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ABSTRACT

Agricultural production capacity contributes to food security in Afghanistan and is largely dependent on irrigated farming, mostly utilizing surface water fed by snowmelt. Because of the high contribution of irrigated crops (>80%) to total agricultural production, knowing the spatial distribution and year-to-year variability in irrigated areas is imperative to monitoring food security for the country. We used 16-day composites of the Normalized Difference Vegetation Index (NDVI) from the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor to create 23-point time series for each year from 2000 through 2013. Seasonal peak values and time series were used in a threshold-dependent decision tree algorithm to map irrigated areas in Afghanistan for the last 14 years. In the absence of ground reference irrigated area information, we evaluated these maps with the irrigated areas classified from multiple snapshots of the landscape during the growing season from Landsat 5 optical and thermal sensor images. We were able to identify irrigated areas using Landsat imagery by selecting as irrigated those areas with Landsat-derived NDVI greater than 0.30–0.45, depending on the date of the Landsat image and surface temperature less than or equal to 310 Kelvin (36.9 ° C). Due to the availability of Landsat images, we were able to compare with the MODIS-derived maps for four years: 2000, 2009, 2010, and 2011. The irrigated areas derived from Landsat agreed well $r^2 = 0.91$ with the irrigated areas derived from MODIS, providing confidence in the MODIS NDVI threshold approach. The maps portrayed a highly dynamic irrigated agriculture practice in Afghanistan, where the amount of irrigated area was largely determined by the availability of surface water, especially snowmelt, and varied by as much as 30% between water surplus and water deficit years. During the past 14 years, 2001, 2004, and 2008 showed the lowest levels of irrigated area (~1.5 million hectares), attesting to the severe drought conditions in those years, whereas 2009, 2012 and 2013 registered the largest irrigated area (~2.5 million hectares) due to record snowpack and snowmelt in the region. The model holds promise the ability to provide near-real-time (by the end of the growing seasons) estimates of irrigated area, which are beneficial for food security monitoring as well as subsequent decision making for the country. While the model is developed for Afghanistan, it can be adopted with appropriate adjustments in the derived threshold values to map irrigated areas elsewhere.

1. Introduction

With three decades of war, civil unrest, recurring natural disasters (such as flooding, droughts, earthquakes, landslides, and avalanches), and widespread food vulnerability, monitoring food security for the people of Afghanistan has never been more important in the recovery of their livelihoods. Approximately 30% of the total population of 31 million (Banks & Soldal, 2002; WHO, 2009) in Afghanistan are food insecure to some degree (NRVA, 2009; Viola, Najimi, & Bacon, 2007). The country's economy is highly dependent on the agriculture sector, which contributes one-third of the country's Gross Domestic Product (USDA-FAS, 2011) and employs approximately 80% of the total population (ICARDA, 2002; USDA-FAS, 2011). Only 12% (7.9 million hectares) of the total land area (65 million hectares) is arable, of which about half (3.7 million hectares) is cultivated annually, leaving the other half (4.2 million hectares) mostly as fallow land (USDA-FAS, 2011). The annual average precipitation in Afghanistan varies between 50 mm in the southwest to over 1000 mm in the east (Banks & Soldal, 2002). Also, the annual potential evapotranspiration is about six times higher than the annual average precipitation, implying that the direct recharge of precipitation to groundwater is likely to be extremely low (Banks & Soldal, 2002). As a result, 55–70% of total cultivated land is irrigated

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for successful production(Qureshi, 2002; USDA-FAS, 2011), and 85% of that irrigation comes from surface water, mostly in the form of snowmelt (Reeling, Lee, Mitchell, Halimi, & Carver, 2012).

