, Dadhwal et al. 1996), some specifically in the case of rice systems (Panigrahy and Parihar 1992, Tennakoon and Murty 1992, Okamoto et al. 1998). Our results are in accordance with these studies, given the marked spectral contrast between rice and other classes in the MIR range. The sensitivity to the presence of water in the soil and plants gives MIR bands excellent informational value when using optical remote sensing for mapping and monitoring rice crops. At the early stages of rice growth, the contribution of water to spectral reflectance is greater than the contribution of the plant canopy and MIR values are very low. As plants mature, MIR reflectance values increase (figure 3), both because of a higher plant cover and contribution to total reflectance and because of a decrease in the plants' water content throughout the cycle. However, this increase is significantly smaller than that experienced by other land uses.

In order to discriminate rice from other crops, several authors (e.g. Tennakoon and Murty 1992, Turner and Congalton 1998) have chosen acquisitions at either ploughing or harvesting times (or both), which offer windows of spectral contrast between rice fields and the surrounding vegetation. In our study area, it is virtually impossible to obtain images early in the season (July–August) due to large cloud cover. We show here that an acquisition at harvesting time (November) allowed a very accurate classification of land uses. If too many rice fields are harvested at this time, however, the informational value of this scene will be diminished for the classification into rice cohorts, and an additional acquisition some time during the cycle will greatly increase the quality of the classification.

We present in this paper an approach that can be followed to partially solve two problems facing the use of Landsat sensor data for time-sensitive mapping in tropical areas: (1) the uncertainty as to the date at which a cloudless Landsat ETM+ scene will be acquired, which makes it difficult to collect simultaneous reference ground data; and (2) the difficulty in obtaining cloud-free data during the earlier stages of the crop cycle. Figure 1 illustrates how, even if ground reference data are acquired in the middle of the cycle and they do not coincide with the dates of satellite data, inferences can be made as to the stages present at other times during the cycle, provided that all stages are represented at that time. Additional ground data acquisitions during the cycle would likely improve the quality of the classification and increase the precision when estimating the growth stage present at any particular point in time.

7. Summary and conclusions

Larval production peaks during the early stages of rice growth. Many rice fields are at this stage in July/August, during the rainy season, when it is extremely difficult to obtain a cloud-free Landsat ETM+ scene, especially with the low acquisition frequency in our study area. In order to understand malaria vector population dynamics and their effects on malaria transmission, it is essential, however, to be able to map the distribution of the fields having peak density at different times during the season. We propose here a methodology to do so. This method is based on classifying single-date or, preferably, multi-date Landsat ETM+ data into rice 'cohorts', which are groups of fields that follow slightly different agronomic calendars. The cohorts are described in relative (i.e. rice planted 'early', 'on time', 'late') rather than absolute (i.e. late, on time, ripening rice) terms, based on the stage at which they were when ground reference data were collected. The cohorts can be therefore identified at any time during the season. One or two Landsat ETM+ scenes—preferably acquired during the spectral windows of ploughing and harvesting—are then used for classification into land uses and rice cohorts.

The next step will be to integrate these maps with data on larval densities in rice fields, adult vector numbers and disease transmission data in the nearby villages. Studies on malaria

transmission usually acquire data only once or twice in a cropping season (see review by Ijumba and Lindsay 2001). Therefore, 'static' maps like the ones presented in this paper could be used to compare malaria transmission in villages surrounded by different patterns of cultivation. To illustrate the application in our study area, consider malariometric data acquired simultaneously with ground reference data on rice stages. If a village were surrounded by 'early' rice, we could infer that peak vector production occurred about 100 days prior (see figure 1), and the effect of peak mosquito density on malaria transmission later in the cycle could be examined. Another possible application would involve using datasets acquired in the past and integrate them with archived satellite data. If no ground reference data were available to train the classification, unsupervised or hybrid classification approaches would have to be implemented, potentially using the spectral classes derived from later studies in the same area.

In non-synchronous cropping systems like the one in Niono, villages are likely to be surrounded by patches at different rice growth stages. Landscape features have long been recognized as important determinants of transmission of vector-borne diseases (Kitron 1998). The 'landscape maps' obtained in this study could be used in the future to relate the relative number and distribution of patches of different rice cohorts to malariometric parameters. As we increase our understanding of these relationships, crop maps may be used as drivers in spatial simulation models to investigate ecological processes and strategies to control mosquito populations, by changing water management practices or by controlling the timing of rice cultivation. Irrigation for rice cultivation is likely to expand in the future, and a better understanding of the relationship between vector population dynamics and malaria transmission could lead to better planning and management of existing or future irrigation schemes to minimize malaria incidence.

A future development in the remote sensing methodology would be to integrate optical with Synthetic Aperture Radar (SAR) data. SAR has been extensively used to monitor rice, mainly in Asia (e.g. Chakraborty et al. 1997, Le Toan et al. 1997, Panigrahy et al. 1997, Liew et al. 1998). It has the advantage of not being obstructed by clouds and that acquisitions can be requested in advance for the European Remote Sensing (ERS) and Radarsat sensors. Landsat sensor data, however, have more bands and can often better discriminate rice from other land uses. They are also easier to process, since they do not have the problem of 'speckle', and there are long-term archived datasets available. The lack of SAR archived data is an important drawback, since there are extensive historic databases on malariometric data that could be integrated with remote sensing data for further study. The integration of optical and SAR data for crop mapping offers great promise, as pioneering studies by Brisco and Brown (1995), Kurosu et al. (1997), Okamoto and Kawashima (1999), Le Hegarat-Masclé et al. (2000) and Oguro et al. (2001) show.

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Figure 1.

Schematic description of the rice cohorts present in our study area. The cropping cycle lasts about 120 days after transplanting. 'Early', 'on time' and 'late' rice are planted in succession during the cropping season. Between 15–27 October, we collected ground data and recorded the rice stage present at the time (vegetative, reproductive, ripening). Rice in vegetative stage at the time was assigned to the 'late' cohort, reproductive to the 'on time' cohort and ripening to the 'early' cohort. The rice reflectance values from two Landsat ETM+ datasets acquired before (18 September) and after (5 November) ground data collection were used for the classification of the cohorts.

Figure 2. Mean Landsat ETM+ reflectance values of training pixels used for the classification into seven land use classes. ETM+ bands 1–5 and 7 (ETM+1 to 7) from the 18 September 2000 (Sept) and the 5 November 2000 (Nov) scenes are plotted.

Figure 3.

Spectral signature mean trajectories for the land use training pixels in an NDVI/ETM+5 reflectance feature space, for the two Landsat ETM+ scenes (18 September and 5 November 2000). The arrows point from the NDVI/ETM+5 values on 18 September to those on 5 November. Mean NDVI was calculated as the reflectance of (ETM+4-ETM+3)/(ETM+4+ETM+3). The land uses are harvested (H), garden (G), urban (U), wetland (W), rangeland (Rg), roads (Rd) and rice (Rc).

Figure 4.

Land use map of the study area, showing a general view (a); a detailed view (b); and the same area as (b), but with the non-rice land use masked out and the rice class subdivided into cohorts (c).

Figure 5. Mean Landsat ETM+ reflectance values of training pixels used for the classification into rice 'cohorts'. ETM+ bands 1–5 and 7 (ETM+1 to 7) from the 18 September 2000 (Sept) and the 5 November 2000 (Nov) scenes are plotted.

Figure 6.

Spectral signature mean trajectories for the three rice cohorts training pixels in an NDVI/ETM+5 reflectance feature space, for the two Landsat ETM+ scenes (18 September and 5 November 2000). The arrows point from the NDVI/ETM+5 values on 18 September to those on 5 November. Mean NDVI was calculated as the reflectance of $(\text{ETM}+4 - \text{ETM}+3) / (\text{ETM}+4 + \text{ETM}+3)$.

Table 1

Classification accuracies (in percentage) for the seven main land use classes. For each class, 100 test pixels were used to compare the ground data pixels to the class they were assigned to by the maximum likelihood classification algorithm when we used both scenes combined (A) or only the September (B) or the November (C) scenes. The codes for the land uses are in the first column. For both scenes combined, the overall accuracy for the classification was 89.7% and the kappa coefficient was 0.88.

		H	G	U	W	Rg	Rd	Rc
Harvested (H)	A	95.0	7.0	—	—	—	4.0	—
	B	84.0	6.0	—	2.0	—	11.0	10.0
	C	91.0	8.0	—	—	4.0	10.0	—
Garden (G)	A	2.0	82.0	5.0	—	4.0	3.0	—
	B	1.0	61.0	7.0	—	12.0	16.0	1.0
	C	5.0	78.0	7.0	1.0	8.0	2.0	—
Urban (U)	A	—	7.0	90.0	—	12.0	1.0	—
	B	—	11.0	83.0	—	14.0	1.0	—
	C	—	8.0	78.0	—	16.0	2.0	—
Wetland (W)	A	—	—	—	96.0	—	—	—
	B	—	3.0	—	81.0	—	1.0	6.0
	C	—	—	—	95.0	—	—	2.0
Rangeland (Rg)	A	1.0	1.0	3.0	1.0	83.0	1.0	—
	B	—	4.0	8.0	—	73.0	—	—
	C	2.0	1.0	13.0	—	70.0	3.0	—
Road (Rd)	A	2.0	2.0	2.0	1.0	1.0	84.0	2.0
	B	5.0	13.0	2.0	6.0	1.0	65.0	1.0
	C	2.0	4.0	2.0	1.0	2.0	67.0	6.0
Rice (Rc)	A	—	1.0	—	2.0	—	7.0	98.0
	B	10.0	2.0	—	11.0	—	6.0	82.0
	C	—	1.0	—	3.0	—	16.0	92.0

Table 2

Transformed divergence separability index between pairs of the seven main land use classes. For each land use class, we used the 300 training pixels to estimate the index for both scenes combined (A) and only the September (B) or the November (C) scenes. The codes for the land uses are in the first column.

		H	G	U	W	Rg	Rd
Garden (G)	A	1.99					
	B	1.99					
	C	1.89					
Urban (U)	A	2.00	1.99				
	B	2.00	1.65				
	C	1.99	1.67				
Wetland (W)	A	2.00	2.00	2.00			
	B	1.97	1.99	2.00			
	C	1.99	1.99	2.00			
Rangeland (Rg)	A	2.00	1.89	1.79	2.00		
	B	1.99	1.34	1.34	1.99		
	C	1.98	1.54	0.91	2.00		
Roads (Rd)	A	1.99	1.86	1.99	1.99	1.99	
	B	1.82	1.06	1.94	1.95	1.83	
	C	1.83	1.50	1.94	1.99	1.90	1.99
Rice (Rc)	A	1.99	1.99	2.00	1.99	2.00	1.92
	B	1.38	1.99	2.00	1.52	2.00	1.94
	C	1.99	1.99	2.00	1.95	2.00	

Table 3

(a) Classification accuracies (in percentage) for the three rice cohorts. For each class, 100 test pixels were used to compare the ground data pixels to the class they were assigned to by the maximum likelihood classification algorithm when we used both scenes combined (A), only the September (B) or the November (C) scenes. For both scenes combined, the overall accuracy for the classification was 84% and the kappa coefficient was 0.76. In (b), we combined the ‘early’ and ‘on time’ classes. The overall accuracy was 94% and the kappa coefficient was 0.87.

(a)				
		late	on time	early
late	A	91.18	3.03	9.09
	B	85.29	6.06	9.09
	C	85.29	6.06	18.18
on time	A	8.82	81.82	12.12
	B	11.76	57.58	9.09
	C	11.76	72.73	27.27
early	A	—	15.15	78.79
	B	2.94	36.36	81.82
	C	2.94	21.21	54.55
(b)				
		late	early+on time	
late	A	97.06	7.58	
	B	85.29	9.09	
	C	85.29	15.15	
early+on time	A	2.94	92.42	
	B	14.71	90.91	
	C	14.71	84.85	

Table 4

Transformed divergence separability index between pairs of the three rice cohorts. For each cohort, we used the 100 training pixels to estimate the index for both scenes combined (A), only the September (B) or the November (C) scenes. We also show the separability between the ‘late’ cohort and the ‘early’ and ‘on time’ cohorts combined.

		late	on time
on time	A	1.91	
	B	1.43	
	C	1.31	
early	A	1.92	1.88
	B	1.26	0.86
	C	1.16	0.89
early+on time	A	1.78	
	B	1.22	
	C	1.05	