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Changes in agricultural cropland areas between a water-surplus year and a water-deficit year impacting food security, determined using MODIS 250 m time-series data and spectral matching techniques, in the Krishna River basin (India)

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# Changes in agricultural cropland areas between a water-surplus year and a water-deficit year impacting food security, determined using MODIS 250 m time-series data and spectral matching techniques, in the Krishna River basin (India)

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The objective of this study was to investigate the changes in cropland areas as a result of water availability using Moderate Resolution Imaging Spectroradiometer (MODIS) 250 m time-series data and spectral matching techniques (SMTs). The study was conducted in the Krishna River basin in India, a very large river basin with an area of 265 752 km<sup>2</sup> (26 575 200 ha), comparing a water-surplus year (2000–2001) and a water-deficit year (2002–2003). The MODIS 250 m time-series data and SMTs were found ideal for agricultural cropland change detection over large areas and provided fuzzy classification accuracies of 61–100% for various land-use classes and 61–81% for the rain-fed and irrigated classes. The most mixing change occurred between rain-fed cropland areas and informally irrigated (e.g. groundwater and small reservoir) areas. Hence separation of these two classes was the most difficult. The MODIS 250 m-derived irrigated cropland areas for the districts were highly correlated with the Indian Bureau of Statistics data, with  $R^2$ -values between 0.82 and 0.86.

The change in the net area irrigated was modest, with an irrigated area of 8 669 881 ha during the water-surplus year, as compared with 7 718 900 ha during the water-deficit year. However, this is quite misleading as most of the major changes occurred in cropping intensity, such as changing from higher intensity to lower intensity (e.g. from double crop to single crop). The changes in cropping

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intensity of the agricultural cropland areas that took place in the water-deficit year (2002–2003) when compared with the water-surplus year (2000–2001) in the Krishna basin were: (a) 1 078 564 ha changed from double crop to single crop, (b) 1 461 177 ha changed from continuous crop to single crop, (c) 704 172 ha changed from irrigated single crop to fallow and (d) 1 314 522 ha changed from minor irrigation (e.g. tanks, small reservoirs) to rain-fed. These are highly significant changes that will have strong impact on food security. Such changes may be expected all over the world in a changing climate.

# 1. Introduction

The water availability in river basins changes in response to inter-annual fluctuations in water supply, especially in a changing climate. In the Krishna River basin in India these changes are prominent due to erratic monsoon rainfall, resulting in significant fluctuations in water availability for irrigation over time. Major canal irrigation schemes in the upper reaches of the Krishna basin often suffer from inequitable distribution of water due to overuse in head reaches, which is partly caused by farmers' preferences for water-intensive crops like rice and sugar cane (Bhutta and Van der Velde 1992, Gaur *et al.* 2008). Thus, the development activities upstream combined with inter-annual variations in rainfall can cause shortages in water supply downstream. Priority in allocation is often given to urban areas and industry, which can exacerbate the supply shock to irrigated command areas during water-deficit years. How these shortages, both temporary and chronic, are distributed over the command area will determine their net impact on agricultural production, equity and farmers' livelihoods. Spatial and temporal analysis of actual water supply in different parts of the irrigation project can identify how and where to improve the performance of an irrigation scheme (Gorantiwar and Smout 2005) and hence improve water availability. Variability in water supply is also linked with the issue of equity, and the spatial uniformity of water supply can be expected to change under different water supply regimes (Gaur et al. 2008).

Census data on agricultural production provide a coarse view of how cropping patterns change under fluctuating irrigation supply (Gaur *et al.* 2008). Satellite imagery can provide detailed maps of where cropping patterns change significantly in response to water availability (Thiruvengadachari and Sakthivadivel 1997). Satellite imagery has been increasingly used to quantify the water use and productivity in irrigation systems (Thiruvengadachari and Sakthivadivel 1997, Bastiaanssen and Bos 1999), but less frequently used to identify how irrigated command areas change in response to variations in water supply.

Studies reporting the use of multi-temporal image data often include relatively few dates, possibly due to a lack of cloud-free image availability, cost and processing requirements (Knight *et al.* 2006). A basic multi-temporal approach is used with both dry- and wet-season images, which provide more information on vegetation phenology than is available with only one image (Varlyguin *et al.* 2001, Goetz *et. al.* 2004, Knight *et al.* 2006). Vegetation phenology represents a potentially significant source of land use/land cover (LULC) information (Reed *et al.* 1994, Senay and Elliott 2000, Loveland *et al.* 2000).

Given the above background, the main objective of this research is to study changes in agricultural land use in response to water availability in the Krishna River basin between the years 2000–2001 (a water-surplus year) and 2002–2003 (a water-deficit year) and to understand the change dynamics of irrigated areas due to fluctuating water availability between the cropping years 2000–2001 and 2002–2003.

