Global Irrigated Area Mapping – Working Document, June 2002

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1 Introduction

The Global Irrigated Area Mapping Project is part of IWMI's Comprehensive Assessment of Water Management in Agriculture. Work began on the development of a methodology to assess irrigated area using coarse resolution imagery (AVHRR and MODIS) in 2000 in Pakistan (IIMI-PAK) and in 2001 at IWMI Colombo. Peter Droogers investigated the potential of relating vegetation cover derived from high resolution imagery (ASTER) to vegetation index in coarser MODIS images, and the methodology and much background to the project is summarized in IWMI Working Paper 36 " Global Irrigated Area Mapping – overview and recommendations" (IWMI, 2002).

FAO (Aquastat) has collated much of the existing statistics on global irrigated area and has collaborated with the University of Kassel to produce a map showing the extent of <u>equipped</u> irrigated areas on a global basis. Before the Comprehensive Assessment funding was confirmed in March, the remote sensing unit at FAO (Jelle Hielkema) had collaborated with IWMI to prepare a joint funding proposal to USAID. A meeting was held in Rome in early March between IWMI (Droogers, Molden and Turral), FAO-Aquastat (Jean Marc Faures) and FAO-Remote Sensing (Jelle Hielkema) to further develop the work programme and responsibilities. The work chart arising from that meeting is given in Appendix A. A report and sample maps for Pakistan, India and Sri Lanka are expected to be ready for distribution by the end of July 2002, and will provide an evaluation of the Working Paper 36 methodology for one month – January 2001.

This document has been prepared to develop the work programme on a broader basis, recognizing that a range of remote sensing techniques need to be investigated in order to be able to map irrigated area at a global scale. The document focuses on work in the initial research phase, which is expected to continue until early 2004. It outlines the different contexts of scale and climatic limitations to analysis and proposes a number of parallel investigations to derive suitable techniques for mapping in these different conditions. At the end of the period, there will be an evaluation of the various techniques, and a comparison of their implied costs for full scale mapping. The final output will be a recommended protocol and a detailed cost estimate to map the world's irrigated area.

We revisit the justification and objectives of the project before considering the options and proposed investigations in more detail.

1.1 Project Justification

The collated statistics on irrigated area are presumed to be very accurate in the case of a country like the USA and to be rather speculative in the case of a developing country with considerable informal irrigation. The FAO statistics collate equipped area, which in some countries ignores the informal sector, particularly groundwater. These published statistics are accompanied by data on cropping intensity and crop pattern. In some countries, reported statistics reflect only the area on which irrigation charges are successfully levied, and may therefore underestimate actual cropped area. In other countries, the extent of equipped area may far exceed the available water supply, and therefore the actual area irrigated should be considerably lower than that reported. We do not have a clear idea of the regional and total errors in the estimation of irrigated area, but remote sensing offers a relatively cheap and cost-effective means of assessing **actual** irrigated area. Of course, there are seasonal and long term variations in water supply which also impact the actual irrigated area observed in any one season.

2 Objectives

The overall objective of mapping global irrigated area is to define the current state of irrigation development, so that options for intensification, expansion and land retirement can be investigated in a realistic and spatially disaggregated way. Ideally this will be able to explicitly account for water resource availability and reliability.

a) To improve on equipped area estimates of irrigation in the world, we ideally need to know how much area is actually irrigated, which requires the following:

1. Seasonally disaggregated area of actually irrigated crops, where crop seasons are distinct (some tropical, semi-arid and arid zones, and temperate zones).
2. Cropping intensity (Fig.1) and average irrigated area in tropical conditions where "continuous" cropping[1] is undertaken.
3. Area of supplemental irrigation.

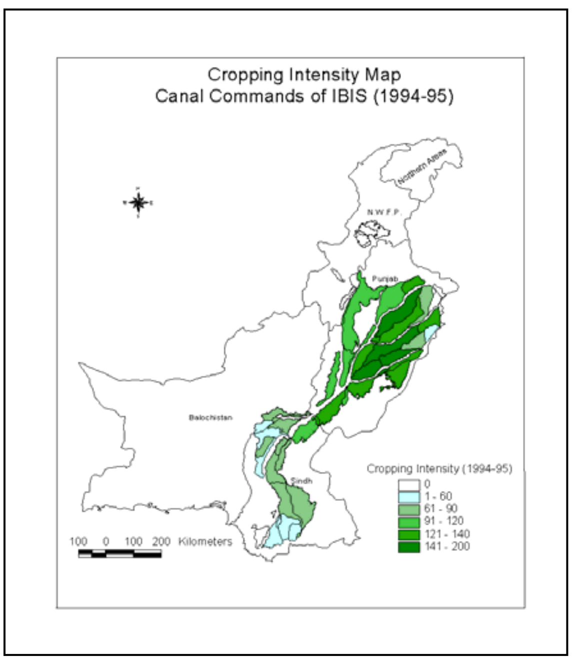


Figure 1 Annual cropping intensity variations within the Indus Basin, 1994-95 (Salman Asif, IIMI-Pakistan).

[1] This could be continuous rice production with as much as 3.5 crops per year; rotations with sugar cane, that require continuous watering; or could include lower intensities of production that do not occur over defined seasons.

b) We wish to be able to answer such secondary questions as:

1. How much water is presently used by irrigation?
2. What is the global environmental impact of irrigation?
3. How much informal irrigation is there? What is the breakdown between formal and informal irrigation?
    - What is the proportion of surface and groundwater use in irrigation?[2]
4. What is the role of irrigation in providing food production and food security?
5. What is the potential for intensification?
6. How much investment is actually used?

We also need such information to improve inputs into water supply/demand/food & climate models for scenario exploration in food security, water and environmental management strategies.

c) In the longer term, we seek to develop a set of tools that are potentially useful for irrigation monitoring at country level, and which take into account seasonal and annual variations in actual irrigated area.

3 Approach

3.1 Principles

Here, we list the basic principles behind our understanding of the best way to approach global mapping of irrigated area.

- We require the simplest possible solution at lowest cost, especially in consideration of future monitoring.
    - We should use coarse imagery wherever possible for reasons of cost, availability and consistency.
    - Where high resolution imagery is required, we should use single-pass imagery per season wherever possible to minimize imagery and processing costs.
- The use of masks is essential at all scales of analysis. Climate, topography, forest cover and historical average moisture availability masks provide essential contextual information for classification.
- Multi-temporal analysis is required in humid tropic conditions with complicated vegetation structures and overlapping irrigation seasons.
- Ground truth of appropriate scale test areas is highly desirable to check the accuracy of classification.
- Decentralised approaches to mapping and validation are desirable, with good supervision and common standards (GOFC Working Group, 1998).

[2] This is a hard question to answer, and in many locations definitive answers may need considerably more intensive investigation than envisaged in this research.

- Automation of all processes is essential for production mapping – selected methods must be amenable to automation. Image registration is a "killer" process as it is effectively a manual operation. Registration tasks include registration of fine resolution images to coarse ones for "training" and classification purposes; co-registration of time-composited images; mosaics of fine resolution images; co-registration of fused images (MODIS 250 with MODIS 500 or 1 km or optical imagery with SAR data). Therefore, where possible we should obtain well-registered imagery.

3.2 Overall methodology

3.2.1 Research phase

In parallel with investigations of appropriate techniques of image analysis, we need to make a coarse zonation of the irrigated world by country and region, so that we understand the specific requirements for production mapping in the future. This section outlines some of the factors to be considered.

Crop pattern catalogue

In order to determine when and how many remote sensing images are required for analysis, we need to pull together as much secondary information as possible. A first step is to collate "standard" irrigated cropping patterns for characteristic regions in each country (FAO Aquastat) and to derive expected signatures of vegetation cover over time (as indicated in Fig. 2).

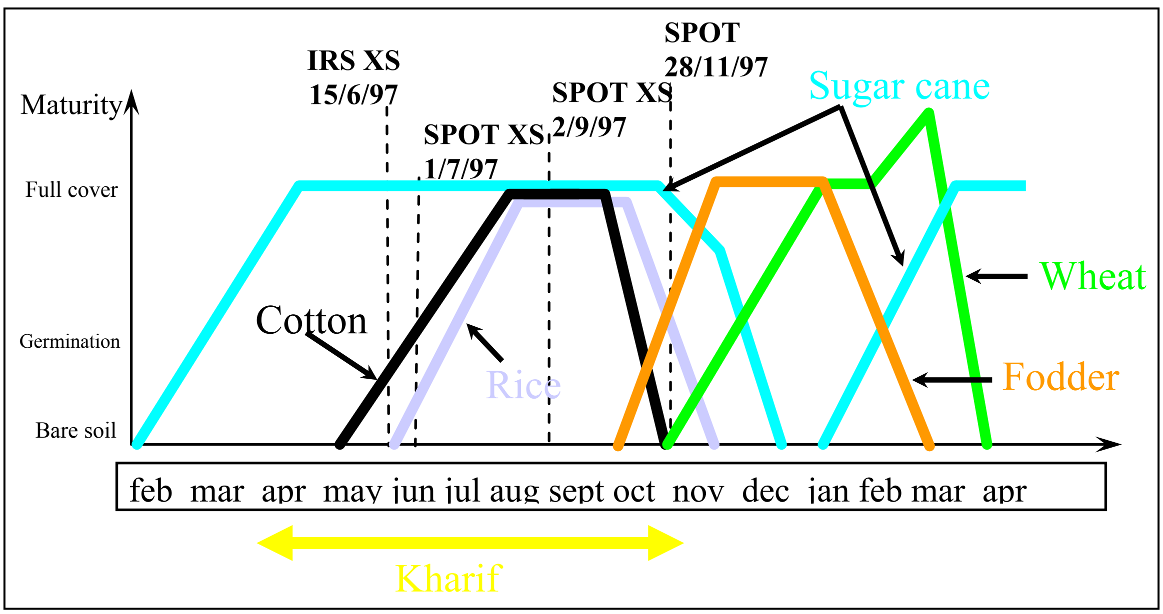


Figure 2 Example crop pattern from Pakistan, showing overlaps and overpass times for remote sensing data acquisition using hi-resolution imagery (SPOT)

Cloud cover durations

In order to understand where we can minimize the number of images used in classification (within a season), we need to prepare summary tables of cloud-free days per month for each of the regions defined above. This will highlight locations and seasons where assessment may be difficult or impossible using optical and thermal imagery. For example, ACRoRS (AIT) conducted a remote sensing classification of the Ganges Basin in 1988, using historical daily AVHRR imagery, but was unable to develop land cover estimates for June, July and August, due to persistent cloud cover and haze. Data for these months therefore had to be excluded from the analysis (Lacoul et al, 2000). In irrigation mapping, such a gap presents us with problems even though, in this particular case, we would expect maximum crop development of Kharif crops to be visible in September.

Other secondary data

Increasingly GIS is available for medium and large irrigation systems in many parts of the globe, and hopefully most of them are correctly geo-referenced. We should try to harvest at least the layers containing boundaries and canal layouts. There are a number of challenges to be overcome including 1) the identification of agencies or irrigation systems that have already created GIS and 2) accessing the data.

In some countries, for instance Kenya, GPS has already been used to mark the central location of an irrigation area (Bancy Mati, personal communication, 2001). We need to try to collate whatever such data exists.

Small scale irrigation

We need to collate secondary data on the relative importance and area of small scale irrigation in different regions. It will be very hard to avoid having to use higher resolution imagery to map irrigated area, since one full MODIS pixel (112ha) may be larger than many small scale irrigation and groundwater systems. Small scale irrigation in hill areas, such as Nepal, Philippines, Indonesia etc. pose further difficulties, even if their total net area is small relative to the global total. Considerations include topographic effects of slope and aspect on spectral and reflectance values, small scale and awkward shape, masking by forest vegetation and shadow and high probabilities of cloud cover.

If GPS locations are available, as in Kenya, it allows us to choose imagery more precisely and we may have to consider commissioning teams to do a very rapid GPS location exercise in some countries.