The landscape of Afghanistan is characterized by high mountains with snow-covered peaks, fertile valleys, and desert plains. The lowland fertile valleys and desert plains are located in the northern, western, southwestern, and southeastern areas, while the highlands are located in the central, eastern, and northeastern parts of the country. In general, irrigated areas are found throughout Afghanistan, especially along flood plains of rivers. However, their greatest concentrations are found in the lowlands of the northern, western, and southwestern parts of the country. Agriculture in Afghanistan is primarily smallholder farming using non-mechanized skills and techniques. The median size of an irrigated farm is 1.4 hectares compared to 6–7 hectares for rainfed farms (Qureshi, 2002), which makes irrigated agriculture production vulnerable to wide fluctuations depending on available water resources. Although dependence on annual rainfall regimes makes variability in rainfed systems even more vulnerable, in this study we have concentrated on irrigated area estimation since rainfed production accounts for a much smaller portion of overall production. Climate change is believed to be impacting water availability, since renewable freshwater (the sum of mean annual surface runoff and groundwater recharge) resources are expected to be below the calculated demand threshold of 1500 cubic meters annually per capita by 2030 (Yang, Reichert, Abbaspour, & Zehnder, 2003).

As is often the case in developing countries, Afghanistan does not possess adequate information on the spatiotemporal distribution of their irrigated agriculture. The first known classification of irrigated areas at the national scale was initiated by the Food and Agriculture Organization of the United Nations (FAO) in the early 1970s as part of an agricultural land cover database for the country. The 1972 land cover scheme included three classes of irrigated lands: a) orchards and gardens, b) intensively cultivated, and c) intermittently cultivated. The land cover classes were identified and hand-drawn based on visual interpretation of aerial photographs acquired between 1960 and 1970 (FAO, 1972). The quality and reliability of the 1972 land cover map were reported to be suspect (FAO, 1972) because the map identified only major irrigated areas in the northern and southwestern parts of the country with no validation.

During the 1990s, FAO updated the land cover maps through interpretation of Landsat Thematic Mapper satellite imagery acquired in 1990 and 1993 with the help of KFA-1000 (a film camera type) space photographs of various regions of Afghanistan, which were acquired between 1988 and 1992 (FAO, 1999). The 1993 land cover classification scheme included three classes of irrigated land: a) intensively cultivated (two crops per year, wheat followed by rice), b) intensively cultivated (one or two crops per year, wheat followed by other crops), and c) occasionally cultivated (every two or three years, generally wheat). About 3.2 million hectares of land were identified as irrigated in the 1993 land cover map. Recently, FAO released a 2010 land cover map of the country (FAO, 2013). The 2010 land cover classes were identified from high resolution (20 m, 10 m, and 5 m) Système Pour l'Observation de la Terre (SPOT) images, historical and recent Landsat images, and aerial photographs. The amount of identified irrigated areas in the 2010 map was 3.4 million hectares.

Apart from FAO initiatives, Afghanistan was included in several land cover mapping studies that were mostly optimized for global application. The Kassel digital Global Map of Irrigated Areas identified the percentage of each $0.5° \times 0.5°$ cell area that was equipped for irrigation in 1995 (Döll & Siebert, 1999). The map was subsequently improved and upgraded to $5' \times 5'$ cell size for 2000 (Siebert, Döll, Feick, Frenken, & Hoogeveen, 2007). The U.S. Geological Survey Global Land Cover Characterization (GLCC) dataset included four types of irrigated croplands from 1-km Advanced Very High Resolution Radiometer sensor data from 1992 to 1993 in a multi-temporal unsupervised classification method (Loveland et al., 2000). More recently, the International Water Management Institute produced a fractional global map of irrigated areas at 10-km resolution from a multi-resolution blend of satellite earth observations, topography, and climate data in an unsupervised classification method for 1999 (Thenkabail et al., 2009). The datasets were inconsistent in temporal frequency and nearly impossible to aggregate because of their differing classification systems.

The objective of this study is twofold. First, we develop a methodology capable of identifying irrigated areas consistently, annually, and at a national scale, as 80–85% of total crop production comes from irrigated land in Afghanistan (Qureshi, 2002). We primarily focus on mapping irrigated areas, although rainfed agriculture contributes one-third to overall cereal production (MAIL, 2012). Wheat (winter and spring) is the single most important crop grown on both irrigated and rainfed land. However, production from irrigated wheat contributes the most due to its 2.5 times higher yield than that of rainfed wheat (MAIL, 2012). The contribution of rainfed wheat to total cereal production varies between 5% and 26%, depending on the rainfall regime (MAIL, 2012). Due to the large contribution from irrigated lands, food security is affected by the availability of freshwater for irrigation, which in turn determines the extent of irrigated area for the country. In addition to the link between irrigated area and production, with increased irrigated area comes more need for agricultural labor, an important component of livelihoods in many parts of Afghanistan. Hence, identifying variability in the spatial extent of irrigated lands on an annual basis is important for food security monitoring. Second, we apply the method of mapping irrigated areas historically to establish a spatiotemporal irrigated area database for Afghanistan. The ability to apply such a method for mapping irrigated areas on an annual basis, with reference to a consistently mapped historical database, will aid in assessing potential food security scenarios for the country.