### 2. Study area

The Krishna basin (figure 1) is India's fourth largest river basin and covers 265 752 km<sup>2</sup> (26 575 200 ha) of southern India, traversing the states of Karnataka (116 247 km<sup>2</sup>), Andhra Pradesh (78 256 km<sup>2</sup>) and Maharashtra (71 249 km<sup>2</sup>). The basin is relatively flat, except for the Western Ghats and some forested hills in the centre and north-east. River Krishna originates in the Western Ghat mountains, flows east across the Deccan plateau, and discharges into the Bay of Bengal. The Krishna has three main tributaries that drain from the north-west, west and south-west (figure 1). The climate is generally semi-arid, with some dry, sub-humid areas in the eastern delta and humid areas in the Western Ghats. The annual precipitation varies widely in the basin: decreasing gradually from 850–1000 mm in the Krishna Delta to 300–400 mm in the north-west, then increasing to >1000 mm in the Western Ghats (figure 1), which in the extreme western parts of the basin have annual precipitation as high as 1500–2500 mm. Most of the rainfall occurs during the monsoon from June to October (table 1). But the biggest problem during water-deficit years is the amount of water available for irrigation in dams and barrages. For example, one barrage had



Figure 1. The Krishna River basin, India. The figure shows major reservoirs and the basin areas in three Indian states (Note: River network extracted from Shuttle Radar Topographic Mission 90 m digital elevation module (SRTM 90 m DEM), http://gcmd.nasa.gov/records/GCMD\_DMA\_DTED.html).

Table 1. Average rainfall at basin level. From 1999 to 2005, the year with highest rainfall was 2001–2002 (water-surplus year; 1109 mm) and that with the least rainfall was 2002–2003 (water-deficit year; 984 mm). The normal rainfall was 1033 mm.

				Average ra	infall (mm)		
Month	Normal rainfall (mm)	1999–2000	2000–2001 <sup>a</sup>	2001–2002	2002–2003 <sup>b</sup>	2003–2004	2004–2005
Jun	180	176	194	159	217	166	171
Jul	202	280	253	164	102	214	201
Aug	208	135	284	198	227	180	226
Sep	139	163	134	187	85	109	152
Oct	121	176	105	147	126	112	61
Nov	20	18	18	25	18	16	23
Dec	26	16	14	10	27	39	50
Jan	14	9	9	22	8	24	12
Feb	15	19	12	18	10	17	10
Mar	19	10	13	19	24	34	13
Apr	39	23	46	27	31	48	58
May	51	62	26	59	19	89	50
Annual rainfall	1033	1087	1109	1034	894	1048	1027

<sup>a</sup>water-surplus year; <sup>b</sup>water-deficit year.

only  $3.0063 \times 10^8 \text{ m}^3$  of water during the water-deficit year of 2002–2003 compared to  $1.06995 \times 10^9 \text{ m}^3$  during the water-surplus year of 2000–2001.

Cropping occurs in three seasons: *Kharif*, during the monsoon (June to mid-December), *Rabi*, in the post-monsoon dry season (mid-December to March) and the summer season (April and May). Irrigated areas may have double cropping of rice and other grains, single cropping of sugar cane, chilli, cotton, fodder grass and, in some areas of light irrigation, corn, sorghum and sunflower. Rain-fed crops include grains (sorghum, millet), pulses (red and green gram, chickpea) and oilseeds (sunflower, groundnut).

Irrigation systems include major (>10000 ha water-spread area), medium (20–10000 ha) and minor (<20 ha) command areas. Major canal irrigation schemes occur along each of the three main tributaries in the upper basin, and along the main stream in the lower basin and in the delta. One major hydroelectric project has a limited irrigated command area (Srisailam), and several new projects have large reservoir volumes but as yet small irrigated command areas (e.g. Alamatti, in figure 1). Minor irrigated systems include small tanks, small riparian lift schemes and groundwater irrigation. Groundwater sources include dug-wells, shallow tube-wells and deep tube-wells.

#### 3. Satellite data

#### 3.1 Processing of satellite data

The Moderate Resolution Imaging Spectroradiometer (MODIS) data for the Krishna River basin was downloaded from calibrated global continuous time-series mega-data sets (see www.iwmidsp.org) composed from individual files from the NASA website

MODIS Bands <sup>a</sup>	Band width (nm)	Band centre (nm)	Potential application <sup>b</sup>
1	620–670	648	Absolute land cover transformation, vegetation chlorophyll
2	841-876	858	Cloud amount, vegetation land cover transformation

Table 2. MODIS 250 m two-band reflectance data characteristics used in this study<sup>a</sup>.

Notes: Of the 36 MODIS bands, the two bands reported here are specially processed for land studies. <sup>a</sup>MODIS bands are rearranged to follow the electromagnetic spectrum (e.g. blue band 3 followed by green band 4). <sup>b</sup>Taken from MODIS website (http://modis-land.gsfc.nasa.gov/).

(www.modis-land.gsfc.nasa.gov/). The MODIS 250 m two-band data (centred at 648 and 858 nm; table 2) collection five (MOD09Q1) were acquired for every eight-day period during two crop-growing seasons: (a) June 2000 to May 2001 for a water-surplus year and (b) June 2002 to May 2003 for a water-deficit year. Original MODIS data were acquired in 12-bit (0 to 4096 levels), and were stretched to 16-bit (0 to 65 536 levels). Further processing steps are described subsections in 3.2–3.4.

## 3.2 Cloud-removal algorithm

The Krishna basin, located at about 18° N, is subject to the influences of the oscillating Sub-Tropical Convergence Zone, which includes monsoonal activity from June to September (Kharif season). It is during this part of the year that there is a significant change in vegetation cover, rapid changes in dynamics of vegetation, and biomass accumulation. It is also a period when cloud cover is more frequent. In order to retain the highest possible number of time-series images, we: (a) retained all images with <5% cloud cover and (b) developed a cloud-masking algorithm in order to eliminate areas of cloud cover and retain the rest of the image in an unchanged form (Thenkabail *et al.* 2005). Of the 46 images for the year 2000–2001, there were 16 images with 25–40% cloud cover. During 2002–2003, there were seven images with cloud cover >25%. For these images, we used the cloud-masking algorithm described in section 3.3 and eliminated the cloud-covered areas while retaining the cloud-free areas. This resulted in retaining all 46 images during the water-surplus year and the water-deficit year by eliminating parts of the image with cloud cover. It is important to retain non-cloud areas, to get maximum temporal coverage.