Using this information we should be able to define regions and approximate areas that require different methodologies for mapping – i.e. where fine resolution imagery is required, and where radar imagery is required because there is too much cloud cover for conventional methods to provide adequate results.

3.2.2 Research into remote sensing techniques

In parallel with these scoping exercises, we will investigate options and select promising techniques, as described in section 6. We will develop and trial these classification methodologies in Pakistan, India and Sri Lanka, which should cover the full range of expected climatic and land cover conditions. However, we may find that there are other niches identified which require further refinement or development of other mapping techniques. Where possible, these will be incorporated into the work programme as it proceeds.

3.2.3 Test and evaluation

The project will conduct a staged assessment of classification accuracy. We will make comparisons at two scales:

- Coarse resolution imagery against classified fine-resolution imagery – to determine the accuracy at a medium scale.
- Comparison with selected large-scale ground truth, covered by both high and low resolution images. We will conduct field surveys on the ground using GPS and also make use of reliable crop census statistics for specific areas.

There are some interesting scale issues to be tackled in this work. If we hypothesize that the official statistics are in error by approximately 25%, then we have to achieve a classification accuracy of at least 75 % to do the same job. Using high resolution imagery and good ground truth data, it is possible to achieve better than 90% classification accuracy of crop land, if not individual crops.

If we use fine resolution imagery to train coarse products, we run the risk of compounding classification errors from ground level to fine image, and from fine image to coarse image. Thus one could end up with overall classification accuracies of less than 50% (0.75*0.75 at each stage), which would not be an effective result. Offset against this, are sampling bias and errors when comparing coarse imagery with relatively small ground truth areas in the field. From this point of view, accuracy estimation against a larger sample, such as a (hi-res) Landsat image is preferable. This topic will be researched as one component of the project.

Generally speaking we will be working at the limits of classification accuracy for remote sensing of irrigated land cover.

The most important comparison to be made is with the Aquastat statistics and University of Kassel Irrigation Map. The project partners will compare remote sensing results for the test areas (mainly Pakistan, India and Sri Lanka) with the official statistics and the Kassel map. We will try to identify where there are explicable differences (informal or groundwater irrigation, limited water supply, drought or other special conditions) between the two and focus further investigations on discrepancies that cannot be easily explained or quickly cross-checked by other means.

The overall flow chart for this process is given in Fig. 3, below.

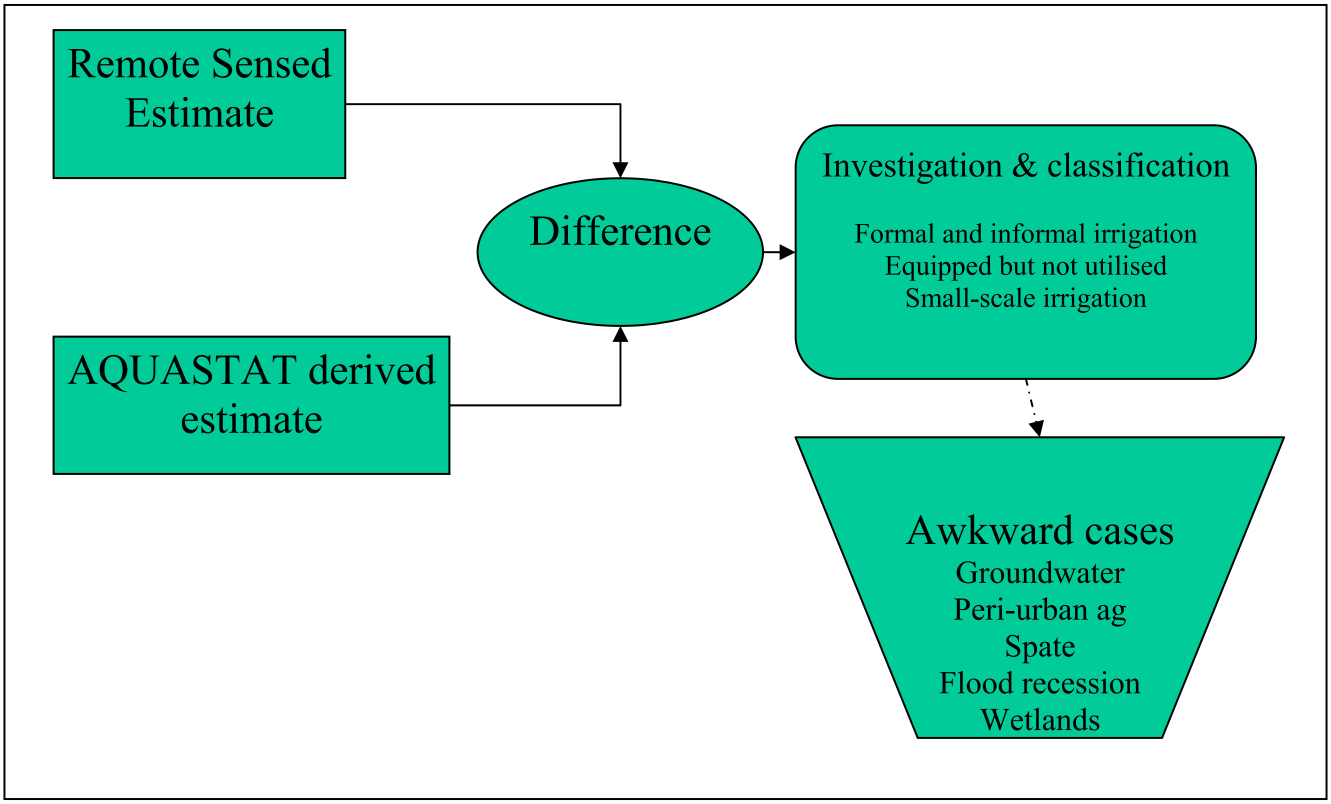


Figure 3 Comparison of Remote Sensed and Statistical estimates of irrigated area

3.2.4 Final methodology

The final methodology for mapping will be evaluated on the basis of the effectiveness and accuracy of the different classification methods, in different zones of the world. The cost and cost comparisons of different techniques will be considered and compared with costs of data collection by other means (census, survey etc).

3.2.5 Production mapping of the "whole" world

IWMI may or may not choose to get involved in production mapping of the entire world's irrigated area. This will depend on the success of the research phase, the cost, staffing requirements, infrastructure and time involved in completing the global task, and the anticipated benefit of the final product.

4 Characteristics of irrigated areas

Acceptable RS techniques must distinguish between the various characteristic land covers and identify cloud cover. As far as possible we need to lump land use classes so that we identify either irrigated crops or non-irrigated vegetation and bare soil etc. The ground conditions to be distinguished include:

- Bare soil
- Water bodies
- Urban and settled areas

The range of vegetation conditions normally considered in global-scale land use mapping includes:

- Forest cover – deciduous, evergreen and plantation
- Woodland
- Shrubs
- Grassland and wooded grassland
- Rainfed crops – rice (wet) and non-rice
- Irrigated crops – wet rice and non-rice crops
- Pasture
- Fallow land

Cloud, moisture vapour and other aerosols mask some or all visual and thermal wavebands, and can obscure parts of an image, and sometimes the whole view. Cloud and moisture vapour must be detected and masked out of the classification to avoid incorrect attribution. Partial cloud, aerosol and shadow affected images pose the practical problems as severely cloud contaminated images will not be selected.

There are a number of land classes that are hard to separate, and these will be described briefly. Remote sensing of vegetation principally relies on greenness (chlorophyll) and infra-red characteristics of plant canopies. Secondarily, surface temperature can provide useful information because a healthy transpiring crop has a low surface temperature and a bare rock surface with no evaporative cooling has a higher one.

Classes that present some challenges are discussed next:

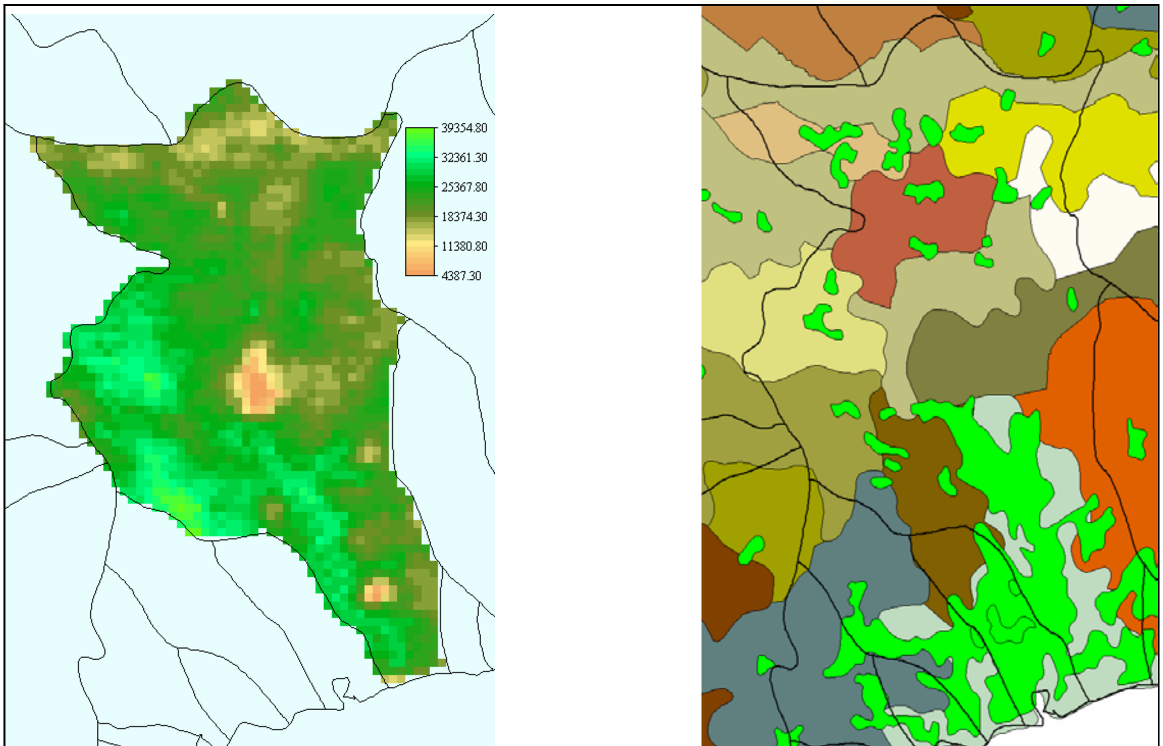
- Forest and plantation (un-irrigated but transpiring at or close to potential Et) and irrigated crops (Fig. 4). They can be separated by Synthetic Aperture Radar, because of differential backscatter characteristics and phase change, or by temporal profile of vegetative cover (vegetation index, VI): trees will have constant vegetation index, but crop VI will vary with the growth cycle (see below). There may still be confusion between forest and irrigated crops 1) if irrigation water supply is low and crops experience some stress compared to trees and 2) where there are deciduous trees and a single irrigated crop such as pasture.

Digital elevation models will separate trees from crops if they have a vertical discrimination of better than 5m, but require 3 m or better for adequate separation from scrub and bushland.

A map of biomass growth (derived from NDVI) is shown in Figure 5 for the Uda Walawe catchment in southern Sri Lanka and shows very poor correlation to irrigated rice land delineated from a GIS.

Figure 4 Typical field conditions in tropical Sri Lanka, where irrigated land is surrounded by forest and plantations.

- Grassland and crops – the NDVI signature should be long season for grassland (Julian Day 90 to JD 310 in temperate USA (Pringle, 2001), but may be ambiguous in tropical conditions, where both crop and pasture will show considerable temporal variation in growth.
- Wooded grassland and forest are commonly confused in land cover classification, which may not matter to use if we can adequately and reliably distinguish them from crops (DeFries et al, 1997).
- Rainfed crops are hard to separate from irrigated crops during the rainy season, and it is common for irrigation to be practiced in the rainy season in South and South East Asia and China. In theory, the crop density, and transpiration rates of irrigated crops should result in cooler surface temperatures and higher vegetation index than rainfed ones. However, this may only be evident during short drought periods when irrigation is optimally practiced and rainfed crops exhibit temporary stress.
- Similarly irrigated rice can be hard to distinguish from wet rice in the rainy season. Rice is adapted to aquatic environments, and is the crop of choice in areas that are prone to surface water logging and ponding. In many instances, irrigation infrastructure is provided in such areas and irrigation is supplied directly or by re-use (pumping) of captured drainage water. It is common to find irrigated and rainfed rice side by side in parts of southern China, the Mekong Basin and elsewhere, with only small topographical variations to separate them.
- Flooded rice at early growth stages is hard to differentiate from ponds and other water bodies, except by contextual information on shape and extent of the plots and land units.