2. Data and methods

2.1. Definition of irrigated area

The irrigated area is defined as the agricultural area that receives full or partial application of water to the soil to meet water requirement by the standing crops at least once in a given year. Irrigated area only refers to extent of the physical area, meaning that agricultural area that is irrigated multiple times a year is counted once. The MODIS 250-m pixel spatial resolution equivalent to 6.25 hectares is kept as the mapping unit; however the lone identified single cell areas were removed from the irrigated area maps. Binary irrigated area maps are produced where 100% of the pixel area is considered irrigated. In Afghanistan, cereal crops (wheat, maize, barley, sorghum and rice), fruit trees, nuts, vineyards and other crops are commonly grown on irrigated land where irrigation is provided through formal and informal systems. Formal irrigation systems (large irrigation schemes developed with central government assistance with outside technical and financial support) account for only 10% of the irrigated areas while the rest (90%) of the irrigated areas draw upon informal systems (traditionally developed and managed by local communities e.g. karez, springs, wells, rivers and streams) mostly using surface water.

2.2. MODIS NDVI for mapping irrigated areas

The Normalized Difference Vegetation Index (NDVI) is a sufficiently good indicator of irrigation presence (Ozdogan, Woodcock, Salvucci, & Demir, 2006) because of its ability to measure green biomass (Tucker, 1979; Tucker, Newcomb, Los, & Prince, 1991) and its strong positive correlation with available moisture for vegetation (Pervez & Brown, 2010). Prior studies show that the Moderate Resolution Imaging Spectroradiometer (MODIS) NDVI dataset has the sufficient spatial, spectral, and temporal resolutions to capture quantitative vegetation dynamics over space and time (Wardlow & Egbert, 2008; Wardlow, Egbert, & Kastens, 2007), and can be used to identify irrigated areas

(Biggs et al., 2006; Ozdogan et al., 2006; Pervez & Brown, 2010) and crop types (Gumma, Nelson, Thenkabail, & Singh, 2011; Thenkabail et al., 2009; Wardlow & Egbert, 2008; Wardlow et al., 2007). In this study we have used 250-m spatial resolution 16-day composites of MODIS NDVI (MOD13Q1, collection 5). The MODIS NDVI is retrieved from daily, atmosphere-corrected, bidirectional surface reflectance, and then composite using methods based on product quality assurance metrics to remove low quality pixels. The 250-m spatial resolution is the finest spatial resolution provided for the NDVI dataset, and the 16-day composite was selected to ensure high probability of having the best quality pixel (reduced cloud affects) representing the compositing period's NDVI.

A 23-point time series of MODIS NDVI was created for each year from 2000 to 2013. The NDVI data were re-projected from the Sinusoidal to Geographic to Albers Equal Area projection and subset over Afghanistan for each composite period. Composites were sequentially stacked to produce the time series dataset. Despite the NDVI being calculated from atmospherically corrected bi-directional surface reflectance that has been masked for water, clouds, heavy aerosols, and cloud shadows, data are still subject to atmospheric perturbations and imperfect sensor calibration. To minimize these effects on time series NDVI, a temporal smoothing technique (Swets, Reed, Rowland, & Marko, 1999) was applied to produce continuous temporally smoothed NDVI for the entire time series. The smoothing technique uses a temporal window to calculate multiple weighted least-square regression lines, and then estimates the smoothed NDVI value by averaging the values from the regression lines at each point.