# 3.3 Minimum reflectivity threshold for cloud removal

The minimum reflectivity of clouds in the MODIS bands 1 and 2 (b1 and b2) provided the best separability in which cloud cover was removed. If the reflectance value in b1 was more than 18 (the cut-off value is arrived at by selecting several samples over cloud patches throughout the basin), then the values in b1 were replaced with a null value. When the b1 value was null then the corresponding value in b2 was replaced with a null value. If the reflectance value in b1 was less than 18 then the corresponding value in b2 was retained as it is. For further detailed description of cloud-removal algorithms for MODIS refer to Thenkabail *et al.* (2005).

# 3.4 Mega-data set

The data set was prepared by combining many bands of data of a study area taken on different dates, forming a stack of single files referred to as a mega-file data cube (MFDC). The MFDC data set has no limitation of size or dimension. The continuous time-series analysis of MODIS data requires construction of MFDCs that involve multiple bands of different dates in a single file. We created two MFDC maximum value composite (MVC) normalized difference vegetation indices (NDVIs) for: (a) the water-surplus year of 2000–2001 and (b) the water-deficit year of 2002–2003. Each MFDC consisted of 92 bands (from 46 images per year, each of two bands; table 2). Separate 46-band NDVI MFDCs were also composed for the water-surplus year and the water-deficit year using the 92-band MFDCs of the respective years.

# 3.5 Field-plot data sets

Field-plot data were collected during 13–26 October 2003 from 144 locations (figure 2) covering major cropland LULC classes. The data from the plots were collected from precise locations where local agricultural extension officers provided local knowledge and ensured that the data were collected from locations where same crops were grown during 2000–2001 (the water-surplus year) and 2002–2003 (the water-deficit year). The local experts also provided a cropping calendar and information on cropping intensity



Figure 2. Field-plot data point locations in the Krishna River basin. There are 144 field-plot locations where data on crop types, cropping intensities, watering sources (irrigated vs. rainfed) and a number of other parameters (e.g. digital photos) were collected.

and per cent canopy cover for these locations from their recorded data for these years. In addition, field-plot data from 482 other specific locations were collected based on interviews with local farmers, covering a distance of 6500 km by road throughout the basin, and marking manually on topographic maps (1:250 000). These data included the crops grown during 2000–2001 and 2002–2003 as well as their intensity (whether single or double crops). Further, the GeoCover 2000 (http://Zulu.ssc.nasa.gov/mrsid/, Tucker *et al.* 2005) products were used as additional information on class identification.

The MODIS data require a minimum sampling unit of  $500 \times 500 \text{ m}^2$  for field-plot validation. Very few locations in the basin fulfil this criterion due to its diverse land-use pattern. The approach adopted was to look for contiguous areas of homogeneous classes within which we could sample (Thenkabail *et al.* 2005). A large contiguous information class constituted our sampling unit, within which we sampled a representative area of  $90 \times 90 \text{ m}^2$ . The emphasis was on maximizing the degree to which the sample location represented one of the classes to determine the precise geographical location of the pixel. Class labels were assigned in the field. Classes are flexible such that a class can merge with a higher class or break into separate classes based on the per cent land cover observed at each location.

The precise locations of the sample sites were recorded using a Garmin hand-held Global Positioning System (GPS) receiver (Garmin (eTrex) 12 Channel GPS, Olathe, KS, USA). The sample size varied from 5 to 25 samples for each major crop LULC class. Though it is ideal to have at least 50 samples per land-use class (Congalton and Green 1999), this was not feasible due to limited resources. The LULC classes which are more vulnerable to sample size are rain-fed cropland, range land and groundwater-irrigated areas, and rain-fed combinations. Class labels were assigned in the field.

At each of the 144 locations the following data were recorded for the years 2000–2001 and 2002–2003, based on interviews with local agricultural extension officers:

- LULC classes: levels I, II and III, Anderson approach;
- Land cover types (per cent cover): trees, shrubs, grasses, built-up, water, fallow lands, weeds, different crops, sand, rock and fallow farms;
- Crop types: for Kharif, Rabi and summer seasons;
- Cropping pattern: for Kharif, Rabi and summer seasons;
- Cropping calendar: for Kharif, Rabi and summer seasons;
- Irrigated, rain-fed, supplemental irrigation at each location;
- 311 digital photos of the 144 locations were 'hot-linked' using Arcview software (Redlands, CA, USA) to ensure geographically located photos appear at click of a mouse.

The data thus obtained were organized in Arc Geographical Information System (ArcGIS) format, ER Mapper 7.1, and ERDAS (Earth Resources Data Analysis System) Imagine 9.2 (Norcross, GA, USA) compatible formats with accompanying metadata that can be overlayed over the MODIS image data (figure 2). In the 482 observation locations, only data on crop types and cropping intensities were gathered.