Annual Biomass – Walawe Ganga

Paddy area (green) in Walawe Ganga

Figure 5 Comparison of biomass growth in Uda Walawe (left) with delineation of rice paddy areas – there is minimal correspondence (IWMI, Colombo: courtesy Yann Chemin).

Other ambiguous cases include:

- Sugar cane, which may grow for up to 18 months and may be cut and ratooned.
- Irrigated orchards. At a coarse scale there is nothing we can say about orchards, since they will rarely be of a size to fill a whole pixel and will be indistinguishable from other tree cover. At higher resolution, the relatively low density of trees allows orchards to be distinguished from forest and scrub, but detecting whether they are irrigated is probably impossible using remote sensing, except in arid and semi-arid areas such as Baluchistan, Iran and southern Afghanistan.
- Small scale irrigated horticulture is hard to identify even with hi-resolution imagery, as it is indeed very small and usually fragmented, and often located close to or within urban areas. The total area of such agriculture may not be significant in the overall context, but may be important economically in many locations. Peri-urban (irrigated) agriculture may include more extensive areas of pasture and fodders (for livestock and dairying), but is likewise going to be hard to distinguish without resorting to aerial photographs or similar ultra hi-resolution space products, such as IKONOS or QuickBird, which are all too expensive for this exercise.

- Highly heterogeneous mixes of rainfed and irrigated cropping and forest or grassland combine some of the challenges described above with complex landholding patterns (Fig.6). Ground truth may help defining usable classifications where this situation is known to be the norm on the ground.
- Crops that may be irrigated, but insufficiently so that, experiencing water stress, they appear similar to rainfed crops.
- Crops that transpire water sourced through capillary rise from high water tables.

Figure 6 Mixed agriculture on a hillside in Sri Lanka: late and early irrigated rice, trees, horticulture, fallow land and nursery.

4.1 Distinguishing irrigated vegetation from other land cover.

Clearly, where rainfall is non existent (seasonally or absolutely), we can be sure that green vegetation is irrigated. If there is low rainfall we can track soil moisture availability and separate rainfed crops from irrigated on the relative contributions of rainfall and its derived soil moisture. Peter Droogers (2001) has constructed masks using historical average meteorological data and rainfall. Soil moisture masks derived from this data and soil plant water modeling unfortunately will not allow separation of rainfed and irrigated crops during the rainy season.

In many cases we will have to use 16-day composites or monthly images to obtain enough time-signature information to identify irrigated crops from other vegetation. If a crop season is 90 to 100 days, we can only obtain 3 images at monthly intervals, but this may be sufficient if there are two or three crop seasons per year and we have the vegetation signature for the whole year.

In theory, it is possible to distinguish forest from irrigated crop and irrigated crop from rainfed crop (except under conditions of zero moisture stress) on the basis of vegetation index or change in that index and crop surface temperature. Well watered vegetation (irrigated, or rainfed vegetation with adequate soil moisture, such as trees with deep root-Zones, rainfed crops in the rainy season) will be cooled by transpiration whereas more water stressed vegetation will have a higher temperature.

A complete review of vegetation indices can be found in Bastiaansen (1998). The normalised vegetation index (NDVI) has been most commonly used to date for vegetation classification, but standard MODIS products include 16 day composites of Enhanced Vegetation Index (see IWMI Working Paper 36, 2002). Bastiaansen et al. (2001) prefer the use a Soil adjusted Vegetation Index (SAVI) for use in irrigated areas, which is an empirical modification of NDVI, with generalized calibration constants, that reduce sensitivity to soil brightness (see also IWMI WP 36).

NDVI is commonly defined as follows:

$$NDVI = \frac{NIR - R}{NIR + R} \qquad 1$$

where:
NIR = reflectance in near infrared band
R = reflectance in red band.

The physiological basis for this index is that reflectivity of NIR increases as leaf chlorophyll content increases, whilst the absorption of red wavelengths decreases (Tucker, 1979).

A surface temperature index, the normalized temperature difference index (NDTI) has also been found to be a specific time-of-day analogue of Crop Water Stress Index (Jackson et al., 1981), in Australia (McVicar and Jupp, 2000). It has been used to spatially interpolate soil moisture condition and the surface temperature (T_s) is derived from AVHRR channels 4 and 5, using the split-window algorithm. It is defined as:

$$NDTI = \frac{(T_\infty - T_s)}{(T_\infty - T_0)} \qquad 2$$

where:
T_∞ = Modelled surface temperature assuming no available soil moisture
T_s = Surface temperature derived from remote sensing.
T_0 = Modelled surface temperature assuming no surface resistance (or fully available soil moisture).

The modelled values are obtained by inversion of a resistance energy balance model (Monteith and Unsworth, 1990) that requires adequate meteorological data and information on surface and canopy roughness for correct calibration. It may be possible to derive suitable values for existing meteorological data and published values of crop and soil resistances for predominant crop types.

We could therefore combine surface temperature (Ts) or NDTI with vegetation index to make an initial separation of irrigated crops from other vegetation as shown in Table 1. The absolute value of VI could be replaced by a change in VI between two or more dates.

Table 1 2-way classification of vegetation based on vegetation index or better, change in vegetation index over a time period and surface temperature.

	T_S High	**T_S Low**
(Δ)VI High	Rainfed Crop	Irrigated crop
(Δ)VI Low	Stressed trees or deep rooted vegetation.	Forest

A set of heuristic rules could be developed from this matrix, such that classifications would be made on the vector of change (increasing or decreasing vegetation index with increasing or decreasing surface temperature).

The general temporal pattern of NDVI change for different examples of land cover is shown in Figure 7. The values for a tropical forest should remain more or less constant over the year, whereas a deciduous forest will have a characteristic pattern dependent leaf growth in spring and fall in autumn. The temporal profile for grassland should in theory be longer and less pronounced than for a rainfed crop, but may be complicated by grazing and cutting. Three arable crops grown in one year should have an identifiable profile as shown in the third window. In practice, the absolute values of NDVI overlap for different land cover types, with values for grassland, forest and crops ranging from 0.2 to 0.7 (RST, NASA, 2000).

A real NDVI profile for two rice crops in Uda Walawe, Sri Lanka is shown in Figure 8, and the pattern is somewhat attenuated with maximum NDVI values of 0.4. Biomass and yield have been empirically related to NDVI (see inter alia, Bastiaansen, 1998), and used to derive estimates of productivity in cropping. This can be better achieved from seasonal and annual evapotranspiration and crop models, using the SEBAL technique (Bastiaansen, 1995 et seq.). An example of an estimate of rice productivity for Sri Lanka is shown in Figure 9, but requires accurate classification of ground cover, using conventional medium resolution remote sensing and supervised classification techniques, using adequate ground truth.

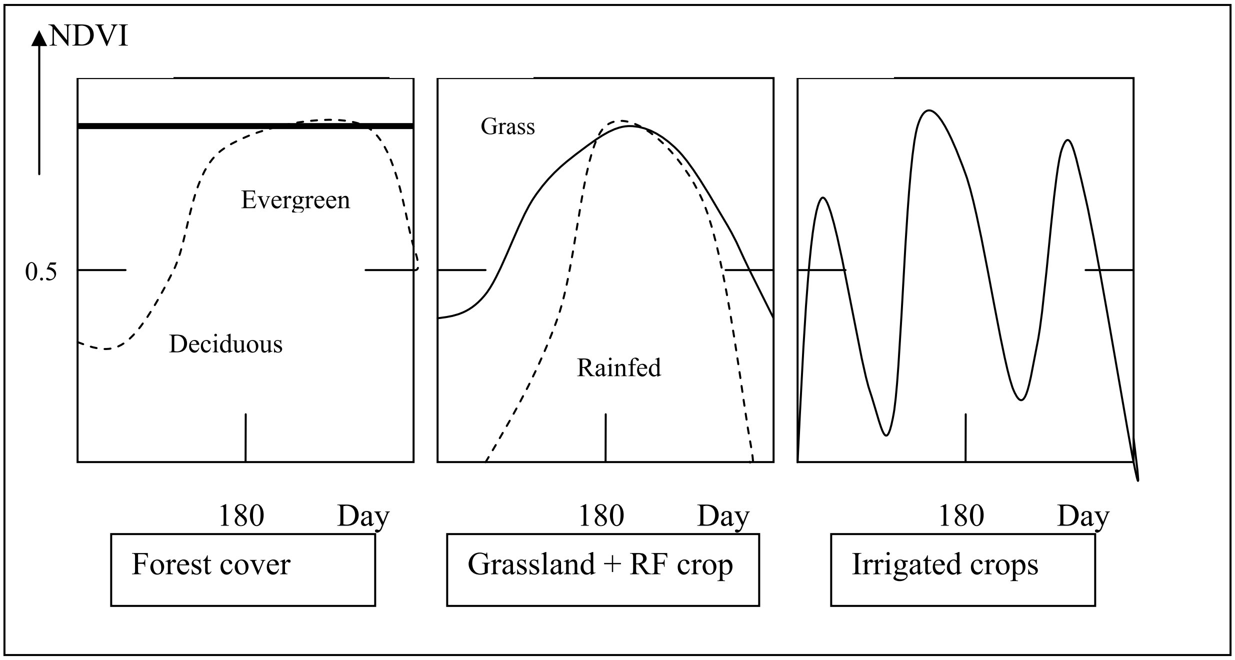


Figure 7 Idealised vegetation index values for different vegetation covers over one year

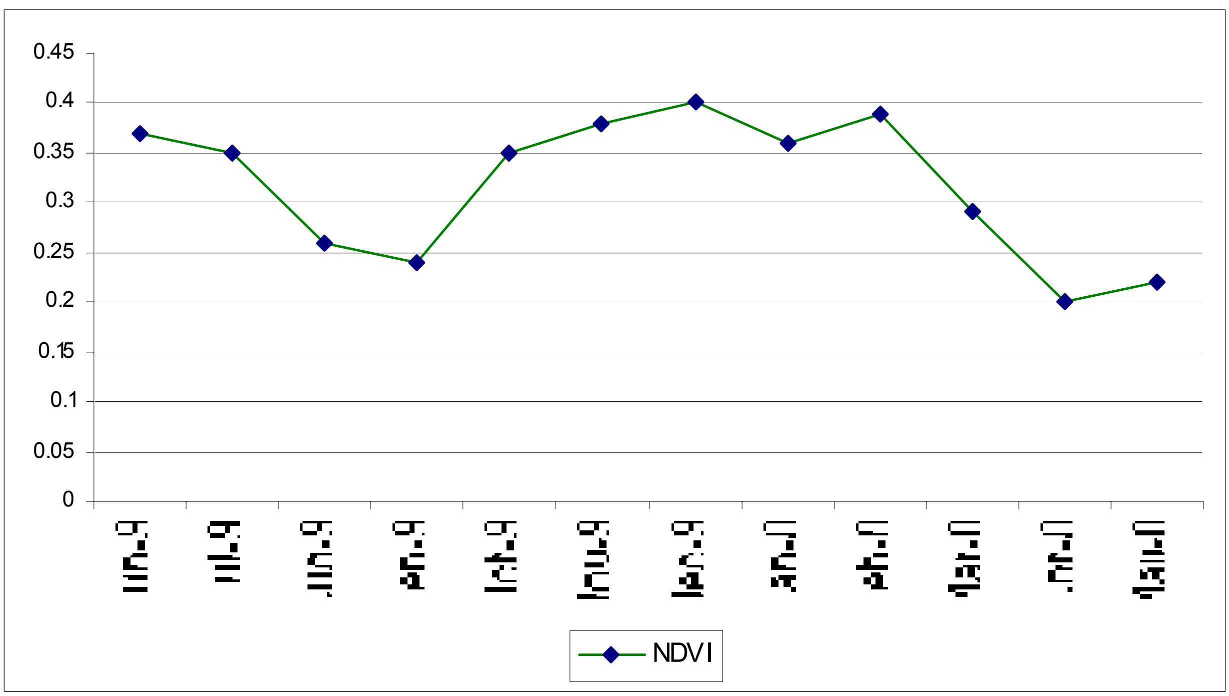


Figure 8 Annual variation of NDVI over two rice seasons in Uda Walawe, Sri Lanka, June 1999-May 2000 (Chemin, 2001) .