Prior studies have shown that maximum NDVI in an annual time series is a proxy for the peak level of photosynthetic activity, the highest biomass, and densest vegetation cover (Pervez & Brown, 2010), and in general irrigated crops exhibit higher (maximum) NDVI than non-irrigated crops, especially for corn and wheat (Aparicio, Villegas, Casadesus, Araus, & Royo, 2000; Pervez & Brown, 2010; Wardlow & Egbert, 2008). The temporal NDVI profiles of major land cover types of Afghanistan presented in Fig. 1 show that peak NDVI of irrigated crops is higher than peak NDVI of non-irrigated crops, with a distinct temporal difference in the occurrence time. Pervez and Brown, (2010) argued that the highest annual peak NDVI for any agricultural crop is the result of consistent adequate soil moisture as is delivered by irrigation throughout the growing season; hence, the maximum NDVI for irrigated crops generally exceeds the peak NDVI for non-irrigated crops. Therefore, peak NDVI for the growing season was used to differentiate irrigated areas from non-irrigated areas. To calculate season-specific

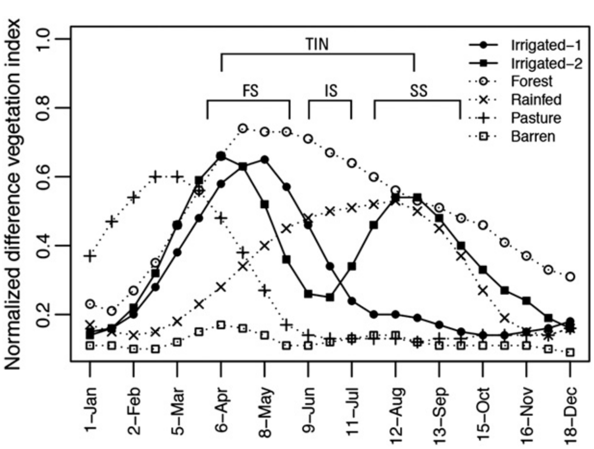

Fig. 1. Normalized Difference Vegetation Index (NDVI) temporal profiles for major land cover types in Afghanistan. To generalize the profiles, they are created by summarizing multiple profiles extracted for respective land cover types. The growing seasons used to identify irrigated crops are marked as FS-first season, Mar 21 through May 25, SS-second season, Jul 27 through Sep 29 and IS-intermediate season, Jun 9 through Jul 11. TIN-time integrated NDVI, Apr 6 through Aug 28, is the period for which NDVI values were integrated.

peak NDVI, the composited NDVI layers were subset temporally for the respective growing seasons (Fig. 1) from the annual stacked NDVI layers. The seasonal peak NDVI was then calculated for each pixel by identifying the pixel with the maximum value within the subset of the compositing periods.

In general, single cropping (one crop per year) prevails in much of Afghanistan; however, there are areas, especially in the northern and southwestern parts of the country, where multiple irrigated crops are grown each year. Consulting the NDVI profile of Fig. 1 for both single and multiple cropping irrigated areas, the peak growing periods were identified centered on the occurrence of peak NDVI. The period from March 21 to May 24 was defined as the first season peak growing period, and July 27 to October 15 was defined as the second season peak growing period. A transition period of June 9 to July 11 was also identified, which was also useful for identifying non-irrigated crops. Peak NDVI from each of these three periods was extracted, and a Time Integrated NDVI (TIN) for the period April 6 to August 28 was calculated. Therefore, the 23-point time series of NDVI for each year was reduced to four discrete layers.

2.3. Non-irrigated area mask

First, a non-irrigated area mask was built by identifying permanent pasture/range land areas in the north and northwest, mountain forests, areas with slopes greater than 20%, and relatively flat hill tops. The mask was applied to the seasonal peak NDVI and TIN layers before feeding those to the classifier model.

2.3.1. Permanent pasture/range land and forest

In Afghanistan, nearly half of the land (30 million hectares, or 46% of the total land area) is covered by permanent pasture/range land, and another 1.7 million hectares (3% of the total land) are covered by mountain forest (USDA-FAS, 2011). Permanent pasture/range lands are located in the central, northern, and northwestern parts of the country. The mountain forests are concentrated mostly in the eastern and northeastern parts of the country. While the phenology of the mountain forests exhibits similar temporal dynamics across the country, the temporal dynamics of the permanent pasture/range land varies spatially depending on the availability of surface water. The NDVI profile of the forest closely resembles the NDVI profile of the first season irrigated crops. However, peak NDVI from the forest is generally higher than peak NDVI from the irrigated crops, while both peaks occur around the same period (Fig. 1). In addition, the permanent pasture/range land in the north and northwest reaches peak NDVI during the peak growing time of the first season irrigated crop. These similarities can cause misidentification of these land cover types as irrigated areas, especially in the central and northwestern parts of the country. To avoid the misidentification of these two land cover types, we classified them first using Spectral Angle Mapper (SAM) and included them in a mask for non-irrigated areas.