## 3.6 Rainfall and discharge data

Monthly rainfall data for the years 2000–2001 and 2002–2003 (table 1) were obtained from: (a) the Bureau of Economics and Statistics, Andhra Pradesh, (b) the Directorate of Economics and Statistics, Karnataka and (c) the Department of Agriculture,

	Discharge	$(\times 10^6 \text{ m}^3)$
Month	2000–2001	2002–2003
Jun	618.04	103.50
Jul	1383.08	531.52
Aug	4599.45	802.66
Sep	1325.81	694.50
Oct	1215.16	640.45
Nov	921.82	500.17
Dec	566.11	101.92
Jan	509.06	55.73
Feb	558.07	61.02
Mar	623.01	1.47
Apr	375.64	61.78
May	144.20	52.85
Average	1069.95	300.63

Table 3. Discharge at Prakasam barrage (total canals + surplus) during the water-surplus year (2000–2001) when compared with the water-deficit year (2002–2003).

Maharashtra. Data on the discharge volume at Prakasam Barrage were collected from the Irrigation Department, Andhra Pradesh (table 3).

# 4. Methods

# 4.1 Methodology for mapping irrigated areas using MODIS 250 m

A comprehensive methodology for mapping irrigated areas using MODIS 250 m data was developed (figure 3; also see Thenkabail *et al.* 2005). The MODIS images (MOD09 product) are already provided as surface reflectance values (Thenkabail *et al.* 2005). The following protocol was followed in developing and implementing the methods.

**4.1.1 Unsupervised classification.** Unsupervised classification using Interactive Self-Organizing Data Analysis Technique cluster algorithm (ISODATA in ERDAS Imagine  $9.2^{\text{TM}}$ ) followed by progressive generalization (Cihlar *et al.* 1998) was used on 46-band MODIS 250 m NDVI MFDCs constituted for: (a) the water-surplus year of 2000–2001 and (b) the water-deficit year of 2002–2003. The classification was set at a maximum of 40 iterations and a convergence threshold of 0.99. In all, 40 classes were generated for the water-surplus year as well as for the water-deficit year. Use of unsupervised techniques is recommended for large areas that cover a wide and unknown range of vegetation types, and where landscape heterogeneity complicates identification of homogeneous training sites (Achard and Estreguil 1995, Cihlar 2000). Identification of training sites is particularly problematic for small, heterogeneous irrigated areas.

The 40 classes obtained from the unsupervised classification were merged using rigorous class-identification and labelling protocols (described below; see also Thenkabail *et al.* 2005), field-plot data (previously described) and GeoCover mosaics of Landsat imagery from 1990 to 2000 (Tucker *et al.* 2005).

**4.1.2** Class identification and labelling. Class identification and labelling is a stepby-step process described in detail in subsections 4.1.2.1–4.1.2.4.



Figure 3. Overview of the methodology for mapping irrigated areas using MODIS data.

4.1.2.1 Class spectra generation. Class spectra were generated using unsupervised ISOCLASS *k*-means classification (Tou and Gonzalez 1974) using the MODIS NDVI MVC 250 m mega-file data (figure 4). The 46-layer NDVI stack, generated from the mega-data set was classified using unsupervised classification with 40 classes initially.



Figure 4. Class spectral signatures of unsupervised classes derived using a MODIS 250 m MFDC for: (*a*) the water-surplus year (2000–2001) and (*b*) the water-deficit year (2002–2003).

The signature file was used to plot the signature of each LULC class over time. This NDVI signature indicates the profile of vegetative intensity.

The time-series NDVI plots (e.g. figure 4) are ideal for understanding the changes that occur: (a) within and between seasons, and (b) between classes (e.g. irrigated vs. rain-fed). Figure 4 shows the distinct differences between an irrigated and a rain-fed



Figure 5. Ideal spectral signatures for irrigated classes. Ideal spectral signatures are obtained by first having precise knowledge of crop characteristics from precise geographic location and then developing spectral signatures of the same using a MODIS 250 m MFDC.

class. Irrigated areas have much higher NDVI and are double-cropped (two crops in a calendar year). In contrast, the rain-fed crops have significantly lower NDVI and are limited to one crop per year. Further, through climatic data, it was known that 2002 was one of the worst drought-affected years (table 1). This led to a near failure of rain-fed crops and the impact can be seen in one season on irrigated crops, where they had a much shorter growing season compared to the normal year of 2000–2001 (figure 4).

4.1.2.2 Ideal spectra creation. Continuous time-series satellite sensor data enable the creation of ideal spectra for various land-use themes, such as irrigated areas, rainfed areas, classes within irrigated areas and classes within rain-fed areas (figure 4). Ideal spectral signatures for LULC classes have been extracted from MODIS timeseries data using representative field-plot samples. A total of 144 ground truth (GT) points and 110 ideal pure signatures were collected (see figure 5). These data were streamlined in digital form for classification inputs and these have been made available online via the International Water Management Institute Data Storehouse Pathway (IWMIDSP) site (www.iwmidsp.org).

Ideal signatures (figure 5) were selected based on large continuous areas with single cropping, including major irrigated crops in the Krishna basin like rice, sugar cane, cotton, chilli and maize, and rain-fed crops like bajra, sorghum and sunflower.

4.1.2.3 Spectral matching techniques. Spectral matching techniques (SMTs) match the class spectra derived from classification with the ideal spectra derived from the



Figure 6. The SMT for grouping similar classes. The class spectral signatures (derived using unsupervised classification) are matched with ideal spectral signatures (derived from ideal spectral data bank; figure 5) in order to group and identify classes as illustrated for the irrigated class in this figure.

mega-file data cube based on precise knowledge of crops from specific locations (Thenkabail *et al.* 2007; figure 6).