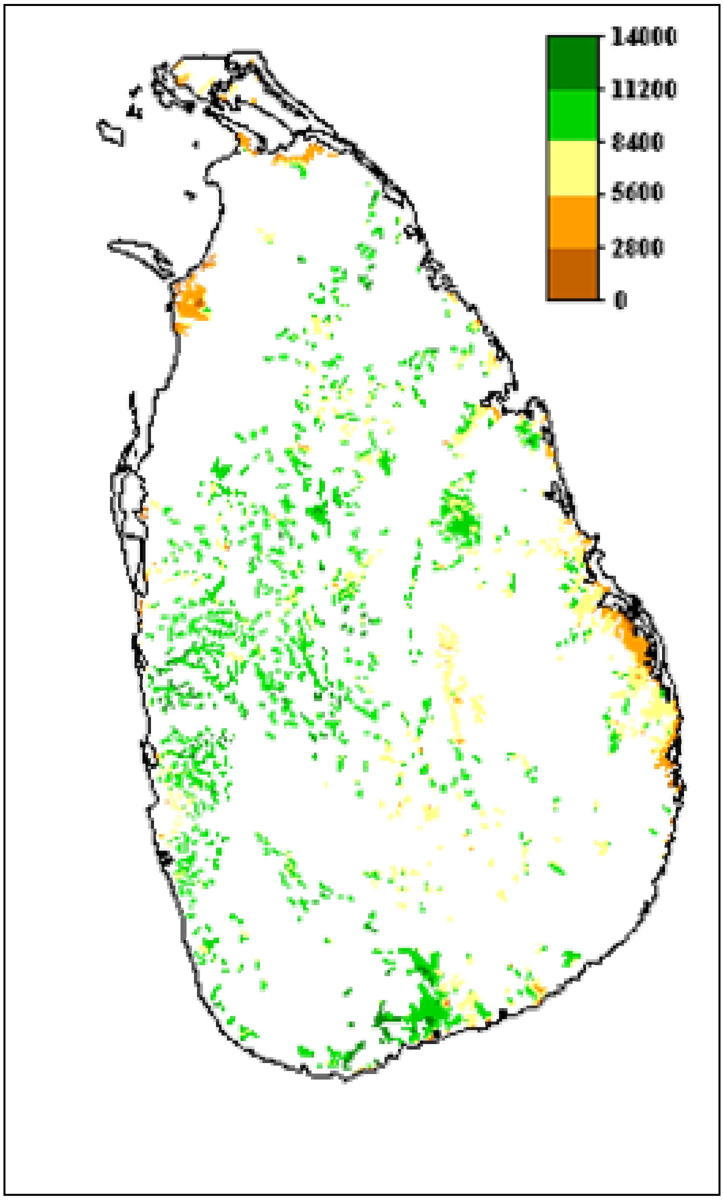


Figure 9 Annual irrigated rice yields over one and two crop seasons (kg/ha) in Sri Lanka, 1999-2000, determined from Landsat NDVI. (Chemin, 2001)

Therefore, other metrics need to be used to better differentiate land classes, and these are summarized in detail by Hansen et al. (2000) for global forest mapping and land cover classification. These include maximum, minimum, mean and amplitude of NDVI over greenest and warmest months, and similar measures of individual bands of AVHRR. For trees, the most frequently used metrics were minimum annual red reflectance, and maximum annual NDVI. Work is required to establish a similar set of useful metrics for irrigated cropping in general or sub-groups of irrigated cropping, such as rice and non-rice crops.

Structural characteristics of vegetation are observable with active remote sensing techniques such as Synthetic Aperture Radar (Briscoe and Brown, in Henderson 1998). Wet rice can be distinguished from dryland crops on the basis of reinforced backscatter in C and L band SAR, due to reflection from the water surface beneath the crop (Turral, 2002). Broadleaf and cereal crops can be separated (Bouman, 1999) and with fully polarimetric radar, elaborate classifications can be made, including separation of rice growth stages (Turral, 2002). In space, only ENVISAT has multi-polar capability in C-band, whereas other satellites (Radarsat and ERS2) are single band, single polarisation sensors. The current cost of radar imagery is too high (up to 5000 US$ per scene for Radarsat fine mode) for routine mapping at a global scale. There are good possibilities in fusion of radar imagery with optical thermal imagery for more awkward conditions, but cost is likely to be a major constraint. This can be investigated and properly quantified in the research.

There is potential to use the Surface Energy Balance Algorithm, SEBAL (Bastiaansen et al., 1998) and its derivative, SHEBA (Gieske, 2002) to determine actual seasonal evapotranspiration over an area as an additional means of classifying irrigated land. Although the SEBAL technique is currently rather time consuming, SHEBA incorporates optimization of manual iterations to determine sensible heat flux, which makes it potentially more attractive as a tool in a global mapping exercise.

However, there is possibly poorer performance of SEBAL-type algorithms in humid areas, compared to the arid conditions where they have mainly been applied (Pringle 2001). With particular reference to the Mississippi Delta in the USA, Pringle states that in humid environments, the surface temperature depression due to cooling by evapotranspiration is attenuated. Therefore, temperature differences between vegetation transpiring at maximum rates may be as little as 4 K from those at minimum rates, posing problems for correct discrimination of crops and calculation of crop Et. There is evidence of this in IWMI Et studies in Sri Lanka using Landsat (Bandara, manuscript under review) and in Hubei province in China (Chemin and Alexandridis, 2001), using both Landsat and MODIS data. A visual indication of this phenomenon is presented in Figure 10, which compares tropical Sri Lanka with the Indus Basin in Pakistan.

5 Options in global irrigation mapping

5.1 Imagery

Workable solutions depend on achieving a cost-effective match between available data, processing techniques and the particular ground conditions we seek to identify. Working Paper 36 contains a detailed summary of the satellites available for GIAM applications.

- MODIS on the Terra satellite and since mid 2002 also on Aqua.
- AVHRR on multiple NOAA satellites.
- Land Sat 7
- ASTER also on the Terra and Aqua satellites.

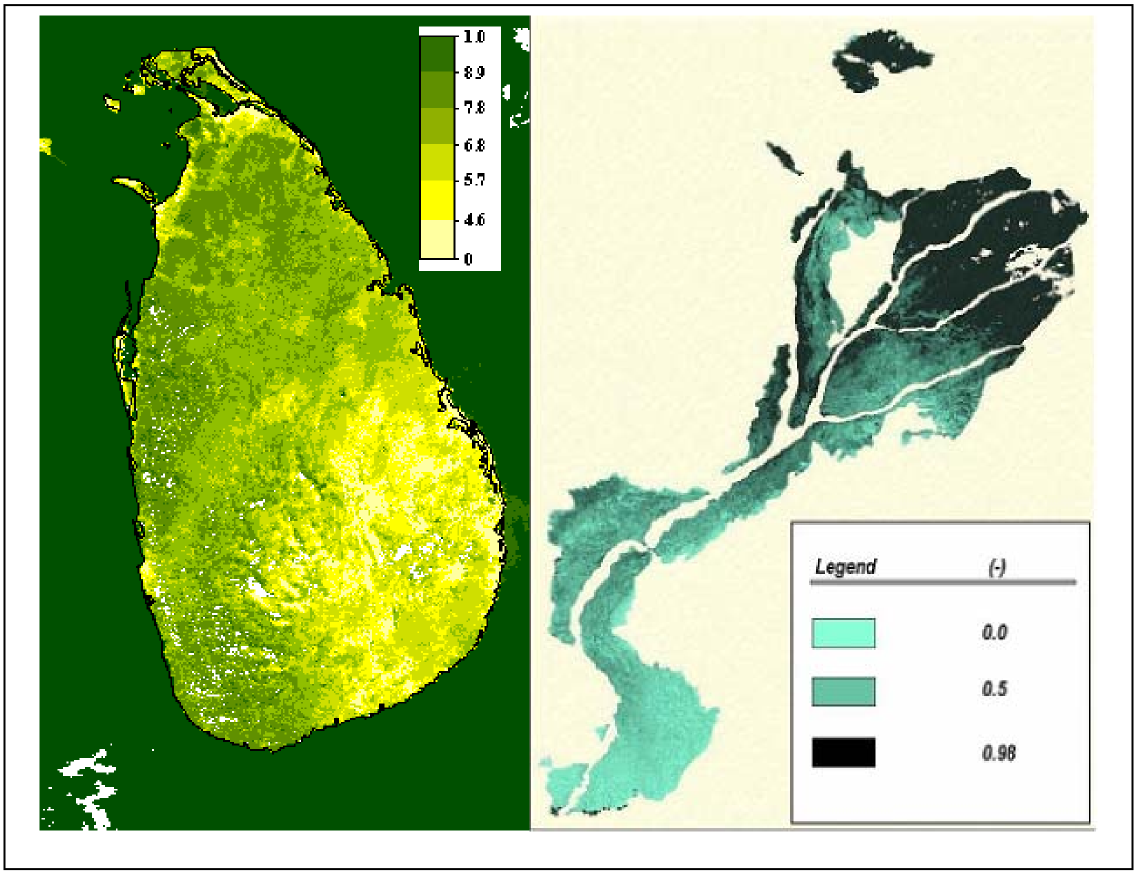


Figure 10 Evaporative fraction (**Λ**) (derived from SEBAL, for Sri Lanka (scaled 1-10) and for the Indus Basin (scaled 0-1). The images show that there is a much compressed dynamic range of **Λ** in tropical conditions compared to arid ones.

A few further points are worth making before we consider the option paths for classifying irrigated area.

Both AVHRR and MODIS images are acquired daily and are coarse resolution products. MODIS is the platform of choice for GIAM, since it has multiple resolutions (250m for Bands 1 and 2 (R and IR), 500m for NIR-MIR bands and 1000m over some MIR and thermal bands. Data is free and is archived for download via the internet and is also distributed free on CD. MODIS has better atmospheric correction algorithms than AVHRR, and has a more constant look angle over repeat passes. The level 1 images can be registered to approximately 1-2 pixel accuracy using a freeware tool supplied by NASA. Some 30 higher level products are available from (level 1 to level 4), including 16 day composites of 500m resolution EVI (MOD13), which come registered with an approximate accuracy of 1-2 pixels.

The Enhanced Vegetation Index (EVI), is derived from red and near infra red bands, as NDVI, but includes a correction term for aerosols (cloud shadow and smoke plumes) using the blue waveband (Huete et al., 1999) and soil brightness adjustment as in SAVI. The EVI data is previously corrected for cloud contamination and BRDF effects.

$$EVI = \frac{NIR - R}{NIR + C_1 R + C_2 B + L}(1 + L) \qquad 3$$

where:

NIR = near infra read reflectance
R = red reflectance
B = blue reflectance
C_1 = aerosol correction factor for red band = 6.0
C_2 = aerosol correction factor for blue band = 7.5
L = soil correction factor as used in SAVI = 1.0

A full list MODIS products can be found at the following web address:
http:modis.gsfc.nasa.gov/data/dataprod/descchart.html

If all bands are required, lower level imagery (Level 1b) must be acquired and pre-processed. Therefore, wherever possible, high level products will be used in analysis. At present, there is a time lag of up to 4 months before some high level imagery is available via the EOS gateway. A MODIS receiving station with an Asian footprint has been operating at ACRoRs (AIT) since May 2001 (Koki and Honda, 2002) and can provide Level 1b products very close to the time of acquisition for a nominal cost (c. $30 US / scene).