The SAM is a physically based spectral classification method that permits rapid mapping by calculating the spectral similarity between the endmember spectrum and each pixel spectrum, treating them as vectors in n-dimensional space. Small angles between the two spectra indicate high similarity and large angles indicate low similarity (Crósta, Sabine, & Taranik, 1998; Hunt, Gillham, & Daughtry, 2010; Hunter & Power, 2002; Schwarz & Staenz, 2001; Yang, Goolsby, Everitt, & Du, 2012). Since the SAM algorithm uses only the vector direction and not the vector length, it is known to perform well in areas of homogeneous land cover types. Here, we apply SAM on annual temporal NDVI, treating the NDVI temporal profile as the spectra. We extracted 47 endmembers for permanent pasture/range land in the north and northwestern provinces and 7 endmembers for mountain forest from the time series image by identifying appropriate land cover pixels from high spatial resolution (1.7–3.2 m) Google Earth multi-spectral imagery provided by Digital Globe. Multiple endmembers were

extracted to capture minor variability in the NDVI profile of the various land cover types. A qualitative assessment of the classified results of the pasture/range lands of the north and northwest and forest area of the central highlands with Landsat and Google Earth imagery reveals that SAM yields good classification results for these land cover types in Afghanistan. Fig. 2 shows the map of north and northwestern permanent pasture/range land and central highland forest areas classified using SAM.

2.3.2. High slope areas

The slope and surface roughness of the land potentially determines whether or not irrigation is feasible. Typically, up to 8% slope (NRCS, 2010) is considered feasible for any surface irrigation system. Using Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) data at 90-m resolution, the DEM cells with slopes of more than 20% were identified and considered not feasible for irrigation. Those high slope (>20%) areas were included in the non-irrigated area mask.

The rugged mountain landscape of Afghanistan also includes some relatively flat lands (slope < 20%) situated on hill tops. These areas were considered not feasible for irrigation because of their remoteness and/or lack of accessibility to water. Applying Eq. 1, these relatively flat lands situated at high elevations were identified, and included in the non-irrigated area mask.

$$E > E_{[5x5]\,\min} + E_{[5x5]range} * 0.9 \tag{1}$$

where E is the elevation at each cell, $E_{[5x5]\min}$ is the minimum elevation within a 5×5 kernel, and $E_{[5x5]\mathrm{range}}$ is the range of elevation within a 5×5 kernel. A cell is identified as non-irrigated land if it is greater than the sum of minimum and 90% of the range of the elevation in a 5×5 kernel around the cell.