Spectral signature matching techniques are traditionally developed for hyperspectral data analysis of minerals (e.g. Homayouni and Roux 2003, Thenkabail *et al.* 2004a, b, 2007, 2009a, b). Time-series data, such as the monthly MODIS NDVI data, are similar to hyperspectral data, with 12 months in time-series data replacing 12 bands in hyperspectral data. These similarities imply that the SMTs, applied for hyperspectral image analysis, also have potential for application in identifying agricultural land-use classes from historical time-series satellite imagery.

4.1.2.4 Google Earth imagery and GEOCOVER imagery. The Google Earth application (http://earth.google.com/) provides increasingly comprehensive image coverage of the globe at very high resolution (sub-metre to 30 m), allowing the user to zoom into specific areas in great detail, from a base of 30-m-resolution data, based on GeoCover 2000. Geocover imagery (Tucker *et al.* 2005) is the most comprehensive coverage of the planet at 30 m or better resolution imagery. In this study, Google Earth and Geocover data were used for: (a) identifying and labelling the classes and (b) overlaying the classified output on Google Earth to verify the classes (figure 7).



Figure 7. Class identification and labelling using Google Earth imagery. The Google Earth very high resolution imagery (sub-metre to 4 m) was used to supplement the information we have from field campaigns, ideal spectra and other sources to help identify and label classes.

# 4.2 Resolving the mixed classes

In the class identification and labelling process, a few classes mixed with other classes. These were resolved by using the following methods:

**4.2.1 Decision tree algorithms.** Decision tree algorithms (DeFries *et al.* 1998) use factors such as NDVI, band reflectivity and thermal temperatures to identify and label a class and/or resolve a mixed class. A rule-based decision tree algorithm for NDVIs of classes will help group distinct classes together (figure 8) and label them.

**4.2.2 Spatial modelling.** When classes continued to be mixed, in spite of the various methods and techniques discussed in previous subsections we adopted the Geographical Information Systems (GIS) spatial modelling approaches to resolve classes. This involved taking a mixed class and applying spatial modelling techniques such as overlay, matrix, recode, sieve and proximity analysis (ERDAS Imagine 9.2) based on the theory of map algebra and Boolean logic (Peuquet and Marble 1990, Tomlin 1990, Tomlinson 2003). Spatial data layers used include precipitation zones, elevation zones and tree-cover categories. Any one or a combination of these data layers usually helped to separate the mixed classes.

**4.2.3 Masking and reclassification.** In spite of the rigorous class identification process described in the above subsections, there were often 'mixed' classes. Typically, the unresolved classes were split up into 5–10 or more sub-classes



Figure 8. Decision tree algorithms. A rule-based decision tree algorithm to resolve and group a wide array of classes using NDVI threshold by writing a rule-base as illustrated.

(depending on the extent of area and complexity) and the class identification and labelling process as described previously was repeated (figure 3).

**4.2.4 Land use/land cover (LULC) system.** A standardized hierarchical classification scheme (Klijn and Udo de Haes 2004, Thenkabail *et al.* 2009a) was adopted. This enabled obtaining classes at different levels which could be 'cross walked' (Torbick *et al.* 2006). The 'cross walk' procedure shows how the classes are aggregated or disaggregated. This allows an aggregated class to be tracked to determine which disaggregated classes were combined to form it or vice versa. All classes were named using a standard class-naming protocol (Thenkabail *et al.* 2009b). When multiple analysts provide class names, the standardized class-naming protocol is very useful (Thenkabail *et al.* 2009b).

**4.2.5** Accuracy assessment. The accuracy assessment was carried out using the equations of Congalton and Green (1999):

$$A_{\rm ia} = \frac{(\rm IFPCIA)}{(\rm TIFP)} \ 100\% \tag{1}$$

$$E_{\rm c} = \frac{(\rm NIFPIA)}{(\rm TNIFP)} \ 100\%$$
 (2)

$$E_{\rm o} = \frac{(\rm IFPNIA)}{(\rm TIFP)} \ 100\% \tag{3}$$

where  $A_{ia}$  is the accuracy of irrigated area classes (%),  $E_c$  the errors of commission for the irrigated area class (%),  $E_o$  the errors of omission for the irrigated area class (%),

IFPCIA the irrigated field-plots classified as irrigated areas (number), TIFP the total irrigated field-plots (number), NIFPIA the non-irrigated field-plot points classified as irrigated area (number), TNIFP the total non-irrigated field-plots (number) and IFPNIA the irrigated field-plots classified as non-irrigated areas (number).

# 5. Results and discussion

## 5.1 LULC fractions

Each agricultural land-use class mapped using the SMTs is a combination of several land cover types (see table 4). For example, in table 4(a) cultivable areas dominate in class 6 (84.4%) but there are other land cover types including 1.5% trees, 1.1% shrubs, 2.9% grass and 3.7% others, the last including fallows, weeds, rocks and built-up lands. In these cultivable areas, cotton was the predominant crop, whilst rice and grains were the next most commonly seen crops. Accurate estimation of various thematic areas was obtained by joining classes as follows (see table 4):

Using the same approach, there was 86 699 km<sup>2</sup> (sum of areas of classes 5–8 in table 5(a)) net irrigated area in 2000–2001, and 77 189 km<sup>2</sup> (sum of areas of classes 5–8 in table 5(b)) net irrigated area in 2002–2003, including surface water.

## 5.2 LULC maps and area statistics

Nine exactly similar classes were mapped for the water-surplus year (2000-2001; figure 9(*a*) and table 5(*a*)) and the water-deficit year (2002-2003; figure 9(*b*) and table 5(*b*)). The spectral characteristics of these classes are shown in figure 10(*a*) (water-surplus year) and 10(*b*) (water-deficit year).

Classes were identified based on field-plot data, including GPS-referenced digital images and field observations. The LULC area in the Krishna River basin for 2000–2001(table 5(a)) was: water bodies 1.9% of the total area, shrub lands mixed with range lands and fallows 24.5%, rain-fed agriculture 22.2%, rain-fed + ground-water irrigation 11.3%, minor irrigation, including tanks and small reservoirs, 8.0%, classes with surface irrigation by canal 19.6% and forest 8.4%.

The LULC area in the Krishna River basin for 2002-2003(table 5(*b*)) was: water bodies 1.0%, shrub lands mixed with range lands and fallows 28.1%, rain-fed agriculture 17.4%, rain-fed + groundwater irrigation 22.0%, minor irrigation, including tanks and small reservoirs, 7.6%, classes with surface irrigation by canal 10.2% and forest 8.6%.

By using spectral signatures, this study identified major changes in groundwaterirrigated areas and rain-fed areas in the major command areas, demonstrating the usefulness of spectral matching techniques. The results show that there was a marginal decrease in the total irrigated area (including surface water and groundwater areas) of the Krishna basin from 2000–2001 (86 698 km<sup>2</sup>) to 2002–2003 (77 189 km<sup>2</sup>). The increase in the groundwater-irrigated area from 2000–2001 (22 789 km<sup>2</sup>) to 2002–2003 (35 268 km<sup>2</sup>) in contrast to the decrease in the surface-water-irrigated area from 2000–2001 (63 909 km<sup>2</sup>) to 2002–2003 (41 921 km<sup>2</sup>) was very significant as a result of lower water storages in the reservoirs in the water-deficit year (2002–2003).

Table 4. Distribution of land cover types for e basin (India): (a) during	ach land use J the water-sur	plus	ding a year (	n underst 2000–200	tanding 11) and (	of sub-p (b) durin	ixel fra ig the w	ctions fo ater-de	or the nine final classes in the Krishna River icit year (2002–2003).
				Fraction	of vege	station co	over (%	(	
LULC	Area (km <sup>2</sup> )	N	Trees	Shrubs	Grass	Others	Open	Crops	Major crops
(a) Class 1: Water bodies	5176	I	I	I	I	I	I	I	
Class 2: Shrub lands mixed with range lands	65223 10441	15	6.7	24.3	6.9	14.2 10.1	8.6	39.3 11 1	Grains, oilseeds
Class 4: Rain-fed agriculture	59122	<u>, 1</u>	4 .8	5.0	0.77 0.6	8.7	4.9	47.7 66.8	Rice. grains. oilseeds. pulses
Class 5: Rain-fed + groundwater	30146	25	2.1	1.3	3.4	7.1	10.6	75.6	Rice, oilseeds, pulses, grains, cotton, chilli
Class 6: Minor irrigated (light/tank)	21208	9	1.5	1.1	2.9	6.3	3.7	84.5	Cotton, grains, oilseeds, rice
Class 7: Irrigated, continuous crop	27187	10	2.7	2.0	1.7	2.3	2.4	88.9	Sugar cane, fodder grass, chilli, cotton
Class 8: Irrigated, double-crop rice, chickpea	24884	22	1.7	3.7	1.9	2.8	2.2	87.6	Rice, grains, pulses
Class 9: Forests	22361	12	60.2	11.2	3.0	2.7	1.6	21.3	Teak, coffee, arecanut, rice
Basin total	265752	140	10.0	6.2	6.5	7.9	6.1	63.3	
(b) Class 1: Water bodies	2532	I	I	I	I	I	I	I	
Class 2: Shrub lands mixed with range lands	64293	28	1.0	34.0	5.6	18.4	10.2	30.8	Grains, oilseeds
Class 3: Range lands mixed with rain-fed	10406	1	4.8	5.0	9.9	15.8	8.7	55.8	Grains, oilseeds, pulses
Class 4: Rain-fed agriculture	46202	22	0.7	1.0	2.0	6.2	1.8	88.3	Rice, grains, cotton, chilli, oilseeds, pulses, vegetables
Class 5: Rain-fed + groundwater	58488	16	2.1	1.3	18.4	10.8	7.1	60.3	Rice, oilseeds, pulses, grains, cotton, chilli
Class 6: Minor irrigated (light/tank)	33788	19	1.5	11.1	6.9	3.7	6.3	70.5	Cotton, grains, oilseeds, rice
Class 7: Irrigated, late single crop	20196	16	6.7	2.0	8.7	12.8	11.3	58.5	Sugar cane, fodder grass, chilli, cotton
Class 8: Irrigated, double-crop rice, chickpea	6991	22	1.7	1.6	5.5	5 8 2 8	- 0 1.00	89.9	Rice, grains, pulses
Class 9: Forests Basin total	265752	0 140	7.0c	8.5	3.0 7.1	10.1	7.7	21.2 59.4	l eak, coffee, arecanut, rice
		•							

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Note: N is no of sample points.



Figure 9. The final nine agricultural cropland classes and other LULC classes for: (a) the water-surplus year (2000-2001) and (b) the water-deficit year (2002-2003).

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Table 5. Agricultural cropland areas along with other LULC areas in the Krishna River basin: (a) during the water-surplus year (2000–2001) and (b) during the water-surplus year (2000–2001) and (b) during the water-deficit year (2002–2003).

			ΓN	LC area with	in the classes	$(\mathrm{km}^2)$		
LULC	%	Water	Trees	Shrubs	Grass	Others	Crops	Basin totals (km <sup>2</sup> )
(a) Cloce 1: Wrotar hadiae	0	5177 82	00.0	00.0	00.0	00.0	00.0	6177 87
Class 1. Watch Joures Class 2. Shriih lands mixed with range lands	245	79.7710	0.00	0.00 15857 40	00.0	0.00	0.00 25631.04	521637 6571637
Class 3: Range lands mixed with rain-fed	3.9	0.00	69.62	104.43	2297.53	3571.62	4404.67	10447.88
Class 4: Rain-fed agriculture	22.2	0.00	2826.60	2933.04	5830.59	8014.60	39501.37	59106.20
Class 5: Rain-fed + groundwater	11.3	0.00	626.23	388.50	1020.53	5315.05	22788.84	30139.15
Class 6: Minor irrigated (light/tank)	8.0	0.00	327.83	231.41	617.09	2121.23	17924.41	21221.96
Class 7: Irrigated, continuous crop	10.2	0.00	740.24	547.63	453.21	1282.59	24182.39	27206.06
Class 8: Irrigated, double-crop rice, chickpea	9.4	0.00	423.12	920.91	472.90	1258.16	21803.18	24878.27
Class 9: Forests	8.4	0.00	13464.18	2497.51	670.97	954.27	4771.36	22358.30
Basin totals	100.0	5177.82	22848.65	23475.82	15851.07	37391.38	161007.26	265752.00
Total surface irrigated area (km <sup>2</sup> )							63909.98	
Total groundwater irrigated area (km <sup>2</sup> )							22788.84	
I otal irrigated areas (km <sup>-</sup> )							80098.81	
(p)								
Class 1: Water bodies	1.0	2531.83	0.00	0.00	0.00	0.00	0.00	2531.83
Class 2: Shrub lands mixed with range lands	24.2	0.00	642.93	21859.50	3600.39	18387.70	19802.13	64292.64
Class 3: Range lands mixed with rain-fed	3.9	0.00	499.50	520.31	1030.22	2549.54	5806.71	10406.39
Class 4: Rain-fed agriculture	17.4	0.00	323.41	462.02	924.03	3696.14	40796.10	46201.70
Class 5: Rain-fed + groundwater	22.0	0.00	1228.25	760.35	10761.82	10469.38	35268.36	58488.26
Class 6: Minor irrigated (light/tank)	12.7	0.00	506.82	3750.50	2331.39	3378.83	23820.73	33788.37
Class 7: Irrigated, late single crop	7.6	0.00	1353.16	403.93	1757.09	4867.34	11814.90	20196.41
Class 8: Irrigated, double-crop rice, chickpea	2.6	00.0	118.85	111.86	153.81	321.60	6285.26	6991.40
Class 9: Forests	8.6	0.00	11587.64	2788.35	685.66	2948.33	4845.32	22855.30
Basin total	100.0	2531.83	16260.57	30656.81	21244.41	46618.85	148439.53	265752.00
Total surface irrigated area (km <sup>2</sup> )							41920.90	
Total groundwater irrigated area $(km^2)$							35268.36	
I otal irrigated areas (km <sup>-</sup> )							//189.26	



Figure 10. The MODIS NDVI spectral signatures of the nine agricultural cropland and LULC classes for: (*a*) the water-surplus year (2000–2001) and (*b*) the water-deficit year (2002–2003).

## 5.3 Accuracy assessment

A qualitative accuracy assessment was performed to check if the irrigated area would be classified as irrigated or not without checking for crop type or type of irrigation. The accuracy assessment was performed using field-plot data, to derive a robust understanding of the accuracies of the data sets used in this study. The field-plot data were based on an extensive field campaign conducted throughout the Krishna basin during Kharif season by the International Water Management Institute researchers and consisted of 144 points.

Accuracy assessment provides realistic class accuracies where land cover is heterogeneous and pixel sizes exceed the size of uniform land cover units (see Gopal and Woodcock 1994, Thenkabail *et al.* 2005, Biggs *et al.* 2006). For this study, we had assigned  $3 \times 3$  cells of MODIS pixels around each of the field-plot points to one of six categories: absolutely correct (100% correct), largely correct (75% or more correct), correct (50% or more correct), incorrect (50% or more incorrect), mostly incorrect (75% or more incorrect) and absolutely incorrect (100% incorrect). Class areas were tabulated for a  $3 \times 3$ -pixel (9 pixels) window around each field-plot point. If nine out of nine MODIS classes matched with the field-plot data, then it was labelled absolutely correct and so on (table 6).

The accuracies and errors of the LULC map were assessed based on intensive fieldplot data. The 140 field-plot data points reserved for accuracy assessment from the Krishna basin field campaigns provided a fuzzy classification accuracy of 61-100%for the various classes (table 6). The fuzzy accuracies were 61-81% for rain-fed and irrigated classes with most of the intermixing occurring between two irrigated classes or two rain-fed classes.

## 5.4 Comparisons with census data

The LULC area statistics of the Krishna basin districts were obtained from the Bureau of Economics and Statistics, Andhra Pradesh, the Directorate of Economics and Statistics, Karnataka, and the Department of Agriculture, Maharashtra. The data were obtained at district level from the respective states. These data were fractionalized based on the district-wise area covered in the Krishna basin for a comparative study with the MODIS data. The fractionized statistics data were compared with the MODIS data for the years 2001 and 2003. Most of the districts' data matched with the MODIS data for the year 2003 as compared to 2001, and the difference between the statistical data and MODIS data varied between -30% and 30% (figure 11).