MODIS has 10 bands in the visual, 6 in NIR, and 6 in thermal portion of the spectrum, which present possibilities for analysis of simplified spectral signatures. Thus MODIS has more possibilities for image analysis than AVHRR, which only has 5 wavebands (R, NIR, MIR and TIR(2)).

AVHRR may still be used, but requires more processing than MODIS. However, if we wish to test MODIS derived methodologies against established ground truth data, we may have to use historical AVHRR data.

High resolution sensors

There are two higher resolution optical/thermal resolution sensors available – Landsat 7 and Aster. Registered Landsat 7 imagery prices (600 US$ per scene) are very much lower than previous comparable products.

One Landsat image covers 170 by 180 km (3.06 million ha nominal area) and, even if 20% of the land area were irrigated and we could get exact co-registration with irrigated area, we would need in excess of 425 images for <u>one season</u> (amounting to 255,000 US dollars excluding image processing costs per season). Additionally, it is unlikely that the accuracy of irrigated area classification would exceed 75% from single images in many cases, necessitating some form of multi-temporal analysis or fusion. Typically we would require between 3 and 5 images for effective multi-temporal classification, which would blow out costs severely at this scale of analysis.

We will have to make selective use of Landsat imagery for

1. training classifications in MODIS images,
2. accuracy estimation on test areas which have been well classified using supervised classification and ground truth information,
3. mapping small scale irrigation areas that need higher resolution imagery.

The 15 m panchromatic band in Landsat ETM offers good possibilities to delineate structure on the ground (especially in small scale irrigation systems) and can be fused with the coarser wavebands. There is also a thermal band at 60 m, which gives surface temperature at high resolution.

Current pricing of SPOT imagery is unattractive compared to Landsat 7 and has therefore this option has not been pursued further.

The Aster sensor has a greater number of wavebands (14) than Landsat (7) and is a free product that can also be downloaded via the internet. However, it is very much a research tool, and because of its high resolution and high frequency orbit (one overpass per day), it samples only a fraction of the earth's surface each day. The sensor is pointable and off-nadir targets can be imaged on request. ASTER offers us free imagery where it is available, but it sadly cannot be used as a mapping tool. The coverage of available ASTER data is very patchy at the moment. We will be able to use it for training coarse resolution imagery (as in the WP 36 methodology) or for accuracy estimation using conventional supervised and unsupervised methods.

Radar satellites

The great attraction of Synthetic Aperture Radar is that it penetrates cloud. There are currently three operational SAR satellites: ERS2, RADARSAT, and ENVISAT. ERS2 and Radarsat have C-band ($\lambda \approx$ 5cm) sensors with only one polarisation and a repeat pass interval of around 28 days (descending orbit). They therefore require multi-temporal processing for most vegetation applications (see inter alia, Liew, 1998; Radarsat International (2000)). The ENVISAT ASAR sensor has multiple polarisations – C_{hh}, C_{vv} and C_{hv}, but is still in an evaluation phase after successful launch in early 2002. The main drawback for Radar data is cost. Commercially supplied un-registered ERS2 images cost approximately $1200 US for a 100 by 100km scene. Radarsat costs 3-4 times more. ENVISAT data is largely restricted to existing research collaboration at the moment, although there are still possibilities to propose research projects. Whilst research pricing is available for both RADARSAT and ERS-2, it is unlikely that this could be extended to a full-scale global mapping exercise.

ENVISTAT will be joined in space by other multi-polar single frequency satellites – C-band RADARSAT 2 (2005), L-band ALOS in 2004 and a private initiative called TERRASAR with X-band and C-band sensors proposed for launch before 2005.

Therefore, investigation into the use of radar will have the lowest priority in this research programme, and although it is required for some parts of the world (See Figure 2), it is unlikely to offer practical solutions in the short term.

5.1.1 Implications of cloud cover on sensor choice

Daily coarse imagery, such as MODIS, gives a high chance of finding at least one cloud free day in each 16 day composite period. This is one major advantage of the NOAA and MODIS products compared to high resolution sensors.

The long repeat pass of LS 7 (16 days) and other platforms (up to 28 days) does not allow the same level of sampling and chance of obtaining a cloudless image. ASTER orbits daily, but only covers a small percentage of the globe each day, which is fine for requests for data in a specific location, but is not workable for time series data acquisition. Where high resolution imagery is essential and cloud cover is frequent, then radar images can be used at critical times in the season. The most likely use of radar data is in time series infill with high resolution data (Landsat TM) (Moran et al. 1996; Briscoe and Brown, 1995; and Leckie, 1990).

5.2 Sources of error

Sources of error must also be considered because of their implications in choice of methodology.

Image registration

Image registration is a constant issue. A 1-2 pixel error in a MODIS image ranges from 500m (at 500m resolution) to 2 km at (1 km resolution). In the work undertaken at IWMI in relating fractional vegetation cover in an Aster image to Vegetation Index in a MODIS image, it has proved necessary to re-register the image manually and then aggregate pixels from 500m to 2 km to overcome registration deficiencies in arriving at correlations with high R^2. It should be noted that manual registration of MODIS and ASTER images is difficult, and is normally done by registration to coastline masks. However, the positional accuracy of pixels in the interior of continents is often not very good using this technique.

Landsat Ortho accuracy is quoted at 50 m for 28.5 meter pixels (i.e. 2 pixel error). This translates to an area error of 0.25 ha per pixel, but the proportional error depends on the size and perimeter: area ratio of the land unit to be classified.

The third source of registration error lies in co-registration of time series, and data fusion between data at two different resolutions or from two different sensors. The 16 day MODIS EVI composites are already well co-registered and therefore save investigators a considerable amount of work.

Other error sources

Missing data is one source of error and can be due to cloud, and missed scan lines resulting from instrumentation or data transmission problems.

Inconsistent recorded reflectance values due to slope and aspect effects in hilly country can be corrected by DEM if available. Vegetation index and surface temperature values can be significantly raised or lowered, resulting in incorrect classification (see ENVIDATA sample exercises for Boulder Colorado, RSI, 2000). The currently available GeoTOPO 30 global DEM is too coarse for this task, but it is hoped the SIR-TM derived global DEMS will enable corrections where necessary.

Pixels may simply be mis-classified due to a) radiometric interference (aerosols) and b) distortion from multiple look angles relative to the sun for time-composited series, which means that AVHRR and MODIS images require BRDF correction. This correction is generally made on the basis of knowing land cover characteristics and the correction algorithms make some assumptions in this case, which may introduce some circularity of argument into the classification procedure.

Error can be compounded through training coarse data sets on the basis of classification in hi-resolution images, which themselves have some misclassification and other errors. A very good unsupervised classification might only have an accuracy of 80%. If ground truth is incorporated, there may also be incorrect identification on the ground and problems of accurate co-registration of ground truth and training images.

Most of the errors mentioned can be improved, but at a cost of more time and care in the processing chain. It is therefore very important that the project pays close attention to estimating and addressing sources of error and estimates the benefits and costs of error correction.

5.3 Options

The flow diagram in Figure 11 should distil the foregoing discussion in to a set of options for each combination of scale, continuity and climate condition (principally cloud cover) that affects our ability to map irrigated area accurately. As discussed earlier, some outcomes, such as c) and i) are not likely to be pursued on the basis of cost and practicality, but have been included in the diagram as logical outcomes.

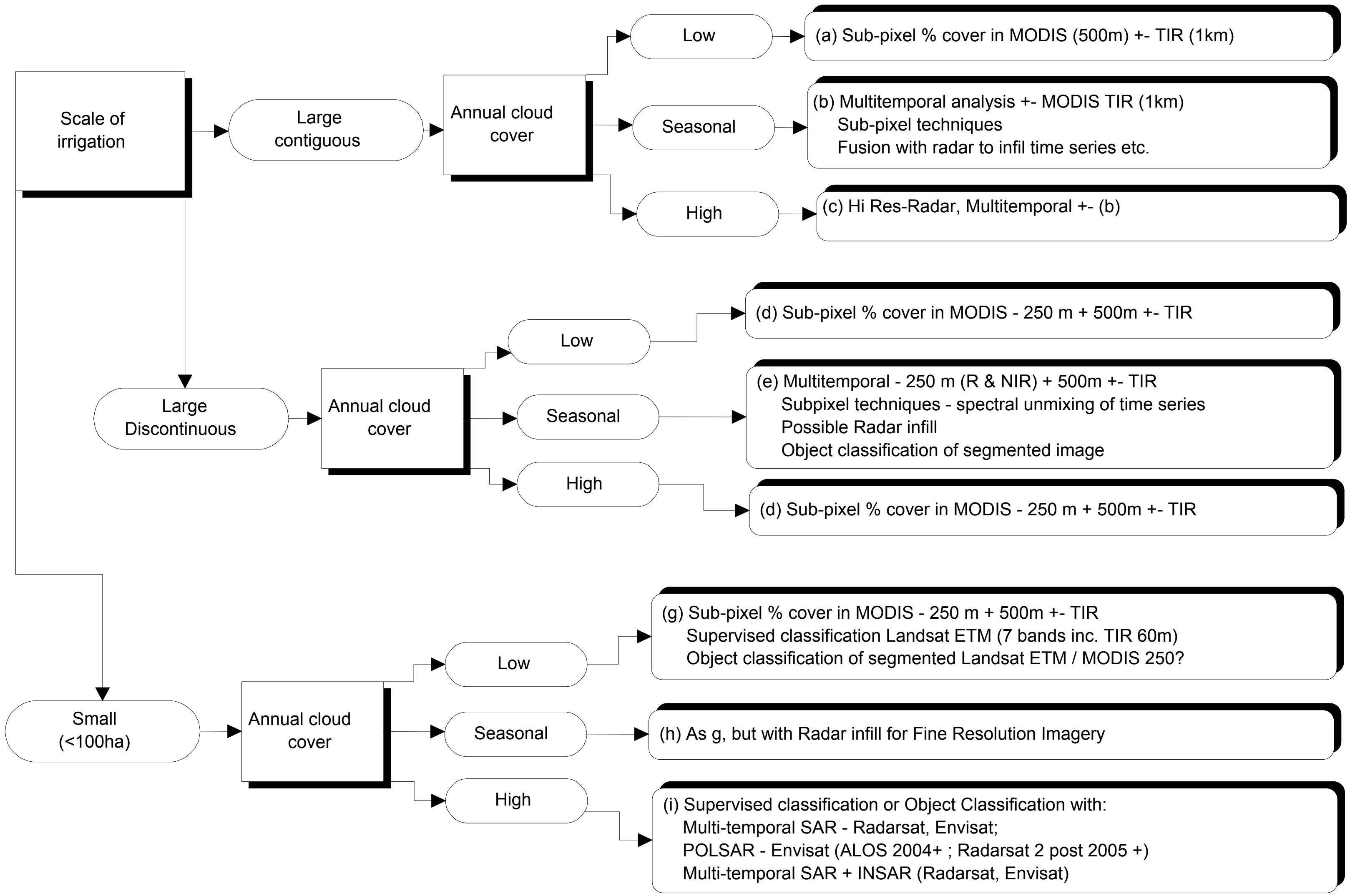


Figure 11 Options for mapping subsets of global irrigated area

6 Work Plan - parallel research activities

6.1 Focus

The focus areas for researching and testing suitable methodologies will continue to be:

5. Pakistan (arid conditions and large contiguous irrigation systems, few problems with cloud cover).
6. India (arid through semi-arid to tropical, large medium and small irrigation systems and groundwater areas, variable cloud cover).
7. Sri Lanka (humid tropics, cloud cover and small irrigated land units interspersed within forest and plantation).

In principle, we would like to conduct some work later in the programme on small scale irrigation in Africa, using techniques that have already been developed by the project. Kenya and South Africa are the most likely locations for this work.

6.2 Collaboration

The existing collaborators in this study are:

1. FAO Aquastat (Jean Marc Faures, Jippe Hoogveen)
2. FAO Remote Sensing (Jelle Hielkemar)
3. University of Kassel (Petra Döll)
4. IWMI

We hope to expand this group to include some more specialist remote sensing expertise, as follows:

5. University of Maryland (Masters Student under supervision of Dr. Ruth De Vries) – multi-temporal classification using decision trees and coarse imagery.
6. Asian Centre for Research on Remote Sensing (ACRoRS), Asian Institute of Technology, Bangkok (Prof. Kiyoshi Honda)

Discussions have been held at various times with both groups, but no formal agreements have yet been made.

IWMI's regional partners will be involved as follows:

7. IWMI-Pakistan: ground truth and spectral unmixing approaches using multi-spectral data.
8. IWMI-India (Murthi) / NRSA, Hyderabad: ground truth, imagery, secondary data and multi-temporal processing of MODIS data.

Additionally there are initiatives already underway on various aspects of remote sensing and irrigation, and we may collaborate with three groups who have been identified so far.

1. South Africa – fine resolution irrigation area mapping in arid conditions and ground truth work being undertaken by the Institute for Soil, Climate and Water, of the Agricultural Research Council.
2. Sri Lanka: Mahaweli Authority / Department of Irrigation / Meteorological Department.

3. Australia: Institute for Sustainable Irrigated Agriculture (ISIA), Tatura, (McAllister and Abuzar).

6.3 Methodologies to be explored

The key task is to test the separability of irrigated crops under different conditions of scale and size of land units; complexity and heterogeneity of landscape and land use and; by seasonal meteorological conditions - rain / no rain; temperature; clear/cloudy/hazy.

The use of coarse resolution imagery implies the need for sub-pixel techniques to identify the **proportion** of a specific land-cover that is likely to be contained within that pixel. In most real-world cases, a MODIS pixel at 500m by 500m (25 ha) will not contain 100% irrigated area. In areas with large scale contiguous surface irrigation, there might be roads, field bunds, channels and houses in an otherwise fully irrigated landscape. In more complex situations there may be other land use types – forest, fallow, grassland and so on. Sub-pixel methods are used to relate the proportion of irrigated land in a coarse pixel to observable remote sensing information, such as vegetation index, temperature and reflectance values.

Conventionally, in higher resolution image analysis, we assume that the land use within one 28.5 m by 28.5 m Landsat pixel is homogenous. In practice, we still understand that some portion of the pixel will not be cropped area, but will contain a proportion of banks, paths, channels and so on. We normally simply factor the pixel area to obtain the net irrigated crop area per pixel (typically 85-90%), if indeed we require such fine adjustment.

Sub-pixel information may be required to identify crop type, but not whether it is predominantly an irrigated crop, a forest or some other land-use. Data at a resolution of 250m pixels (Bands 1 and 2) in MODIS covers 6.25 ha per pixel. Whether this is a good enough resolution to track changes in vegetation index directly to classify irrigated area remains to be seen. Fusion between this scale of information and the coarser resolution images offers a way to avoid the need to develop many different empirical relationships between vegetation cover and VI.

Thus, for all coarse resolution imagery we require some relationship between percentage of irrigation and measurable parameters. For high resolution imagery we identify each pixel as a homogenous unit and aggregate pixels to obtain area and delineation, using conventional metrics of VI, surface temperature, reflectance and temporal changes in their values.

A number of different approaches to sub-pixel parameter estimation will be investigated and coupled with different techniques of multi-temporal analysis for coarse imagery. Analysis of finer imagery will be conducted using more conventional approaches, and add in some new possibilities, such as the use of shape, size and other topological and proximity measures to define land classes, using proprietary software.

6.3.1 Masks

We will use masks in all approaches to help improve classifications from remote sensing data. Such masks include:

1. Digital elevation models – preferably the SIR-TM, 90m posting dataset. These will be used to delineate altitude, slope, and aspect for zoning irrigated area and making corrections to reflectance values where required. The Shuttle Imaging Radar Mission in 2000 collected two complete sets of interferometric C-band radar data covering the whole world between + 60 and – 60 degrees latitude. The advance data is being processed by NASA JPL under contract to the National Mapping Agency (NIMA). The first data sets are scheduled to be made available to the public via the internet before the end of July 2002 and the complete set should be on the web by the end of 2002 (Kobrick, 2002).

2. IWMI Climate Atlas data – for temperature, rainfall and evapotranspiration.

3. Soil moisture availability by month – this mask was produced by Peter Droogers using long term average IWMI climate atlas data. This data allows the probability of the existence of an irrigation system to be assigned to a pixel, since where evapotranspiration deficits occur, there is a higher likelihood of a need for an irrigation system. Actual rainfall and evaporation data might help to separate irrigated from rainfed land in specific years, but it is highly unlikely that we could collate data for the test years of 2001 or 2002.

4. Forest masks. We are testing the use of the University of Maryland's Global Forest Cover data sets in Pakistan, India and Sri Lanka. The results will be discussed in a forthcoming working paper.

6.3.2 Sub-pixel methods

Vegetation cover: Vegetation Index relationships

The idea is to derive a relationship that gives the percentage of irrigation area in a MODIS pixel, on the basis of training data sets derived from ASTER images. An unsupervised classification is performed on the ASTER data to identify irrigated area and the ASTER pixels are aggregated to MODIS dimensions. The percentage of irrigation area is determined from the number of pixels containing irrigation divided by the total number of 15m Aster pixels per 500 m MODIS pixel (1111). IWMI has investigated the relationships between VC_{ASTER} and VI_{MODIS} over Pakistan, India and Sri Lanka, using the methodology proposed in Working Paper 36. The relationship, after improved geo-referencing and pixel aggregation, gives a highish R^2 (>0.6) for arid regions but less than 0.3 in parts of India. So far, the data has been prepared for one month only – January 2001. A working paper reporting the results in detail is under preparation and will be distributed for comment as soon as it is available. The working paper will make initial comparisons with Aquastat data and the Kassel map and provide some initial insight into where and why there are differences. The next steps are to repeat this approach for a 12 month sequence and then investigate the use of various multi-temporal techniques to classify irrigated area by season.

A similar technique was tried for the whole of Pakistan using data for 1993-94 and a relationship between VC_{TM} and VI_{AVHRR} (Bastiaansen et al 2001, IWMI working paper – unpublished). If the value of vegetation cover was < 0.28 (≈ SAVI = 0.19), land was classified as not irrigated and if greater than 0.9 (≈ SAVI = 0.60) it was deemed to be fully irrigated. The total irrigated area estimated by remote sensing in Rabi and Kharif adds up to 17 million ha, which is in fact the quoted area for installed irrigation. The equipped area for the Indus basin is 16.3 million ha (IIMI-Pak) and average cropping intensities in Rabi and Kharif are reported to be 0.9 and 0.6 respectively, which implies a total cropped area of more than 26 million ha for Rabi and Kharif. SAVI was used in preference to NDVI and was adjusted to incorporate SEBAL-derived soil moisture. The authors concluded that it would as effective to use surface temperature as a surrogate for such derived parameters as Et and soil moisture. This data will be revisited.

Decision trees
More sophisticated approaches to sub-pixel classification have been successfully developed and tested by the University of Maryland, Global Tree Cover Project, run by Ruth de Vries. In this work, decision trees and multiple linear regression (MLR) have been used to identify characteristic metrics and combinations for one pass and multitemporally acquired parameters. Over 500 Landsat scenes were used to identify and identify "pure" land and forest cover types, using secondary data and expert knowledge, and aggregate them to AVHRR pixel scale. The metrics that best describe the observed reflectance and vegetation indices at AVHRR (1.1 km pixel) scale were investigated using decision trees and or MLR. A complete description of the metrics and their selection using decision trees is given in Friedl and Brodley (1997).

Decision trees are explicit non-parametric alternatives to supervised classification. They make no assumptions about the distribution of the input data, and are flexible and robust in dealing with non-linear and noisy data. Users have a choice in developing single or multiple variate decision trees, and hybrids of the two, which are reported to give the most consistently high classification accuracies (Friedl and Brodley, 1997). In single decision trees, two classes are divided by a simple metric, such as being greater or less than a parameter threshold, where the parameter can be surface temperature, NDVI, or a channel reflectance (See Figure 11). In multi-variate decision trees, a combination of variables, say NDVI and surface temperature thresholds together, are used to separate classes. One feature of training decision trees is that some manual pruning is required to reduce the number of classes produced.

In back-to-back comparisons of tree-based classifiers and a maximum likelihood estimator, Friedl and Brodley investigated AVHRR derived 1º and 1 km land cover plus Landsat 30 m land cover sets. Classification accuracies were (surprisingly) higher for 1º data than the 1km sets and were poorest for the TM 30 data. Overall the decision tree algorithms consistently out performed the maximum likelihood estimator, but all encountered particular trouble in classifying three classes accurately at 1 km resolution – evergreen needle leaf forest, woody savannah and permanent wetland. Cropland was classified with an accuracy of greater than 72% with all decision tree algorithms compared to 64% for the maximum likelihood technique. Cropland mosaic was classified at 78% accuracy with a hybrid tree classifier compared to only 31% using maximum likelihood.

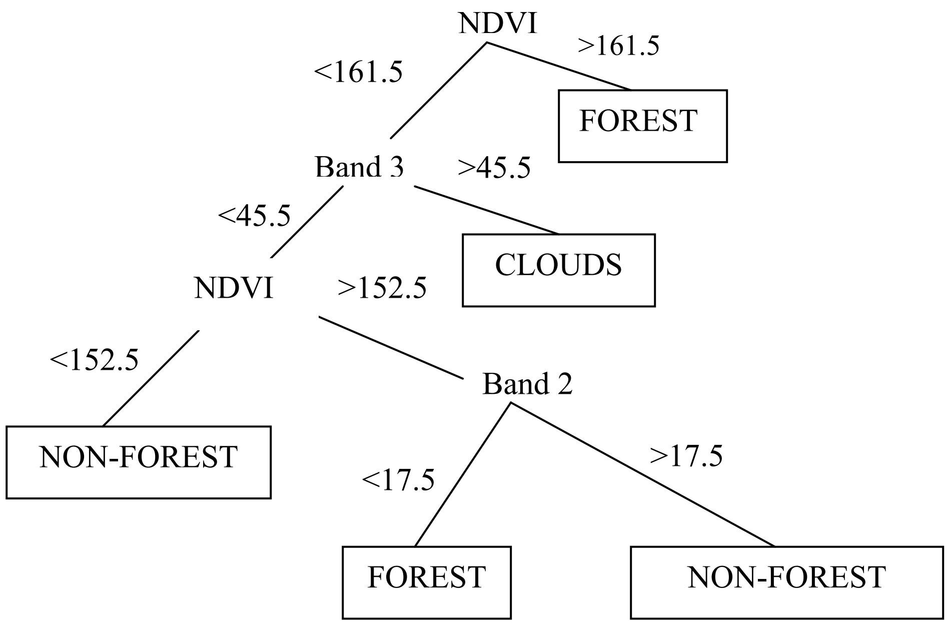


Figure 12 Example simple classification for forest, non-forest and clouds, taken from DeFries et al. 1997.

DeFries and her colleagues (1997) investigated sub-pixel (8km AVHRR data) forest cover in Central Africa and concluded that initially poor average correlations with single pass imagery (R^2 0.5-0.6) was much improved by combining 30 multi-temporal metrics (R^2 0.85-0.89). The strongest correlations were found for annual mean NDVI and mean annual brightness temperature (AVHRR Ch.3). Ch.2 was highly correlated to bare soil (maximum brightness temperature). Metrics also included the ratios of mean optical channel values to mean thermal channel values. Predicted forest cover estimates were within 20% of actual values for 90% of pixels. Landsat MSS training sets were co-registered with AVHRR data by step movements in x and y directions until the best correlation between the NDVI of each image was achieved. They found that Max NDVI was not so highly correlated to grassland and crop land and the areas that were most poorly classified were wooded grassland and fragmented patches.

These techniques have been significantly refined and resulted in the 1 km Global Tree Cover data set, which (to us) appears to be better in delineating forest cover in Sri Lankan and SE Australian locations than the IGBP Discover data sets. In particular there is better discrimination of intermediate tree cover classes (Hansen and Reed, 2000), although the authors point out that it is hard to know which is "better" and that investigation of the differences between the two map products is the most instructive way forward to improving classification accuracy.

IWMI wishes to collaborate with University of Maryland to develop the multitemporal and single pass decision tree methodologies to classifying irrigated area. This requires:

1. Identification of suitable metrics to distinguish irrigated from non-irrigated crops, using hi-resolution Landsat data for known agricultural eco-system types as training data fro MODIS imagery.
2. Development of decision trees and suitable pruning to obtain effective classification accuracy.
3. Test classification against independent ground truth.

A notional tree classification would have to discriminate land covers as shown in Figure 12.

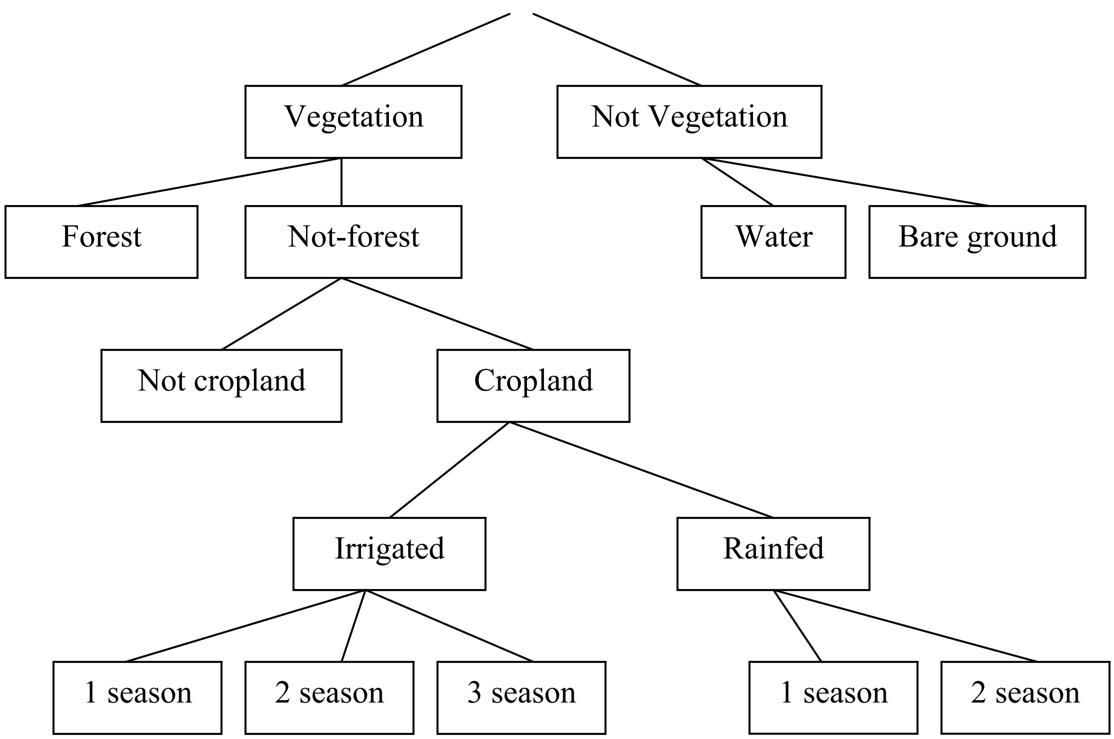


Figure 13 Hypothetical decision tree to identify irrigated area.

We would also like to investigate the development of decision trees for classifying irrigated area in fine resolution imagery, as an alternative to conventional methods (supervised and unsupervised classification) and object based approaches (see 6.4). This will be required for small scale irrigation investigation and can be done using both Landsat and 250m MODIS data.

Spectral Un-mixing

In hyper-spectral imagery upwards of 200 wavebands may be used to create a characteristic spectral signature of the surface. Libraries of characteristic spectra have been developed, which define amongst other things clay mineralogy, vegetation types and conditions, incidence of pests and diseases in crops, flora in aquatic ecosystems and proportions vegetation and bare ground. The recent success of airborne Hyperspectral research resulted in the launch of a research hyperspectral satellite, Hyperion, which has a scan width of only 18 km and generates mind-boggling bytes of data. The research conducted into hyperspectral analysis has resulted in a suite of sophisticated analysis tools that can be found in software like RSI's ENVI.

Spectral mixture analysis can be conducted by determining the characteristic spectra for "end-members" – pixels with a high degree of uniformity and purity. The proportions of different end-member signatures in a pixel can also be analysed to extract the proportions of each one on the ground. A linear mixing model of area (unknown) and spectrum is usually applied. Observed reflectance, r_i in band i is given:

$$r_i = f_1 a_{i,1} + f_2 a_{i,2} + \ldots . f_c a_{i,c} + e_i \qquad 4$$

where:
e = error term
f = fraction of the endmember in a pixel
a = pure characteristic spectrum of the endmember

In a multispectral image of n bands, there will be $n + 1$ equations, incorporating the sum to unity constraint, such that the total value of all fractions adds up to 1. If the number of end-members, c, is less than $n + 1$, then it is possible to calculate the error term e.

Other models of spectral mixing are commonly used, including probabilistic and fuzzy approaches, based on Mahalanobis distance estimation. However, linear un-mixing has been found to be an effective technique for proportions of area of different crops. The output from spectral unmixing is a series of abundance maps, which are more quantitative than simple thematic maps. A number of algorithms exist for linear unmixing of spectra, including Pixel Purity Index (PPI) to select pure end-members from an image and the Spectral Angle Mapper (SAM), which compares component spectra with those of different pure endmembers to determine their similarity. A "rule" image can then created containing multiple layers of spectral angle differences and the selection of the "best" match for each pixel. For a more detailed and precise description, see Samia A, 2002 and Van der Meer, 1999.

Recently there has been considerable interest in applying hyperspectral analysis and tools to sparser multispectral data. Simplified characteristic spectra have been determined for soils, vegetation and so on using 5-7 bands of ETM data. Ali (2002) attempted to classify maize, sugar beet and potato, using Landsat TM data. Since the characteristic spectra for these land types were linearly scaled variants of each other, clear separation was not possible, and there was poor correlation between pixels selected using PPI or Principle Component Analysis and their reference end-member spectra. This is in part due to the small number of bands available in LS-TM. Earlier attempts to do linear mixture modeling of agricultural land use in Europe with limited numbers of bands from multi-spectral data have also met with mixed results (Puyou and Lascassies, 1994).

We propose to conduct some limited exploratory research to test the use of MODIS derived spectra (after PCA reduction of correlated bands) for classifying irrigated area. We will derive simplified reference spectra from existing hyperspectral libraries, covering the wavebands available in MODIS. We will identify characteristic end-members from MODIS images using PPI and PCA and test using the Spectral Angle Mapper and other appropriate techniques to unmix pixel contents. It is likely that some care may need to be taken with atmospheric conditions and corrections. If necessary, appropriate calibration measurements may have to be taken on the ground at the time of data acquisition.

6.3.3 Fusion

A third area for improving classification accuracy in coarse imagery is to fuse it with higher resolution data. This results in a pixel based classification analysis, rather than a sub-pixel approach. The options that we have are:

1. Fusion of 250 m data from MODIS with other infrared, visible and thermal bands. Bands 1 and 2 are Red and Near Infra Red, which allow the derivation of VI, and mean, min and max band values. This should delineate the structure of vegetation and cropland more precisely.
2. Fusion of fine resolution mosaics (Landsat TM) with multi-temporal MODIS imagery. In effect we make masks of forest cover and other land types from the high resolution imagery and monitor vegetation change with cheaper coarse resolution imagery.
3. Fusion of radar imagery with MODIS or Landsat ETM imagery. The principle attraction of this is that some structural vegetation characteristics and the presence of water (in rice paddies) will be detected by the SAR image. However cost is likely to be prohibitive for global mapping.

Fusion of IRS-Pan (5.6 m pixel) with Landsat-7 ETM (28.5m) is presented by Müschen et al. (2000) using a technique called Adaptive Image Fusion (Steinnocher, 1999). It uses adaptive filters (commonly used for speckle suppression in SAR images) to produce a higher resolution multispectral image without distorting the spectral properties of the fused image. These fused images are then used in multi-temporal analysis of NDVI change to categorise 14 crop and grassland classes.

IWMI would like to collaborate with ACRoRS (AIT) in investigating a number of approaches to image fusion for irrigated area classification and these have to be elaborated in more detail. The eCognition software offers some good possibilities for parts of this work (see 6.4).

6.3.4 Change detection or multitemporal analysis

In an IWMI study of rice productivity at Zhang He in Hubei province, single date classification of rice area using Landsat and MODIS imagery was found to overestimate rice area by 36% before correction for field banks and channels (Chemin et al. 2002). Final accuracy was 72% at the meso-scale test site, and this data was used to extrapolate biomass production from a time series of MODIS data used to calculate and interpolate ET, using the SEBAL algorithm. The authors found that there was little significant difference between rice evapotranspiration and that from other vegetation.

Jiren et al, (1997) combined simple difference of (NIR-R $_{(AVHRR)}$) as a vegetation index with GIS information to map irrigated area in Henan Province in China. They evaluated the results at 19 1km^2 ground truth sites. They ranked and classified the VIs taken as a time series and sorted them into 10 classes, using 10-20 day composite data from AVHRR. A large number of ambiguous conditions were identified and rainfed area was in some cases defined by the absence of irrigation facilities (including ponds and groundwater), derived from GIS. They estimate an overall accuracy of investigation of 97.5% on combining GIS and RS methods, but do not give figures for the remote sensing accuracy alone. They noted that the actual irrigated area was approximately 75% of the potentially irrigable area on the basis of installed infrastructure.

It seems very likely from this review, previous experience with global forest mapping and the emerging experience with the vegetation cover approach to sub-pixel estimation, that multi-temporal approaches offer a way forward, either using simple metrics such as NDVI and surface temperature or more complex analysis such as derived from decision trees.

There are many multi-temporal approaches that can be investigated for both sub-pixel classified data and for pixel or object based classifications. In both cases, the change signature (see 4.1) of Vegetation Index, surface temperature, band differences and band ratios can be quantified. Perhaps the simplest method is to combine multi-temporal images and classify them. Gomez (1999) combines three grey scale images of NDVI in Red, Green and Blue and then classifies them using conventional software tools. A fourth grey scale image in a sequence can be added as a false DEM layer in software that will support draping false colour composites over a DEM. Although this technique is visually appealing, it is time consuming to classify and quantify areas at a global scale. The technique has additional possibilities for high resolution data, and for analysis within software such as eCognition, where topological information can also be used in classification (see 6.4).

Droogers and Kite (2002), show that monthly NDVI$_{(AVHRR)}$ from February to December combined with a DEM clearly identified irrigated area in the Gediz Basin in Turkey. The greatest difference in NDVI between irrigated and non-irrigated crops was in August (peak value for irrigated crops was 0.52 compared to 0.35 for rainfed crops).

Zhan et al (2000) provide a comprehensive review of multi-temporal approaches applied to synthetic MODIS 250m data. Existing AVHRR and Landsat TM data was used to simulate the expected performance of the 250m product in classifying land use at 3 sites subset from 14 from all over the globe. The examples included 1) agricultural expansion near Alexandria in Egypt and 2) forest to agriculture conversion in Bolivia and 3) temperate to mixed woodland development in Washington, USA. They found that the coefficient of variation (CoV) of NDVI of a times series in a 3 x 3 pixel window gave the most effective textural measure of change. A change pixel is defined as one where the CoV between two successive times of sampling is great than 4. Changes in linear features were also detected using Band 1 reflectance to help classify the edge pixels between areas of land use change. Other change detection methods were evaluated including:

- Red-Near Infra-Red partitioning
- R-NIR space change vector
- Modified delta space thresholding
- Linear feature change
- Integration of five methods (the four above plus textural change)

Errors of commission and omission were lowest for 3 x 3 pixel windowing using Red-NIR space change vector, modified delta space thresholding and CoV texture change detection in the Bolivia forest to agriculture data set. Errors of commission or omission were high on per pixel basis for all techniques. However, across all three data sets, the performance of textural measures was not acceptable at a pixel scale, possibly because uniform thresholds for CoV and edge detection were used.

The authors also investigated the effect of mis-registration of T1 and T2 images – on the basis that design registration accuracy of the 250 m product would be 50m (20% of one pixel), resulting in up to 100m geolocation error. They found errors to be within the noise level for atmospheric and bi-directional effects.

IWMI and its partners will investigate the use of similar methods with MODIS 250m data to identify changes in cropping that identify irrigated and non-irrigated crops. Classification to a moving window of 9 pixels (56 ha) may be acceptable for our purposes, compared to classifications using MODIS 1km data.

Multi-temporal analysis has been required for the interpretation of simple space borne SAR imagery, where textural information is good, but data is limited to the backscattering coefficient of only on band at one polarisation (ERS1 and 2, JERS2, and Radarsat). Liew et al. (1998) define change classes based on a change index between two successive dates of acquisition, where the change index is a function of the ratio of backscatter values T2/T1. An arbitrary threshold was applied to each change index map such that no change was determined if values changed by less than 3 dB and were classified as decreasing if less than -3dB and rising of greater than +3dB. Five change class maps were made from 7 satellite passes at 35 day intervals, giving the possibility of 3^5 classes (243). A clustering algorithm was used to group similar change classes, based on a distance threshold defined from the differences in mean divided by the differences in standard deviations of two classes. Hierarchical clustering was then employed to improve the delineation of classes, resulting in 10 classes of production system in the Mekong region of southern Vietnam. A formal accuracy analysis was not presented, but this approach may be worth investigating if other methods do not deliver good results. The main disadvantage of the method is the amount of manual image manipulation required.

Hyperspectral analysis techniques offer new ways of quantifying multitemporal signatures (Ali, 2002). A time series of NDVI or other parameters can be treated in the same way as a spectral signature and can therefore be analysed on a yearly basis with 12-24 or more values "spectrum", depending on whether 16 day or 28 day composite data is used. In theory, temporal "end-members" can be derived from images and homogenous ground truth, and both pixel and sub-pixel based analysis could follow. Ali (2002) showed that 3-date NDVI signatures resulted in different characteristic patterns for 4 test crops in Holland – maize, sugar beet, potato and wheat. However, the variance in the potato classification (from a sample of 10 fields) was too great to allow classification.

IWMI will evaluate multitemporal analysis of irrigated crops at high and low resolution using hyperspectral techniques for single season, multi-season and annual sequences. Intuitively, the best chances of accurate classification lie in longer sequences with larger numbers of temporal values. We will evaluate its use using vegetation cover derived using the WP 36 methodology and also with metrics derived from the 250m MODIS data, with and without fusion with 500m and thermal band data.

Another alternative, that combines sub-pixel classification with multi-temporal values of metrics directly, is to follow the decision-tree approach outlined in 6.3.2. **This will be a major thrust of the research in global irrigated area mapping, as it seems to offer the greatest likelihood of success when using coarse and medium (250m pixel) resolution imagery.**

6.4 Object Classification (eCognition)

New possibilities for image analysis have emerged based on the concept of hierarchical object classes. A high resolution image is segmented into "object primitives" and trained or classified using ground truth data of actual land use, or other estimates. These object primitives can be defined by their spectral / reflectance characteristics and also by their topological properties, such as shape, length, aspect, size and so on. They can be further classified by the proximity of one class to another to refine or to define sub-classes.

Commercial software (eCognition) is available that uses fuzzy classification techniques based on the nearest neighbour method to establish hierarchical classes and test the resulting classification against ground truth data. It gives the possibility of developing unsupervised classification techniques for distinct situations (say mapping rice land in Sri Lanka), where the hierarchical classification develops into a set of rules that can be more widely applied in a given region.

IWMI has evaluated the software, its training exercises and has made a very limited investigation with some MODIS imagery from central China. The software seems to have great potential for highly textured imagery, such as aerial photographs, radar imagery and high resolution optical/thermal imagery, such as Landsat ETM. The main advantages of the software are that the object class approach allows easy fusion of multiple types and resolutions of data and that classification schemes can be set up and adapted for different situations of irrigation.

It would appear that the reduced topological information and heterogeneity at sub-pixel level in MODIS-scale imagery does not offer so much promise. However, IWMI intends to make a serious investigation of its use with 250m scale MODIS imagery, where topological information may be sufficient to help distinguish irrigated area from other land-use. The fact that fusion at multiple scales is "easy" may offer possibilities for direct classification of coarse images based on 250m pixel structure and NDVI with fusion of 500m and 1000m MIR, visual and thermal bands.

The bulk of the research at either scale would be in defining generic object classes and subclasses for irrigation based on spectral, topological and even mask characteristics. It may also be the most appropriate way of investigation SAR fusion with LandsatTM for awkward cases such as small scale irrigation in heavily cloud covered areas.

6.5 Error checking methodology

Fieldwork

Ground truth will be conducted in areas where IWMI is already collecting irrigation related data and has good existing GIS information as well as high resolution remotes sensing and crop classification.

Existing map layers and GIS software (such as ArcPad) running on hand-held PC's will be used to log GPS position and to label fields according to their irrigation condition (crop type, approximate growth stage and whether or not irrigated). This data will then be aggregated and used to derive irrigated area per pixel for high resolution (Landsat) and low resolution (MODIS) images.

The sites will be repeat-sampled for each crop season, and a stratified sampling approach will be taken to locate blocks for GPS sampling within the coverage of both fine and coarse images. Exactly the same fields will be logged.

High and low resolution images will be carefully co-registered. Conventional measures of classification accuracy (such as Kappa coefficient, and confusion matrices) will be used to assess the performance of high resolution imagery. The classification procedures will then be improved in light of this analysis, and a full analysis of errors will be made (correction for atmospheric effects, missed scan lines etc). The ground truth data will be aggregated to MODIS pixel size and the predicted percentage irrigation per pixel will be regressed against the actual. This process will be repeated at a broader scale for areas taken from the fine resolution image that have not been ground truthed, but are classified at a certain level of accuracy as discussed above.

The accuracy of coarse resolution image classification by direct ground truth and by classified image will be compared. Conventional supervised classification of the high resolution image will be compared with ones made using image objects as described in 6.4.

The same accuracy assessment will be conducted for all techniques used at the provisional sites listed in Table 3, which will span a range of agro-climatic conditions.

Country	Location	Climate and ground conditions
Pakistan	Upper Swat Canal	Semi Arid: 600-800mm rainfall: limited cloud. LIS
	Rechna Doab	Arid – Semi Arid: 400-600mm rf; cloud 06-08. LIS
India	Ganges Basin	Semi-arid high rainfall- seasonally cloudy.
	Haryana – Bakra IS	Arid – Semi Arid: 400-600mm rf; cloud 06-08. LIS
	Pala Basin	Tropical. Significant cloud. Tanks.
*	Andra Pradesh	Seasonally wet/seasonally arid.
	Gujurat	Groundwater areas – small scale.
Sri Lanka	Uda Walawe	Tropical, mixed area, small + medium scale IS
	Polanuwarra	Larger scale tropical irrigated system

Table 3. Provisional locations for field work for ground truth.

Local crop census statistics will also be collected for direct comparison – these will be taken from either the irrigation agencies, or from the revenue officers (Patwaris in Pakistan and India).

6.6 Data Management

The following aspects of data management need to be attended to:

1. Open access common file structure, based on location, with sub-directories for each approach to image analysis, and output.
2. Single common directories of ground truth data, with common format.
3. All raw imagery must be properly indexed and backup to CD if that is not its native format. The indexes should be available via the IWMI intranet and FTP server.
4. Intermediate data and image files will not be stored in the long term, but exact documentation of processing and analysis will be prepared and archived with the results. All methodologies will be fully documented.
5. A common data platform will be designed for full scale mapping.
6. All the classification maps, statistics and difference analysis between methods and between RS and FAO-Aquastat data will be available to the public via the IWMI web-site. The first level of access will be the classified maps of irrigated area, which will be downloadable via a map-server.

6.7 Outputs at end of research phase

The following outputs are envisaged by early 2004.

1. Research report comparing costs, time requirements, accuracy and other attributes of alternative classification methods.
2. Recommended standard methodology for Global Irrigated Mapping – includes regionalized recommendations for techniques.
3. Year 2002 maps and summary statistics for Pakistan, parts (all?) of India, and Sri Lanka.
4. Cost estimates to cover whole world.
5. Operational strategy to cover the whole world, including partnerships.
6. Results of independent test on another country (?)
7. Summary analysis of differences between Aquastat and GIAM RS, incorporating error analysis.
8. Detailed recommendations for data management and storage.

6.8 Schedule and Milestones in the Research Phase

	TASK	Who	07	08	09	10	11	12	01	02	03	04	05	06	07	08	09	10	11	12	01	02
1	**Collate global irrigated crop patterns**	IWMI+FAO						R														
	Map global cloud cover durations	IWMI+FAO							R													
2	**Finalise global zoning strategy**	IWMI+FAO																				
3	**Sub-pixel analysis - VC:VI**	IWMI																				
	Jan-2001		R	M																		
	2001						M	R														
4	**Multitemporal analysis (1)**	IWMI										R							M			
	Multitemporal /decision tree	UoMd														M	R					
	Multitemporal Fusion	ACRoRS														M	R					
	Multi-temporal – SAM	IWMI										M	R									
5	**Multispectral subpixel analysis**	IIMI-PAK					R	M							(		)					
6	**Hi Resolution Investigation**	IWMI/FAO/UoK										M					M	R				
	LS 7 +- SAR +- GPS/GIS	ACRoRs												M	R							
		RSA -																				
7	**Ground truth (GT)**																					
	Pakistan	IIMI-PAK																				
	India	IWMI-I																				
	Sri Lanka	IWMI-HQ																				
8	**Comparisons**	ALL																				
	With FAOSTAT and Kassel Map																			R		
	Between methods wrt GT																		R			
	Cost analysis																					
9	**Final report and evaluation**	IWMI																				
	Recommendations for global mapping																					

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Appendix A

GIAM Work programme

		2002										2003			
#	**TASKS**	March	April	May	June	July	August	Sept	Oct	Nov	Dec	Jan	Feb	March	**WHO**
1	Remote Sensing Testing														
	Data acquisition MODIS														IWMI
	Data acquisition ASTER/TM														PD
	Data acquisition RADAR														HT
	India, Sri Lanka and Pakistan - Jan Map														IWMI
	South Africa - Jan Map														IWMI
	India, Sri Lanka and Pakistan - Year Map														IWMI
	South Africa - Year Map														IWMI
	Testing Masks - forest, DEM,,,,,,														
	University of Maryland ?? Method review	ASAP													IWMI
	Remote Sensing Testing - Hi Res/other														IWMI
	Sensitivity Analysis														
2	Seeking National Contacts														
	India														PD/CS
	Sri Lanka														HT/PD
	South Africa														WRC
	Pakistan														IWMI
3	Updating equipped area mapping														
	India														FAO/UoK
	Sri Lanka														FAO/UoK
	South Africa														FAO/UoK
	Pakistan														FAO/UoK
	Updating of Kassel Map														FAO/UoK
4	Interim review meeting														All

5	Integrating results														
	Comparing maps														
	Investigating differences														
	Identifying needs for further research														
	Finalize definition and classification														
5	External Evaluation														Many
6	Phase 2 proposal development														IWMI/FAO
7	Preparation of final maps and tables														All
8	Progress report for the Kyoto WWF														IWMI/FAO