2.4. Building the Decision Tree Classification Model

2.4.1. Defining the NDVI thresholds

We used an NDVI threshold approach (Ozdogan et al., 2006; Pervez & Brown, 2010) to identify irrigated areas. A decision tree classifier model was built by applying a threshold to peak NDVI and TIN from all four seasons (the first and second growing seasons, intermediate season, and TIN season) in logical framework. The approach was based on the temporal dynamics of the NDVI that represent single or multiple crop irrigated areas. This approach was found to be an effective means of identifying irrigated areas in Afghanistan. While the model framework was relatively simple, the accuracy of the classified results was highly dependent on the appropriate selection of NDVI and TIN thresholds. Initial threshold values were determined by carefully extracting seasonal peak NDVI and TIN values from irrigated pixels. At the time of model development the sample irrigated pixels were identified from 2004 high resolution (1.7–3.2 m spatial resolution) Google Earth multi-spectral images provided by Digital Globe and were mostly located in known irrigation project sites. The model was run with the initial peak seasonal NDVI and TIN threshold values from 2004 to produce a map of irrigated areas for that year. The classified irrigated area polygons for 2004 were then overlaid on Google Earth imagery to evaluate the results. The evaluations were conducted at sites centered on known irrigated areas in Afghanistan such as Nad-e-Ali in Helmand province, Beland Ab-e Navin in Hirat province, Baba Kohneh in Balkh province, Du Wandi in Kunduz province, and Tirgari in Laghman province. While the evaluation was both empirical and qualitative, it was observed that the barren landscape around irrigation sites and associated surface channels made it possible to confidently identify irrigated areas using Google Earth images. The initial thresholds of NDVI and TIN were adjusted on an iterative basis until a good match was observed between the classified irrigated areas and high resolution imagery. The peak NDVI and TIN threshold values were found to be highly variable both spatially and temporally. The peak NDVI threshold value varied from 0.11 to 0.40, and the TIN threshold value varied from 1080 to 1700. The NDVI values were scaled to ($NDVI^{*}100 + 100$) before integrating them as TIN. Typically, the threshold values were low for the arid southwestern provinces, and they were high for the north and northeastern provinces because of regional differences in vegetation dynamics due to climate. Although the peak NDVI was relatively low for few instances, the classification was not only based on the single peak NDVI value but also on the combination of relative differences between the seasons and the TIN. The decision tree classification model, along with threshold values obtained for peak NDVI and TIN, for Panjsher province is shown in Fig. 3.

The model was implemented for each of the 34 provinces in Afghanistan with a slight modification in the threshold values to accommodate regional differences in NDVI magnitudes. The first model was built based on 2004 analysis, because at the time of model development the high spatial resolution (1.7–3.2 m) Google Earth Digital Globe images were available for 2004 across Afghanistan. Hydrologically, 2004 was a dry year (World-Bank, 2005; NRVA, 2007) in Afghanistan. Because NDVI values were higher in wet years than dry years for the same land cover type due to positive correlations with water availability (Aguilar, Zinnert, Polo, & Young, 2012; Di, Rundquist, & Luoheng, 1994;

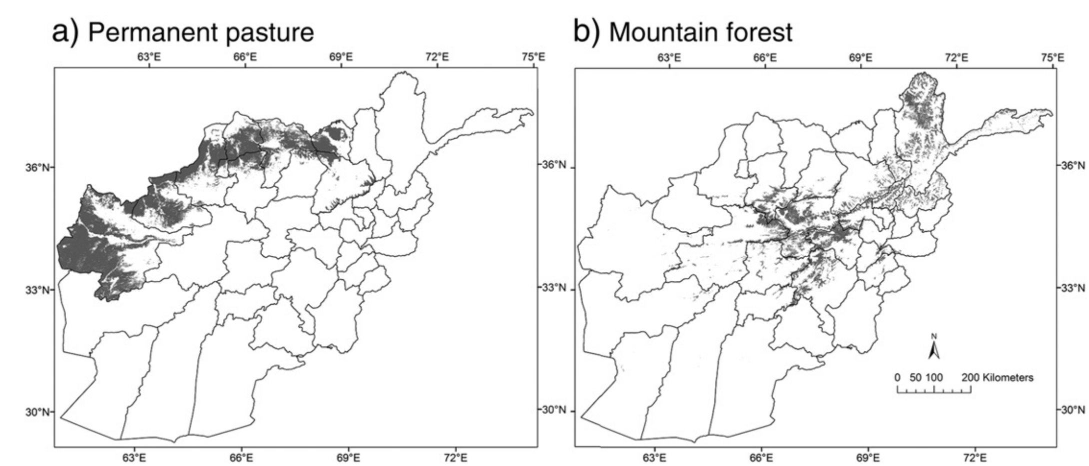

Fig. 2. a) Permanent pasture land in the north and northwest, and b) mountain forest in central and eastern Afghanistan, classified from annual time series of 16-day composite NDVI using Spectral Angle Mapper.

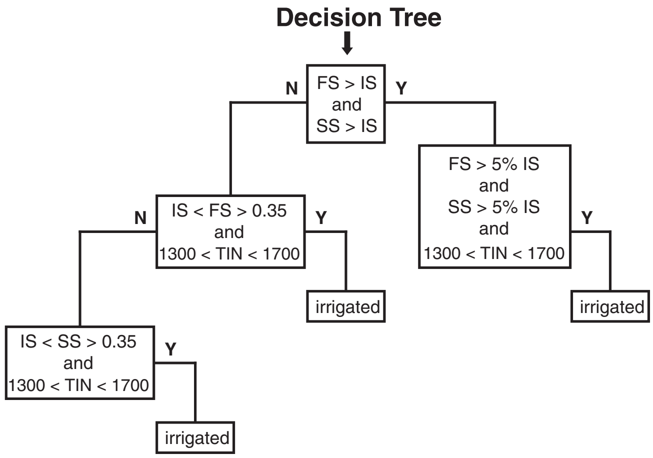

Fig. 3. A sample hierarchical structure of the decision tree classifier model and threshold values for peak NDVI and time integrated NDVI (TIN). NDVI values are scaled to (*NDVI**100 + 100) before integrating them for TIN. FS-first season, Mar 21 through May 25; SS-second season, Jul 27 through Sep 29; and IS-intermediate season, Jun 9 through Jul 11. TIN-time integrated NDVI, Apr 6 through Aug 28, is the period for which NDVI values were integrated.

Ji & Peters, 2003; Kawabata, Ichii, & Yamaguchi, 2001; Wang, Price, & Rich, 2001; Wang, Rich, & Price, 2003), a second model was built for the wet years optimizing the peak NDVI threshold values for these years. The first model was implemented for the dry years (2000, 2001, 2002, 2004, 2006, 2008) while the second model was implemented for the wet years (2003, 2005, 2007, 2009–2013).

2.4.2. Defining wet and dry years

Snow and ice account for 80% of the total water resources (UNEP, 2009), and seasonal snowfall is an important input to the annual water budget that determines water availability for the country. The U.S. Geological Survey monitors snow conditions operationally and provides estimates of Snow Water Equivalent (SWE) on a daily basis for comparison with long-term mean conditions in Afghanistan (USGS, 2013). SWE indicates how much water was contained in the snowpack. These estimates were used to calculate per-basin snow water volume and were presented as 12-month time series. Fig. 4 shows time series of average monthly snow water volume for selected years (October through September) compared to the mean (2002–2012). These snow water volume charts were analyzed to define dry and wet years from a hydrological perspective. The defined dry years were 2000, 2001, 2002, 2004, 2006, and 2008, and the wet years were 2003, 2005, 2007, and 2009 through 2013. Identification of these dry and wet years was confirmed by remote sensing and field-based reports, which indicate widespread droughts in 1999 through 2001, 2004 (World-Bank, 2005; FAO, 2004), 2008 (USDA-FAS, 2008), and well distributed rains and heavy snowfall in 2003 (World-Bank, 2005; FAO, 2004), 2009 (USDA-FAS, 2009), and 2010 (UNOCHA, 2010). The decision tree classifier model optimized for dry and wet years was implemented to classify irrigated areas for the respective dry or wet years as defined above.

2.5. Accuracy Evaluation Criteria

Application of these models yielded 14 maps of irrigated areas from 2000 to 2013. Assessing the accuracy of these maps was challenging because of the lack of ground reference information on irrigated areas. Therefore, we relied on comparisons with irrigated area identified from multi-temporal Landsat images for quality assessment of the coarser resolution MODIS-based calculations. Quality assessment was carried out individually for 2000, 2009, 2010, and 2011. These years were selected based on the availability of multi-temporal Landsat images during the growing season over four predefined path-rows known for a high concentration of irrigated areas. They were in Helmand and Kandahar provinces in the southwest, in Balkh and Jawzjan provinces in the north, in Hirat province in the west, and in Baghlan, Kunduz, and Takhar provinces in the northeast. Multiple Landsat 5 Thematic Mapper scenes (optical and thermal) were obtained for each of these years between March and September. A list of the obtained images is presented in Table 1.

2.6. Identifying irrigated areas using NDVI and thermal information from Landsat

The optical and thermal band DN (Digital Number) values were converted to radiance following the standard process found in the Landsat Data Products document (Chander & Markham, 2003). Band radiance values were atmospherically corrected using parameters from Atmospheric Correction Parameter Calculator (Barsi, Barker, & