# Mapping Crop Types, Irrigated Areas, and Cropping Intensities in Heterogeneous Landscapes of Southern India Using Multi-Temporal Medium-Resolution Imagery: Implications for Assessing Water Use in Agriculture

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## Abstract

*In regions of water scarcity, mapping individual crops, cropping intensities and irrigation can contribute significantly to understanding agricultural water use. But such mapping is challenging in landscapes dominated by small-scale traditional agricultural land holdings with high spatial and temporal heterogeneity. Here, we assessed the benefit of using multi-temporal 24 m resolution LISS-III imagery to characterize cropping systems in the Malaprabha basin of southern India. We used hierarchical stacked supervised classification to create three increasingly detailed maps showing: (a) single rainfed paddy rice versus continuously irrigated sugarcane, (b) irrigated versus rainfed areas, and (c) multiple cropping. Although increasing detail was accompanied by decreasing overall accuracies (89 percent, 74.6 percent and 60.1 percent respectively), using multi-temporal imagery out-performed single imagery alone in all cases. Results also led to higher estimates of total (69.8 percent) and irrigated (34.7 percent) cropland than previous single-imagery studies and census data, revealing the high uncertainty in crop estimates in this region.*

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## Introduction

Agricultural land, including crops and pastures, currently covers a third of the world's land surface (Ramankutty *et al.*, 2008). This has led to dramatic changes in land cover (e.g., deforestation) in many regions of the world. But in areas with a long tradition of agriculture, such as South Asia, the most significant process may be fine-scale intensification in agricultural land use (Ellis *et al.*, 2009), including: changes in crop type, shortening of crop rotations and increased multiple cropping, increased irrigation and fertilizer inputs, and changes in tillage practices. In water-limited regions, such changes are often driven by new technologies that enable groundwater exploitation, as well as expansions in the surface irrigation network. These intensification processes can increase local and downstream water shortages, reduce biodiversity, and alter biogeochemical cycles thereby creating problems of nutrient excess or shortage (Matson *et al.*, 1997; Tilman *et al.*, 2002; Keys and McConnell, 2005).

Detecting and estimating fine-scale changes in agricultural land uses is therefore important from a global as well as regional and local perspective. In particular, estimating irrigated areas, cropping intensities, and areas of crops with different water requirements can be a significant contribution to water resource governance. This is especially true in regions where ground-based data collection systems are weak, inaccurate, and aggregated by administrative rather than hydrological boundaries. Such data can also contribute to the debate on water use efficiencies in agriculture (Vaidyanathan and Sivasubramaniyan, 2004).

Mapping agricultural land cover using remote sensing is challenging in regions with high spatial and temporal heterogeneity, characteristic of areas dominated by small-scale traditional agricultural holdings such as the densely populated rural landscapes of India (Pax-Lenney and Woodcock, 1997).

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Diversity in crop types, small field sizes, and complex intra- and inter-annual crop rotations (Francis, 1986) can make it difficult to select imagery of sufficiently fine spatial and temporal resolutions to capture the detail on the ground while mapping large extents. Temporal availability of data in the tropics can be restricted by frequent cloud cover, possibly obscuring an entire growing season in monsoonal regions (Murakami *et al*., 2001; Ippoliti-Ramilo *et al*., 2003; Diuk-Wasser *et al*., 2004). The spectral similarity of certain crops can also make classification based on a single moderate resolution image very difficult (Jewell, 1989; Rao, 2008).

Various methods have been employed to try to overcome these challenges. High resolution, hyperspectral, and radar data have been used to address issues of spatial complexity (Peña-Barragán *et al*., 2008), spectral similarities (Rao, 2008), and cloud cover (Panigrahy *et al*., 2005). Time-series MODIS data have been used to distinguish between crops with similar spectral signatures, between irrigated and rainfed areas, and to identify multiple crop rotations (Xiao *et al*., 2005; Biggs *et al*., 2006; Xavier *et al*., 2006). Crop classification can also be improved using multi-temporal imagery to create a time profile of vegetation indices (e.g., NDVI) (Murakami *et al*., 2001; Ippoliti-Ramilo *et al*., 2003), or for analysis as a multi-date stacked image (Oetter *et al*., 2001; Murthy *et al*., 2003). Relatively few studies, however, have focused on the problem of mapping irrigated lands, especially in the complex agricultural landscapes of south Asia (but see research by Thenkabail and colleagues (e.g., Thenkabail *et al*., 2007; Thenkabail *et al*., 2009; Velpuri *et al*., 2009) who have pioneered efforts at mapping irrigated lands in this region).

In this study, we tested the benefit of using multi-temporal moderate resolution (~24 m) imagery to characterize cropping systems (including multiple cropping and irrigation) in the Malaprabha basin of southern India (Figure 1). This basin illustrates well the multiple challenges of using remote sensing to map agricultural land cover in an intensively cultivated and dynamic landscape. Spatial heterogeneity is high, with average household land holdings of 2 to 20 individual fields ranging in size from 500 to 5,000 m$^2$. Temporal heterogeneity is also high, due to sequential cropping on individual fields as well as asynchronous cropping calendars between fields (Figure 2). The objectives of the study were: (a) to distinguish two important cropping practices in the region: single rainfed paddy rice versus continuously irrigated sugarcane, (b) to distinguish irrigated from rainfed areas, and (c) to identify areas of multiple cropping. We analyzed multi-temporal IRS LISS III imagery (24 m resolution) using a step-wise hierarchical stacked supervised classification method. We compared accuracies at different levels of thematic resolution and examined the inter-temporal variations in spectral signature to highlight the sources of variation and similarity. Finally, to examine the benefits of our approach, we also compared our work with similar work conducted by researchers using single imagery data.

## Methods

### Study Area

The study area encompasses the entire catchment of the Malaprabha River in the Belgaum district of the state of Karnataka in southern India, extending approximately 100 km from the headwaters in the Western Ghats to the Navilutheertha dam, covering an area of 2,202 km$^2$ (Figure 1). Elevation ranges from 1,018 to 616 m. The climate of the study area is dominated by a monsoon season from June through October. Rainfall is spatially variable, ranging from $>$ 1,700 mm in the west to 600 mm around the reservoir in the east.

Cultivated areas make up approximately two-thirds of the total land area in Belgaum district (Census of India, 2001). The district is densely populated (314 people/km$^2$ in 2001). Total agricultural land has remained stable since the 1970's but agricultural intensification and fragmentation

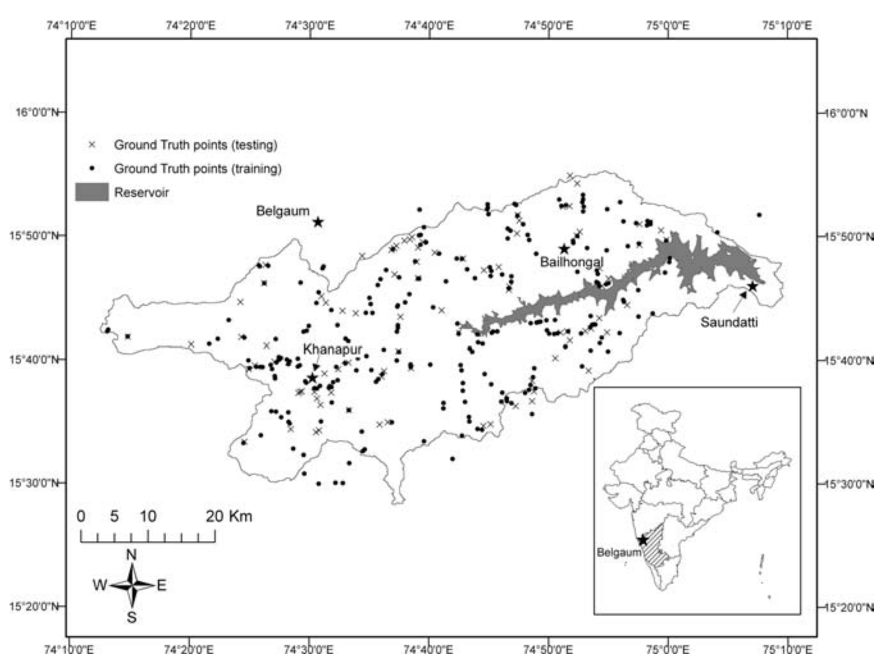


Figure 1. Map of the study area showing the Malaprabha basin (main map) in the state of Karnataka, India.

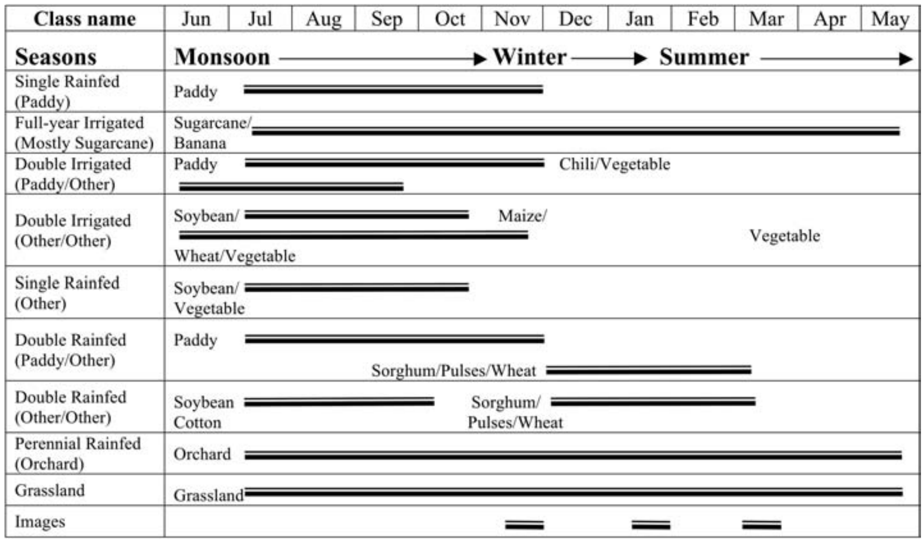


Figure 2. Cropping calendar for the Malaprabha basin, showing the agricultural classes used in this study with some examples of the most common crops for each class and season.

have increased. Double cropping increased from <2 percent of total sown area in 1970 to 33 percent in 2000, and average land holdings decreased from 3.26 to <2 ha (Datanet India, 2008). From 1971 to 2004, subsistence dryland crops (e.g., millet and sorghum) declined while cash crops (e.g., soybeans, maize, and sugarcane) increased (Datanet India 2008). Increased irrigation in the region was driven by the building of the Navilutheertha dam, which provided irrigation downstream and also made water available upstream through lift irrigation projects. There was also a rise in the number of deep borewells used for irrigation in the western part of region (Wallach, 1984; Datanet India, 2008). The majority of fields are cropped during the monsoon (*kharif*, June to November) season, and if double cropped, then planted either in the winter (*rabi*, November to February) or the summer (February to May) (Figure 2).

#### Data Description

Linear Imaging and Self to Scanning Sensor (LISS-III) IRS satellite imagery from RESOURCESAT-1 (IRS-P6) was used in this study. Imagery was 23.5 m resolution and included four bands: green (0.52 to 0.59 μm), red (0.62 to 0.68 μm), near infrared (0.77 to 0.86 μm), and mid-infrared (1.55 to 1.70 μm). The study area straddled two paths of the sensor (96/62 and 97/62). Usable imagery was not available during the peak monsoon growth period (June to October) because of continuous cloud cover. We therefore chose images from the end of the monsoon season [22 November (Path/Row 96/62) and 29 (97/62)], winter [14 January (96/62) and 19 January (97/62)], and summer [03 March (96/62) and 08 March (97/62)] in 2007.

#### Image Preprocessing

Images were geometrically and atmospherically corrected prior to analysis. We georectified the images in ArcGIS© using a first order polynomial equation fit to ground control points obtained from Survey of India topographic maps (1976; 1:50 000 scale) and GPS readings in the field. RMS error for all geo-rectifications was 13 to 21 m (less than one pixel). The imagery was converted to radiance in units of W/(cm$^2$ • nm • sr) using the scaling factors provided with the data. Atmospheric correction was then performed using the FLAASH module in ENVI ver. 4.7, which uses the MODTRAN-4 radiative transfer model (ITT Visual Information Systems, 2007). The model corrected for Rayleigh and aerosol scattering and for general haze (visibility) across all bands for each image.

#### Classification

Because we were principally interested in mapping agriculture, we first masked out most other cover types. Cloud cover and shadows were masked following atmospheric correction and prior to any classification. Water bodies were masked out using supervised classification with unambiguous reservoirs and rivers as training sites. Village areas were masked out using the "built-up" land cover class of the Karnataka State Remote Sensing Applications Center (KSRSAC) 2006 land-cover map (KSRSAC, unpublished data, 2006). The KSRSAC map was developed using merged PAN+LISS3 data, and therefore has a high spatial resolution of 6 m. To mask forest areas, we conducted a supervised classification using training sites derived from both field work and the KSRSAC map to map forest land cover. This forest cover map was then overlaid with the KSRSAC map. Areas designated as forest in both maps were classified as such, while areas classified as forest in only one map were classified as such only after confirmation through manual image inspection. All forested areas were masked out, including degraded forest areas, scrubland, and tree groves. Grasslands were difficult to separate at this stage and hence were not masked out.

Between December 2007 and July 2008, we interviewed farmers in their fields and recorded the crop type and use of irrigation in each field for each month from January to December 2007. We took GPS coordinates of ground-data (GD) points in every field that was larger than 40 m × 40 m ($n$ = 622) in the largest possible area of homogenous crop cover. The GD points were used to designate GD polygons of homogeneous land-cover/land-use. To do so, we overlaid each GD point on the IRS images and manually designated a polygon of at least four pixels around each point that was located in an area of homogenous spectral signature for each of the three images. Where this was not easily accomplished (because of small field sizes and highly variable field cover), we overlaid the GD point on high resolution imagery in Google Earth™ (2008 imagery) and drew a polygon around each point based on clearly visible field boundaries.

We used a stacked hierarchical procedure to create three nested levels of classification (Figure 3). All four bands from each of the three image dates were "stacked" (combined and analyzed as one group rather than classifying each image separately thereby incorporating data from multiple time periods), and a Gaussian maximum likelihood classifier was used to conduct three supervised classifications. Classification was performed in three steps, with each step subdividing classes from the previous step to create a nested classification. We first produced a three-class map which distinguished a single crop of rainfed paddy rice (*Single Rainfed (Paddy)*) and full-year irrigated crops (*Full-year Irrigated (Mostly Sugarcane)*) from all other agricultural land (Objective 1). We then derived a four-class map (again using supervised classification) by sub-dividing the other agricultural land into irrigated and rainfed classes (Objective 2). Finally, we created a nine-class map by further sub-dividing the irrigated class into two double-cropped types (*Double Irrigated (Paddy/Other)* and *Double Irrigated (Other/Other)*) and the rainfed class into five more specific classes, including two double-cropped types (*Double Rainfed (Paddy/Other)* and *Double Rainfed (Other/Other)*), a single crop type (*Single Rainfed (Other)*), a perennial type (*Perennial Rainfed (Orchard)*), and *Grassland*. In all cases, the "Other" refers to a range of different crops that are frequently cultivated in rotation; examples are shown in Figure 2. The classes and hierarchical structure were developed by grouping the GD points into natural groupings based on farmer interviews. Some GD polygons were deleted based on spectral signatures to decrease variability due to uncertainty in the interview data and variability in planting dates of individual crops. The spectral signature of each polygon was compared against the average spectral signature of its group (Figure 4, Figure 5, and Figure 6) and outliers were removed. A total of 341 GD polygons were used for training and 90 for accuracy assessment (Figure 1; Table 1) using the kappa statistic (Story and Congalton, 1986; Congalton and Green, 2009). Accuracy was measured and reported on a pixel (rather than polygon) basis to account for edge effects due to small field size.

The spectral signatures of the nine classes were intercompared using the Jeffries-Matusita (J-M) distance, or separability index, which ranges from 0 (identical classes) to 2 (complete separation of classes) (Online Supplement, *http://www.geog.mcgill.ca/~nramankutty/Heller_PERS2012_OnlineSupplement.pdf*) to determine how well the individual classes were separated in our classification procedure. Values over 1.9 generally indicate good separation, values between 1.0 to 1.9 indicate moderate separation, and values under 1.0 indicate that classes could be reasonably grouped together (Richards and Jia 2006). J-M was calculated between all classes for each image date (four bands each) as well as for a combination of all image dates (12 bands).

### Postprocessing and Analysis

The two images covering the study area were classified separately and subsequently mosaicked in order to minimize bidirectional reflectance and atmospheric effects that could not be corrected during preprocessing of data. Because of clouds in the November image of the east side of the basin, the western set of images was used for all areas of overlap. Accuracy assessments were performed on the mosaicked image. We compared the results of our study to two other datasets: (a) Census of India, 2001 (Part-B: Village amenities directory, including five-fold land-use data), and (b) a land-cover classification for the Krishna River basin by Velpuri *et al.* (2009) at the International Water Management Institute (IWMI). IWMI used unsupervised classification on 30 m resolution Landsat ETM+ imagery (circa. 2000) from a single time period (main cropping season, *Kharif*). We clipped their final map to conform to our study area boundaries, and combined their 19 classes to best match our classes.

## Results

The hierarchical classification resulted in three progressively more detailed maps, but the increase in thematic resolution was accompanied by a decrease in map accuracy.

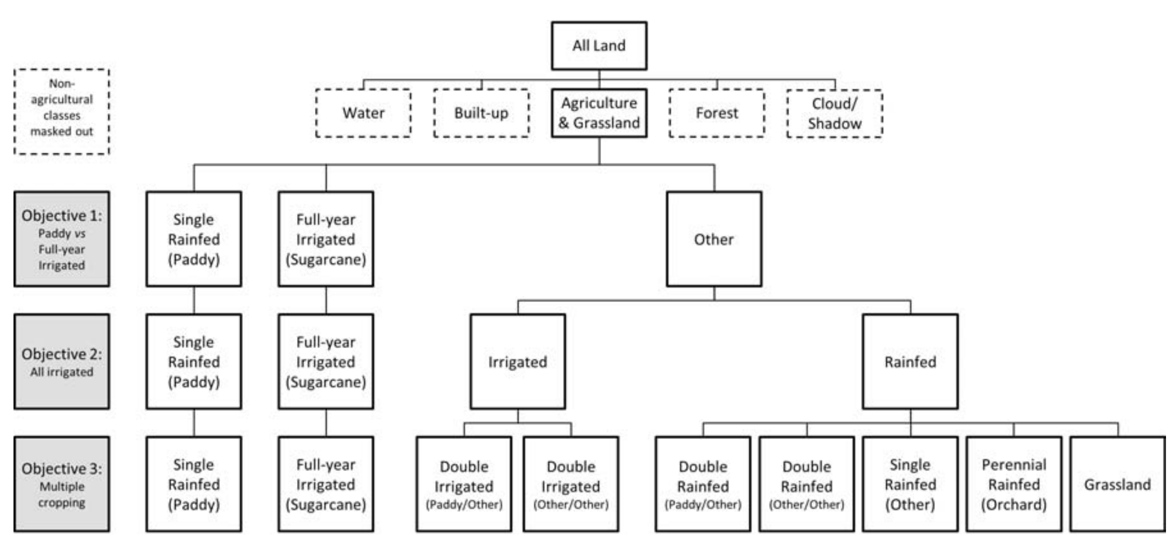


Figure 3. Hierarchical classification of land-use/cover types mapped in the analysis.

TABLE 1. NUMBER OF GROUND DATA POLYGONS AND CORRESPONDING NUMBER OF PIXELS USED FOR TRAINING AND ACCURACY ASSESSMENT

| | Training | | Accuracy | |
|---|---|---|---|---|
| | Polygons | Pixels | Polygons | Pixels |
| Single Rainfed (Paddy) | 49 | 784 | 6 | 140 |
| Full-year Irrigated (Mostly Sugarcane) | 111 | 1522 | 27 | 340 |
| Double Irrigated (Paddy/Other) | 24 | 141 | 7 | 40 |
| Double Irrigated (Other/Other) | 24 | 258 | 11 | 96 |
| Single Rainfed (Other) | 8 | 104 | 5 | 31 |
| Double Rainfed (Paddy/Other) | 17 | 128 | 3 | 21 |
| Double Rainfed (Other/Other) | 72 | 684 | 18 | 233 |
| Perennial Rainfed (Orchard) | 19 | 310 | 4 | 45 |
| Grassland | 17 | 747 | 9 | 215 |
| Total | 341 | 4678 | 90 | 1161 |

#### Accuracy of Classifications

The first objective of this study was to distinguish two key crop types: a single crop of rainfed paddy rice from irrigated full-year crops such as sugarcane (Figures 3 and 4). This three-class map (Plate 1) yielded an overall accuracy of 89 percent with a kappa index of 0.81 (Table 2), with little confusion between the two classes. The J-M index shows that the separability of the two classes was enhanced by the use of three image dates (J-M = 1.99 for 12-band analysis versus 1.51 to 1.92 using imagery from only one time period) (Online Supplement: *http://www.geog.mcgill.ca/~nramankutty/Heller_PERS2012_OnlineSupplement.pdf*), although the November imagery alone was sufficient to separate the classes on the western side of the basin. Both *Single Rainfed (Paddy)* and *Full-year Irrigated (Mostly Sugarcane)* showed higher producer's accuracies (95.0 percent and 89.4 percent) than user's accuracy (82.6 percent and 84.0 percent). This indicates that some areas in the *Other* agriculture class have been misclassified, likely due to the high variability in cropping calendars for different crops, some of which coincide with paddy and sugarcane (Table 2).

The second objective was to further distinguish irrigated from rainfed areas (Figure 3). This four-class map yielded an overall accuracy of 74.6 percent and a kappa coefficient of 0.63 (Table 3). The user's and producer's accuracies of the *Other Rainfed* class were high (83.4 percent and 72.8 percent, respectively), with most of the misclassified pixels originating from the *Other Irrigated* class. Accuracies of the *Other Irrigated* class, however, were low (19.8 percent and 23.5 percent), with frequent confusion with *Other Rainfed.* Both the *Other Irrigated* and *Other Rainfed* classes show high spectral variability for all three image dates (Figure 5).

The third objective was to determine the extent of multiple cropping within the basin (Figures 3 and 6). The overall accuracy of the nine-class map was 60.1 percent with a kappa coefficient of 0.52 (Table 4). Highest user's and producer's accuracy in new classes within the nine-class map were for *Double Rainfed (Other/Other)* (70.2 percent and 57.5 percent, respectively) and *Grassland* (64.6 percent and 38.1 percent). Accuracy for other classes was less than 30 percent. J-M indices showed that using three images resulted in substantially better separability as compared to using only one image (Online Supplement: *http://www.geog.mcgill.ca/~nramankutty/Heller_PERS2012_OnlineSupplement.pdf*), though even the use of three images was insufficient to consistently separate all classes. *Double Irrigated (Other/Other)* and *Double Rainfed (Other/Other)* had particularly low separability (J-M = 1.2 to 1.7).

#### Estimates of Crop Types and Irrigated Area

Given the above accuracies, we relied primarily on the results of the four-class map to estimate the area under different agricultural classes. Overall, net cultivated area, which

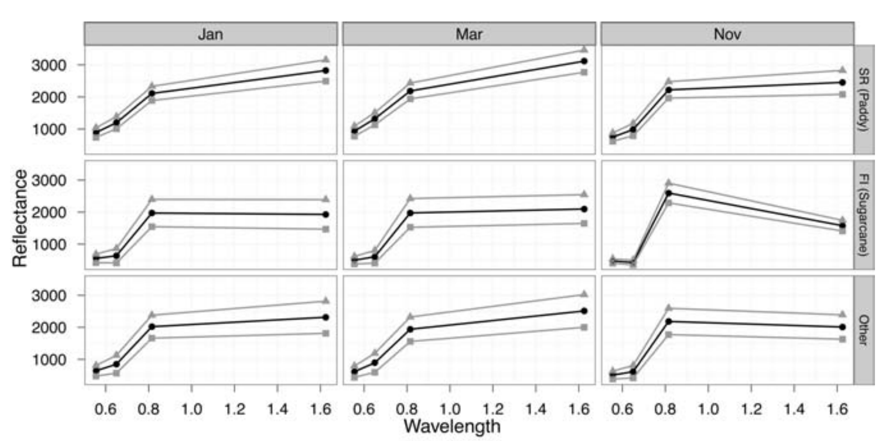


Figure 4. Average spectral signatures (showing one standard deviation on either side of the mean) of the ground data points for the three agricultural classes at each imagery date. SR – single rainfed; FI – Full-year irrigated.

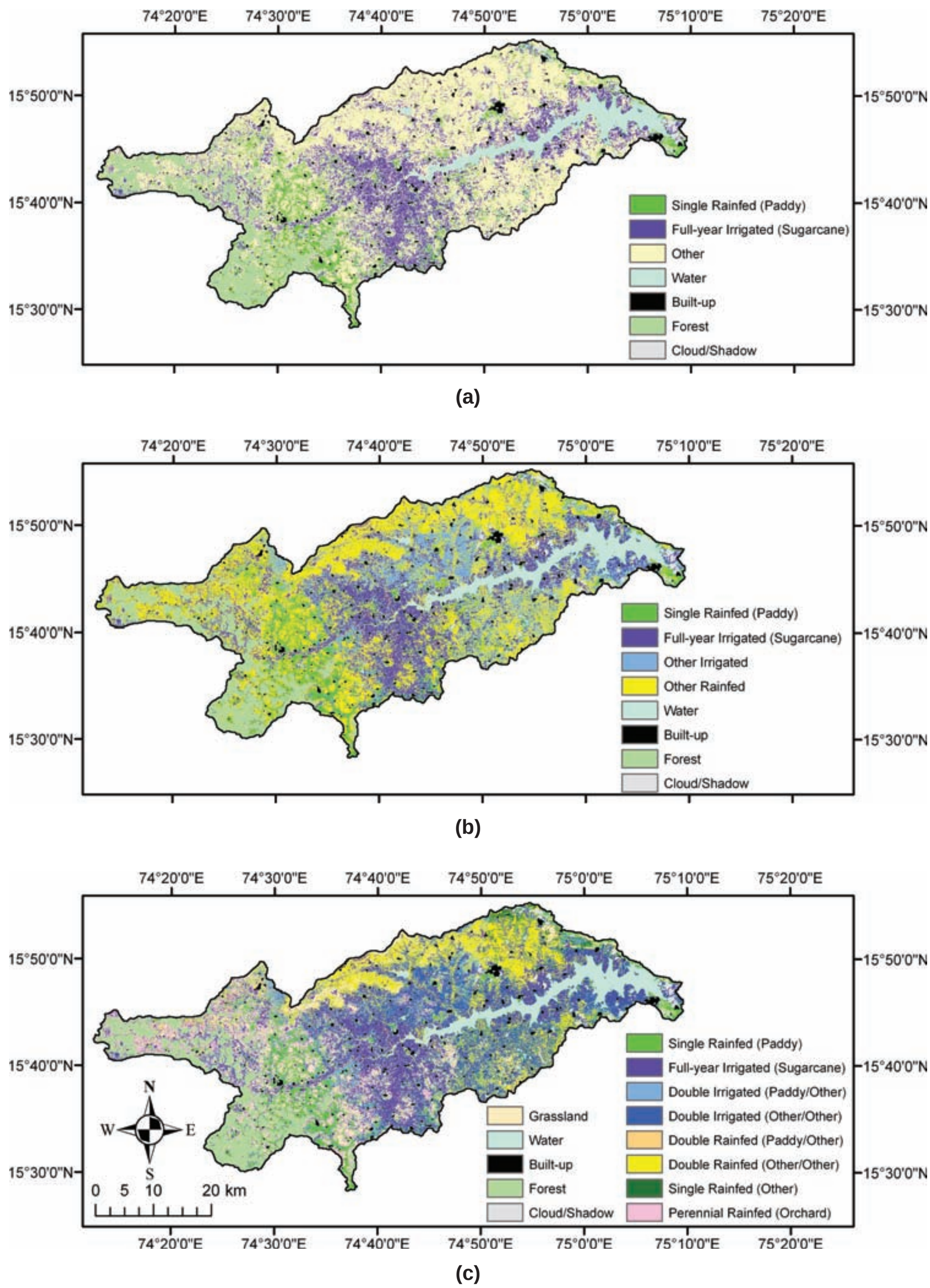


Plate 1. Land cover maps of the Malaprabha Basin showing: (a) three-class, (b) four-class, and (c) nine-class results of the hierarchical multi-temporal remote sensing analysis.

includes all agricultural land covers (not including grassland) made up 69.9 percent of the total land area (Table 5 and Table 6). *Single Rainfed (Paddy)* made up 8.1 percent of the total area (Table 5) and occurred mostly in the western part of the study area (Plate 1a). *Full-year Irrigated (Mostly sugarcane)* crops accounted for 16.1 percent and were located primarily in the central region and along the reservoir in the east. Total irrigated area (*Full-year Irrigated (Mostly Sugarcane)* plus *Other Irrigated*) occupied 34.8 percent of the total study area (Table 5 and Table 6). *Other Irrigated* occurred in the central and western parts of the study area typically somewhat further from the reservoir than the *Full-year Irrigated (Mostly Sugarcane)* class (Plate 1b). Total rainfed area (*Single Rainfed (Paddy)* plus *Other Rainfed,* not including grassland) encompassed 35.1 percent of the total area, with *Other Rainfed* occurring throughout the study area along the outer boundaries, furthest away from the reservoir. Although estimates based on the nine-class map should be interpreted carefully given the high uncertainties, approximately 36.5 percent of the basin was double cropped, 16.1 percent was under full-year crops and a further 7.3 percent under perennial crops (Table 6). Total area

Table 2. Confusion Matrix for Three-Class Map

| Class | Ground Data (# pixels) | | | User's accuracy (%) |
|---|---|---|---|---|
| | Single Rainfed (Paddy) | Full-year Irrigated (Mostly sugarcane) | Other | |
| Single Rainfed (Paddy) | 133 | 1 | 27 | 82.6 |
| Full-year Irrigated (Mostly Sugarcane) | 0 | 304 | 58 | 84.0 |
| Other | 7 | 35 | 596 | 93.4 |
| Producer's accuracy (%) | 95.0 | 89.4 | 87.5 | Overall accuracy: 89.0%<br>Kappa coefficient: 0.807 |

planted in paddy rice (i.e., sum of *Single Rainfed (Paddy)*, *Double Rainfed (Paddy/Other)* and *Double Irrigated (Paddy/Other)*) was 18.5 percent, sugarcane was 16.1 percent, and other crops occupied 35.3 percent of the basin.

Comparison of our results with other datasets shows that our estimate of total agricultural area (70 percent) in the Malaprabha basin is much higher than that of IWMI (43 percent; Velpuri *et al.*, 2009) but similar to the official census statistics (64 percent to 69 percent (Census of India, 2001)) (Table 7; Plate 2). Our study suggests that the total cultivated area was roughly split between rainfed (35.1 percent of basin) and irrigated areas (34.7 percent). The census and IWMI suggest more rainfed than irrigated areas, with both reporting that ~15 percent to 16 percent of the basin was irrigated in 2000/2001, but disagreeing on the extent of rainfed cropland (and therefore total cropland). Compared to IWMI, we estimated 2.2 times greater irrigated croplands and 1.3 times greater rainfed areas. Comparisons of individual crop types and single versus multiple crops were difficult due to differences in land-cover categories. For other land covers, we estimated much lower areas of forests and grasslands than IWMI.

## Discussion

The results of this study suggest that multi-temporal/multi-spectral remote sensing approaches are useful for mapping land cover across broad regions of high spatial and temporal complexity with multiple cropping and mixed irrigation. Although an increase in thematic complexity in classification was accompanied by a decrease in map accuracy, the multi-temporal approach proved useful, relative to using a single-date image alone, for accurate classification of major crop types and land use practices.

### The Value of Multi-temporal Imagery

In all cases, combining late Monsoon (November), winter (January), and summer (March) imagery led to higher separability of agricultural classes than using a single image alone. Imagery from the main cropping season (e.g., November) is typically used for single image land-cover classifications in this region. In our case, using November imagery alone was only sufficient to clearly separate (J-M index $>$ 1.9) land covers in the three-class map (*Single Rainfed (Paddy)* from *Full-year Irrigated (Mostly Sugarcane)*) on the west side of the basin, although multi-temporal analysis was superior (had a higher J-M Index) even in this instance. March and January single images were not sufficient even for the three-class map. Poor separation in the January images for the *Full-year Irrigated (Mostly Sugarcane)* class was likely due to the variability within the class during this time, as January is a time of transition for sugarcane when many fields have recently been harvested, burned or replanted.

Distinguishing among the more detailed land covers in the four- and nine-class maps was dependent on having the multi-temporal data. For example, when distinguishing *Double Irrigated (Other/Other)* from the two *Double Rainfed* classes, J-M indices increased from 0.4 to 0.9 using November images alone to 1.3 to 1.8 with the multi-temporal data. Although the *Double Irrigated (Other/Other)* class still had lower than expected accuracy (see discussion below), using multi-temporal data is one way to enhance its separability. Similarly, separability of the grassland type from other types was substantially better using multi-temporal imagery than the November image alone. For all classes, spectral signatures suggest that the largest differences among crop types were in the mid-infrared band, which is sensitive to water content in plants. Using multi-temporal data thus takes advantage of differing water availability across the seasons combined with individual plant water use characteristics.

### Mapping Irrigation

The three-class analysis showed with high accuracy that irrigated sugarcane covers twice the area of single-cropped rainfed paddy (16 percent versus 8 percent), while the four-class analysis provided an equally good estimate of total rainfed area (35 percent) and much less accurate estimate of total irrigated area (35 percent). From the results of the

Table 3. Confusion Matrix for Four-Class Map

| Class | Ground Data (# pixels) | | | | User's accuracy (%) |
|---|---|---|---|---|---|
| | Single Rainfed (Paddy) | Full-year Irrigated (Mostly Sugarcane) | Other Irrigated | Other Rainfed | |
| Single Rainfed (Paddy) | 133 | 1 | 15 | 12 | 82.6 |
| Full-year Irrigated (Mostly Sugarcane) | 0 | 304 | 28 | 30 | 84.0 |
| Other Irrigated | 0 | 24 | 32 | 106 | 19.8 |
| Other Rainfed | 7 | 11 | 61 | 397 | 83.4 |
| Producer's accuracy (%) | 95.0 | 89.4 | 23.5 | 72.8 | Overall accuracy: 74.6%<br>Kappa Co-efficient: 0.628 |

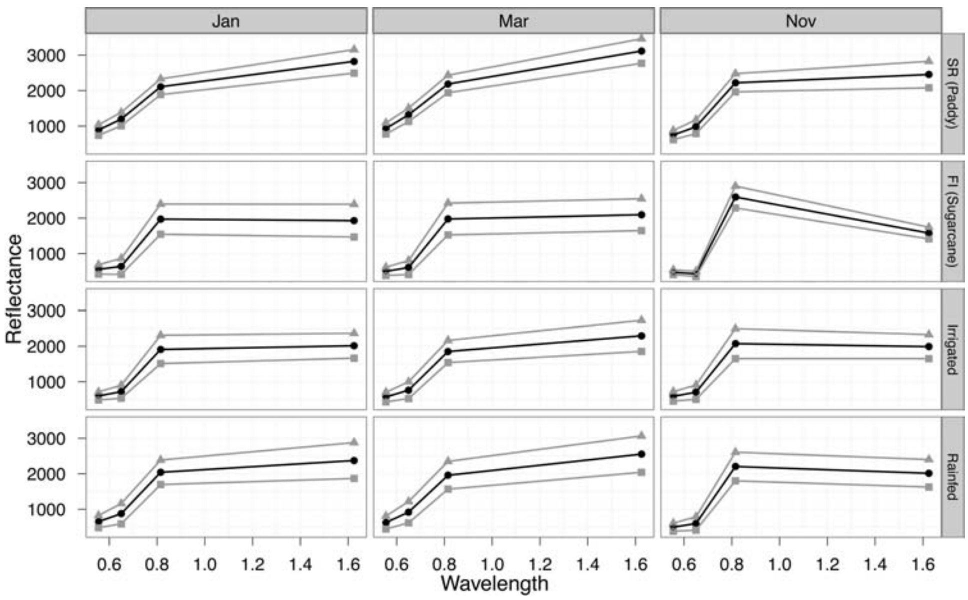


Figure 5. Average spectral signatures (showing one standard deviation on either side of the mean) of the ground data points for the four agricultural classes at each imagery date. SR – single rainfed; FI – Full-year irrigated.

nine-class map, it is clear that the loss of accuracy in this irrigated category was primarily due to confusion between the *Double Irrigated (Other/Other)* and *Double Rainfed (Other/Other)* and, to a lesser degree, *Double Rainfed (Paddy/Other).* There are several reasons for this. First, even in the field, the distinction between rainfed and irrigated is often more of a continuum than the binary classes assigned here. While irrigated crops such as sugarcane require dedicated irrigation systems, our fieldwork showed that farmers can often coax other crops through the dry season by supplementing a primarily rainfed crop with small amounts of emergency manual watering. As such, *Double Rainfed* types frequently include small amounts of manual irrigation. Similarly, *Double Irrigated* is likely to be primarily rainfed during the monsoon season. As such, distinguishing the categories is difficult even with multi-temporal data. From a water-use perspective, it may be more relevant in future land cover classifications to focus on single versus double and multiple cropping systems using multi-temporal data to estimate total water use in a region.

Despite these issues, the results suggest a substantial increase in irrigated crops in the region. Even if one assumes a more conservative figure of 25 percent to 30 percent irrigated, equivalent to 36 percent to 43 percent of net cropped area, this amounts to a dramatic increase from the 11 percent of the net cropped area which was irrigated in 1971 (Census 1971 data). Field visits indicated that this expansion of irrigation has happened due to both a rapid spread of groundwater pumping (borewells) and also direct lift irrigation from the Malaprabha or the backwaters of the Naviluteertha reservoir. The consequence of this dramatic increase in upstream irrigation has been a decline in inflows into the reservoir, resulting in significant water shortages for both urban users (such as the town of Bailhongal) as well as farmers served by the reservoir (Badiger and Reshmidevi, 2010).

#### Intercomparison with Other Data Sets

For comparison of total cultivated area, we used the census estimates (Census of India, 2001) as a baseline. Census data, which are collected every 10 years, are a comprehensive assessment painstakingly compiled from individual village accountants. Our estimate of total cultivated area in 2007 (70 percent) is similar to the official census statistics (64 percent to 69 percent in 2001 (Census of India, 2001)). IWMI's estimate (Velpuri *et al.*, 2009) of 43 percent total cultivated area is significantly lower. It is difficult to gauge why IWMI might underestimate total cultivated area; it could be due to their effort being focused on mapping the entire Krishna River basin, with fewer ground data in the smaller Malaprabha River basin.

When it comes to irrigated versus rainfed cultivated areas, it is well known that the census irrigated area estimates are typically underestimates of the real area because farmers have incentive to underreport irrigation because of the higher taxes on irrigated land as well as the use of clandestine lift irrigation practices (Vaidyanathan and Sivasubramaniyan, 2004). Vaidyanathan and Sivasubramaniyan (2004) report that in one small river of Tamilnadu, actual irrigated area is estimated to be 2 to 3 times the official statistics. Thus, our estimate of irrigated cropland being twice the official census estimates in the Malaprabha basin may be reasonable. Further, irrigated area (but not total cropland area) likely increased over the seven-year period between the census estimate of 2000 and our estimate in 2007 (Belgaum District, 2007; Thenkabail *et al.*, 2007). The IWMI estimates of irrigated cropland area matches the census estimate, and it is their rainfed cropland area which is significantly underestimated compared to the census. However, given the discrepancy in total cultivated area and the foregoing discussion about census estimate of irrigation being typically underestimated, we believe that IWMI may be underestimating both rainfed and irrigated cropland area.

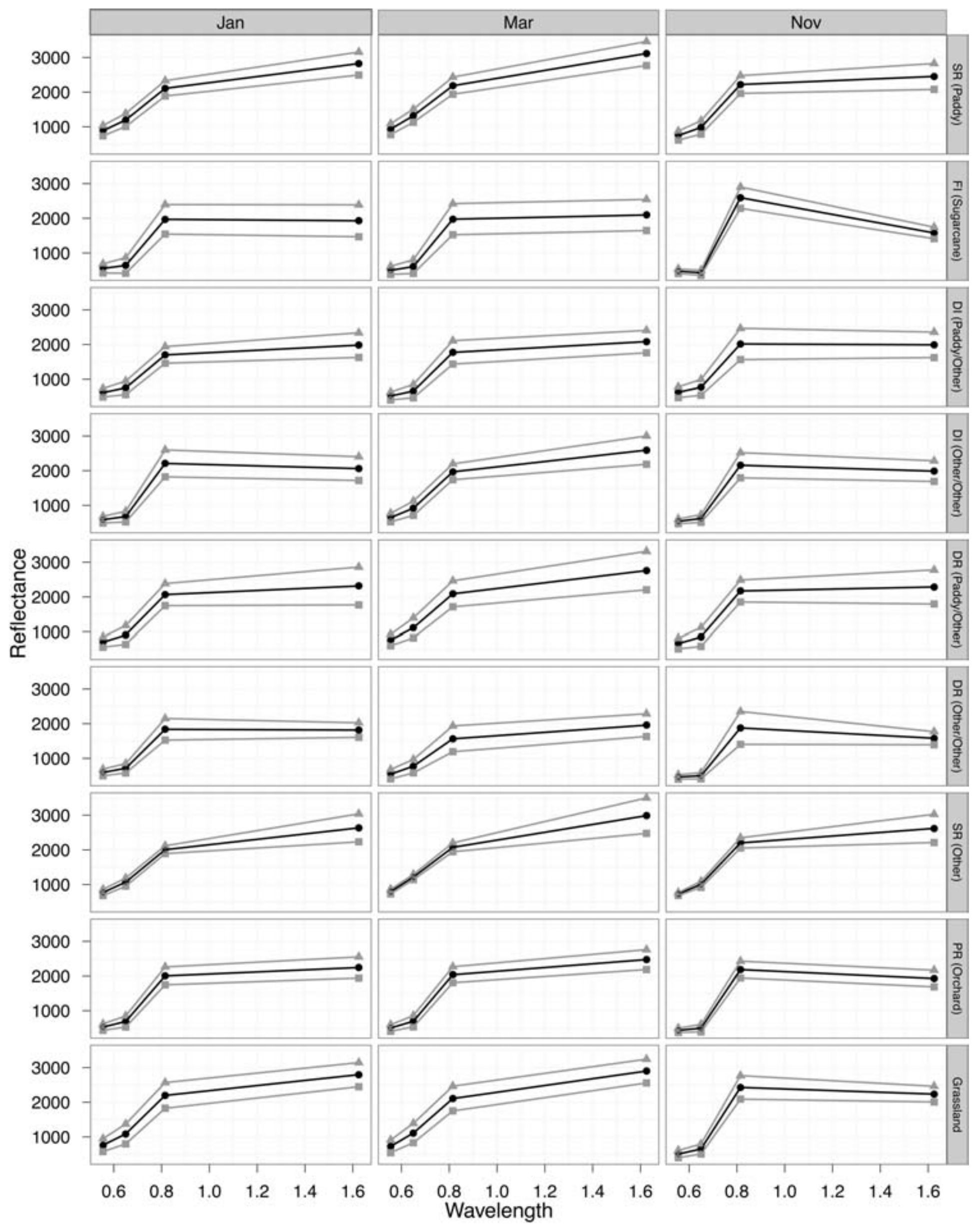


Figure 6. Average spectral signatures (showing one standard deviation on either side of the mean) of the ground data points for the nine agricultural classes at each of the three imagery dates. SR – single rainfed; FI – Full-year irrigated; DI – Double Irrigated; DR – Double Rainfed; SR – Single Rainfed; PR – Perennial Rainfed.

IWMI's higher forest area estimate can be partly explained by the fact that it is not a pure class in their data set, but includes mangroves and riparian vegetation. However, our field investigation shows that the large areas mapped as riparian vegetation by IWMI along the river are actually irrigated agriculture (which lends support to our suggestion that IWMI may have underestimated irrigated area in the basin). Also, our forest cover estimate heavily relied on the 6 m resolution KSRSAC map, which we checked against high-resolution Google Earth™ images for forest cover where available and found to be reliable.

Finally, our estimate of grassland area is much lower than IWMI's. IWMI's grassland class is again not a pure class and includes barren land, scrubs/hilly vegetation, and other land-use/land-cover. However, this alone cannot explain the discrepancy between our estimates because most of the basin is cultivated or in forests as shown in Table 7, and there is not a significant amount of other land cover in the basin. Moreover, our grassland estimate may be robust given our use of multi-temporal data, which substantially improved its separability from other classes when compared to using any single image alone.

Overall, the IWMI study (Velpuri *et al.*, 2009) presents the best available alternate data set for intercomparison. But major caveats need to be noted. First, the IWMI data represents the year 2000, while our study represents 2007, and some differences between the two could be simply due to differences in time periods. However, while our field

TABLE 4. CONFUSION MATRIX FOR NINE-CLASS MAP

| | Ground Data (# Pixels) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Single Rainfed (Paddy) | Full-year Irrigated (Mostly sugarcane) | Double Irrigated (Paddy/ Other) | Double Irrigated (Other/ Other) | Single Rainfed (Other) | Double Rainfed (Paddy/ Other) | Double Rainfed (Other/ Other) | Perennial Rainfed (Orchard) | Grassland | User's accuracy (%) |
| Single Rainfed (Paddy) | 133 | 1 | 8 | 7 | 0 | 3 | 0 | 0 | 9 | 82.6 |
| Full-year Irrigated (Mostly sugarcane) | 0 | 304 | 7 | 21 | 3 | 2 | 18 | 7 | 0 | 84.0 |
| Double Irrigated (Paddy/Other) | 0 | 16 | 12 | 4 | 1 | 7 | 8 | 3 | 1 | 23.1 |
| Double Irrigated (Other/Other) | 0 | 8 | 2 | 14 | 0 | 1 | 62 | 7 | 16 | 12.7 |
| Single Rainfed (Other) | 0 | 0 | 0 | 19 | 6 | 0 | 4 | 0 | 8 | 16.2 |
| Double Rainfed (Paddy/Other) | 5 | 0 | 3 | 3 | 0 | 1 | 3 | 0 | 68 | 1.2 |
| Double Rainfed (Other/Other) | 0 | 5 | 0 | 20 | 10 | 7 | 134 | 1 | 14 | 70.2 |
| Perennial Rainfed (Orchard) | 0 | 5 | 0 | 0 | 4 | 0 | 0 | 12 | 17 | 31.6 |
| Grassland | 2 | 1 | 8 | 8 | 7 | 0 | 4 | 15 | 82 | 64.6 |
| Producer's Accuracy (%) | 95.0 | 89.4 | 30.0 | 14.6 | 19.4 | 4.8 | 57.5 | 26.7 | 38.1 | |
| | | | | | | | | | | Overall accuracy: 60.1% |
| | | | | | | | | | | Kappa co-efficient: 0.517 |

observations suggest large year-to-year fluctuations in irrigated areas within the region, no large changes in total cultivated area, forests, or grassland area are expected over the seven-year time period. Second, the IWMI region of interest was >100 times larger than ours, and not fine tuned for the Malaprabha River basin (for example, they had significantly less local ground data available). Further, the use of multi-temporal data adds significantly to processing time, which would not have been possible in a 200,000 km$^2$ mapping effort such as IWMI's. Finally, the objectives of their classification (to examine how estimates of irrigated areas change with spatial resolution of satellite data) were not the same as ours (the three specific objectives outlined in the introduction). The methodology and choice of land-cover classes were thus different. Despite these caveats, the intercomparison still provides valuable insights, and suggests that using multi-temporal imagery may improve land-cover mapping in regions of high temporal variability.

### Mapping in Regions of High Spatial and Temporal Complexity and Resolution

The difficulty in accurately mapping the most detailed classes (nine-class map) reflects both the spatial and temporal complexity of the landscape. In particular, small field sizes, changing field boundaries through time, and high heterogeneity in cropping pathways contributed to the mapping challenges.

Crop classes labeled "*Other*," which includes vegetables, chilli, and pulses are typically grown in very small patches. Moreover, when two or more crops are grown in sequence on a field, whether irrigated or not, the "second" crop is usually grown on a subset of the total monsoon-season field due to lower water availability. Accurately delineating field boundaries and collecting sufficient and accurate ground data was thus challenging for such rare classes, and it is likely that some or many of these classes included high proportions of mixed pixels, thus contributing to reduced classification accuracies. Moreover, due to the high number of different crops in the region, many of the *Other* crop classes have high intra-class vegetation variability, thus further increasing spectral variability and decreasing accuracy.

Temporal heterogeneity across the landscape was also problematic. The planting and harvest of *Other* crops is less uniform in time than for rice due to the shorter growing periods of these crops. This is especially the case with irrigated crops, where planting and harvesting timing is

TABLE 5. TOTAL AREA BY CLASS FOR EACH OF THE THREE CLASSIFICATIONS

| Class | 3-class (%) | 4-class (%) | 9-class (%) |
|---|---|---|---|
| Single Rainfed (Paddy) | 8.1% 17,836 ha | 8.1% 17,836 ha | 8.1% 17,836 ha |
| Full-year Irrigated (Mostly Sugarcane) | 16.1% 35,452 ha | 16.1% 35,452 ha | 16.1% 35,452 ha |
| Double Irrigated (Paddy / Other) | 57.8% 127,276 ha | 18.7% 41,178 ha | 6.8% 14,974 ha |
| Double Irrigated (Other / Other) | | | 11.9% 26,204 ha |
| Single Rainfed (Other) | | 39.1% 86,098 ha | 1.9% 4,184 ha |
| Double Rainfed (Paddy / Other) | | | 3.6% 7,927 ha |
| Double Rainfed (Other / Other) | | | 14.2% 31,268 ha |
| Perennial Rainfed (Orchard) | | | 7.3% 16,075 ha |
| Grassland | | | 12.1% 26,644 ha |
| Water | 5.4% 11,891 ha | 5.4% 11,891 ha | 5.4% 11,891 ha |
| Cloud | 1.4% 3,083 ha | 1.4% 3,083 ha | 1.4% 3,083 ha |
| Village/Urban | 1.9% 4,184 ha | 1.9% 4,184 ha | 1.9% 4,184 ha |
| Forest | 9.3% 20,479 ha | 9.3% 20,479 ha | 9.3% 20,479 ha |

Table 6. Summary of Main Findings: Proportion of Agricultural Land (Percent of Basin) by Land-use Category

| Water Use | | Cropping Intensity | | Crop type | |
|---|---|---|---|---|---|
| Rainfed | 35.1% | Single crop | 10.0% | Paddy | 18.5% |
| Irrigated | 34.8% | Double crop | 36.5% | Sugarcane | 16.1% |
| | | Full-year crops | 16.1% | Other crops | 35.3% |
| | | Perennial crops | 7.3% | | |

more flexible because farmers are less reliant on natural rainfall. Rainfed paddy and full-year irrigated crops, on the other hand, show more temporal coincidence due to planting with the timing of the rains in the case of paddy or due to the year-round nature of growth in the case of sugarcane.

Improving accuracy in regions of small field sizes and high spatial and temporal complexity can of course be achieved by using higher resolution data (Ozdogan and Woodcock, 2006), but such approaches quickly become prohibitive across large regions. Using high-resolution sampling throughout the basin (e.g., Ellis *et al*., 2009), however, may be a potential intermediate solution.

Table 7. Comparison of the Results of this Study to Those of IWMI (Velpuri *et al*., 2009) and Census of India 2001 Statistics. Census Values are Aggregated from Village-Level Data. As Village Boundaries do not Coincide with the Malaprabha Basin Boundary, We Show a Lower Value Calculated by Aggregating Data from all Villages that Fall Entirely Within the Study Area (Total Village Area of 1,527 km$^2$), while the Upper Value Includes All Villages that Lie Within or Intersect the Basin Boundary (2,871 km$^2$).

| | This study (LISS-III 24 m) | Velpuri (2009) (Landsat 30m) | Census of India (2001); Part-B: Village amenities directory, including five-fold landuse data. |
|---|---|---|---|
| Total cropland | 69.8% | 42.6% | 64 to 69% |
| Rainfed cropland | 35.1% | 26.8% | 49 to 52% |
| Irrigated cropland | 34.7% | 15.8% | 15 to 17% |
| Grassland | 12.1% | 32.8% | |
| Forest | 9.3% | 21.2% | |
| Village/urban | 1.9% | - | |
| Water | 5.4% | 3.4% | |
| Clouds/shadow | 1.4% | - | |
| Representative year | 2007 | 2000 | |

#### Implications for Estimating Water Use

Agriculture is a major draw on water resources in India, contributing to 91 percent of total water withdrawals (FAO, 2010), and leading to rapid groundwater depletion in some parts of the country (Rodell *et al*., 2009). However, a study attempting to estimate the efficiency of agricultural water use in India was hampered by the unreliability of irrigation data (Vaidyanathan and Sivasubramaniyan, 2004). The authors concluded that "an independent and objective estimate of irrigated and un-irrigated areas under different crops" would be needed for refining their estimates of water use efficiency, and that "Satellite imagery, which is available for at least the last 30 years, can be used to compile independent estimates of irrigated and rainfed crop areas in different seasons at different points of time." This study presents an advance in achieving some of these objectives, by developing a data set that would be a key input to analysis of water use in agriculture. By providing separate estimates of cultivated areas of major crops, of single, double, and full-year cropping, and of irrigated area, we would be better able to estimate "green" versus "blue" water components of the hydrological budget. For example, single cropped paddy rice, grown during the Kharif season, is a major user of green water, while full-year irrigated sugarcane is a major user of blue water, and land surface water balance models can be used to estimate these components of the hydrological budget.

## Conclusions

The major outcome of this study is to show the potential of multi-temporal medium resolution satellite imagery to differentiate cropping types, rotations, and irrigation practices in regions of high spatial and temporal complexity. In particular, the results show that it is possible to separate single-cropped rainfed paddy rice from full-year irrigated sugarcane, using only three 24 m IRS LISS images (all from non-monsoon season), with an overall accuracy of 89 percent and high user and producer accuracies. More detailed land-cover classifications can also be produced using this method, although our results showed that increasing detail was accompanied by decreasing accuracy (74.6 percent and 60.1 percent overall accuracies for four-class and nine-class maps, respectively). In all cases, using multi-temporal imagery resulted in substantially better separability (based on J-M Index) than using a single image alone. The results thus suggest the need for multi-temporal images to improve cropland mapping; multisensor-data fusion may offer some promise to better identify complex classes.

Delineating crops accurately is the most crucial step in determining crop water use, and our separation of single-cropped rice from sugarcane thus makes a valuable contribution toward estimating green water use (by rainfed croplands) and blue water use (by irrigated croplands). Despite many years of experience in cropland mapping, large uncertainties in mapping crop types and cropping water sources (irrigated versus rainfed versus supplemental) persist. For example, there were significant differences in croplands mapped using this study with three IRS LISS 24 m images compared to the: (a) International Water Management Institute (IWMI) study which used Landsat 30 m data in fusion with MODIS 250 m temporal data, and (b) non-remote sensing census statistics. Some of the differences can be attributed to differences in: (a) class definitions, and (2) data source and methods used. But it is clear that to enable frequent monitoring of fine-scale agricultural intensification processes and their water use, we need to refine methods that address important elements of the intensification process over large areas, without requiring extensive cost, time, ground data or expertise.

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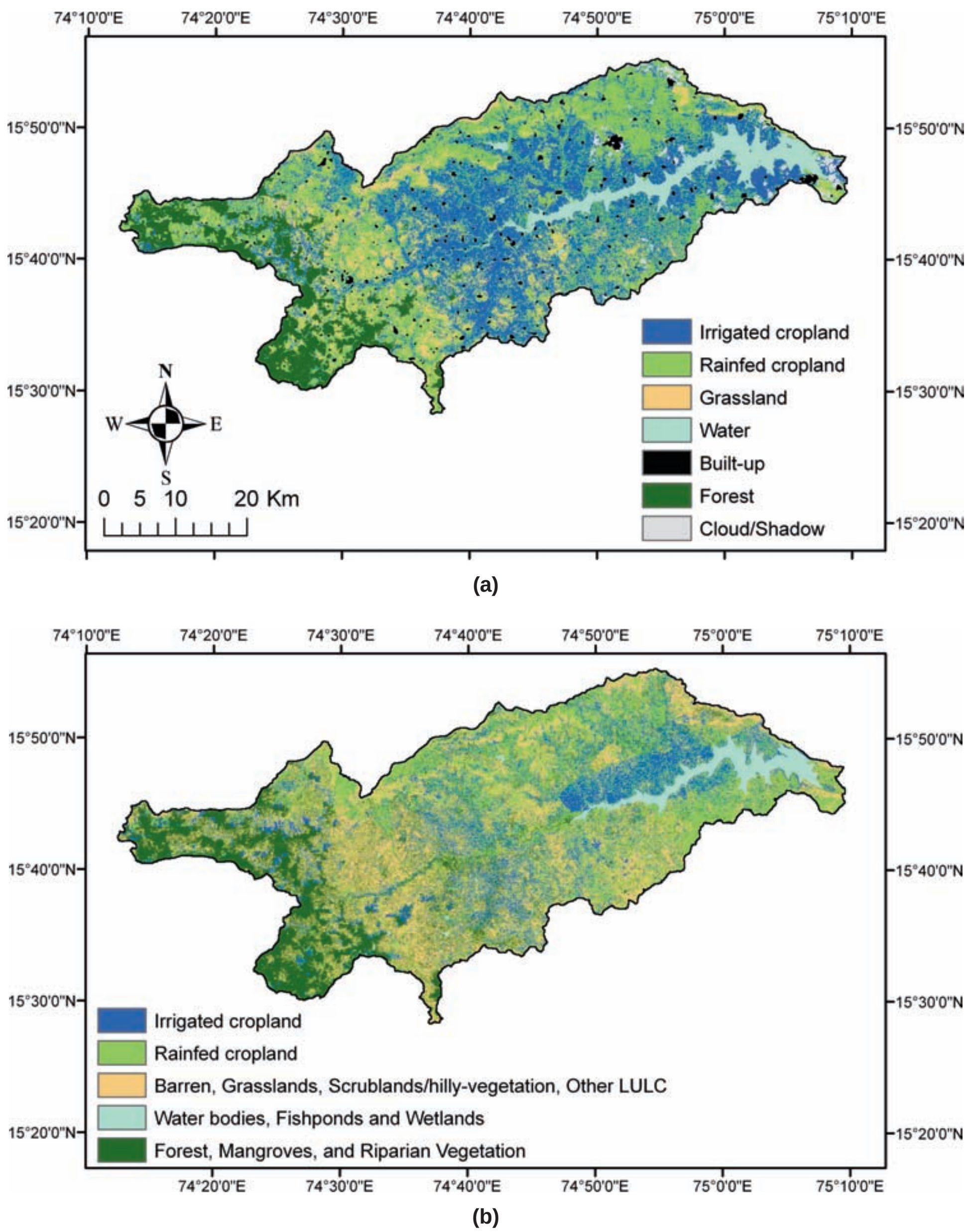


Plate 2. Comparison of (a) our results with those of (b) IWMI (Velpuri *et al*., 2009). Note that we have lumped land-cover classes in each map to make the maps more comparable.

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