## 5.5 Agricultural cropland change map

The changes in agricultural croplands in the water-deficit year (2002–2003) were compared with those in the water-surplus year (2000–2001) for the entire Krishna basin (figure 12 and table 7). The change in irrigated area was not highly significant with an area of 8 669 881 ha during the water-surplus year, compared with 7 718 926 ha during the water-deficit year. However, major changes were observed in the cropping intensity and pattern (e.g. from double crop to single crop; table 7) due to changes in water availability in the Krishna basin. The changes were as follows:

- 1 078 564 ha changed from double crop (in 2000–2001) to single crop (in 2002–2003),
- 1 461 177 ha changed from continuous crop to single crop,
- 704 172 ha changed from irrigated single crop to fallow and
- 1 314 522 ha changed from minor irrigation (e.g. tanks, small reservoirs) to rainfed.

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Table 6. Fuzzy accuracy assessment using field-plot data. Numbers in parentheses indicate the fuzzy correctness per cent. Values in the table indicate the per cent of field-plot windows in each class with a given correctness per cent.

					Fuzzy class	ification accurae	ý		
	Sample	Total	Total	(absolutely correct)	(mostly correct)	(correct)	(incorrect)	(mostly incorrect)	(absolutely incorrect)
	SIZE	collect	IIICOILECI	(100% correct)	(75% and above correct)	(50% and above correct)	(50% and above incorrect)	(75% and above incorrect)	(100% incorrect)
MODIS LULC class	N	(%)	(%)	(%)	(0%)	(%)	(%)	(%)	(%)
Class 1: Water bodies	0	100	0	100	0	0	0	0	0
Class 2: Shrub lands mixed	15	81	19	47	10	23	19	0	0
with range lands									
Class 3: Range lands mixed with rain-fed	33	76	24	15	31	30	20	3	-
Class 4: Rain-fed	17	59	41	45	6	5	Э	15	23
agriculture									
Class 5: Rain-fed +	25	63	37	41	5	17	18		18
groundwater									
Class 6: Minor irrigated	9	80	20	0	62	18	17	0	4
Class 7: Irrigated, late	10	68	32	46	8	14	14	0	18
single crop									
Class 8: Irrigated, double-	22	87	13	64	16	7	4	5	5
Class 9. Forests	5	87	13	86	_	0	0	0	13
Total	140	78	22	49	14	12	12	ŝ	6



Figure 11. Accuracy assessment and validation. The district-wise irrigated areas derived using MODIS 250 m compared with agricultural census data for: (*a*) the year 2000–2001 and (*b*) the year 2002–2003.

Table 7. Agricultural cropland change response to water availability. The table shows how the irrigated croplands changed from 2000–2001 (the water-surplus year) to 2002–2003 (the water-deficit year).

Crop land change from 2000-2001 to 2002-2003	Area (ha)
Irrigation double crop to single crop	1 078 564
Irrigation continuous crops to irrigation single crop	1 461 177
Irrigation single crop to fallow	704 172
Minor irrigation to rain-fed	1 314 522
Other classes	22 113 683



Figure 12. Land-use change map from 2000–2001 (the water-surplus year) to 2002–2003 (the water-deficit year). Most of the changes occurred in intensity (e.g. double crop in the water-surplus year to single crop in the water-deficit year) as shown in the legend.

Areas under continuously irrigated crops like sugar cane were converted to crops like rice and maize (figure 12, class 1). Double-cropped areas were brought under single-crop rice and pulses. Intensively irrigated areas including groundwater-irrigated areas in 2000–2001 were under fallows in 2002–2003. Large areas under minor irrigation changed to groundwater irrigation due to low rainfall. These changes clearly imply heavily reduced food production in the Krishna basin during water-deficit years. The results are specially relevant in a changing climate where there is a need for

adaptability. For example, it may be recommended to go for less water-consuming crops during water-deficit years, which may enable growing crops over larger areas thus helping the farming communities.

## 6. Conclusions

The study highlights the highly significant agricultural land-use changes that took place as a result of inter-annual variations in water availability. The rain-fed and irrigated areas were mapped with a fuzzy classification accuracy of 61-81% using MODIS 250-m time-series images and SMTs. The MODIS-based irrigated cropland statistics for the districts were highly correlated ( $R^2$  coefficient of determination value of 0.82–0.86) with the Indian Bureau of Statistics-reported figures.

The study was conducted in the very large Krishna River basin in India, which has an area of 265 752 km<sup>2</sup> (26 575 200 ha). The changes in the water-deficit year (2002–03) when compared with the water-surplus year (2000–2001) were of great magnitude: (a) 1 078 564 ha changed to single crop (in 2002–2003) from double crop (in 2000–2001); (b) 1 461 177 ha changed to single crop from continuous crop; (c) 704 172 ha changed to fallow from irrigated single crop; (d) 1 314 522 ha changed to rain-fed from minor irrigation (e.g. tanks, small reservoirs). The implication of such changes on water use and food security will be significant. The study is especially relevant in a changing climate where there is a need to see how changes occur in croplands, their implications on water use, and strategies for adaptability to ensure food security. The outcome of this research highlights the value of using MODIS 250 m time-series data and advanced methods like spectral matching techniques in the study of agricultural cropland changes in large river basins.

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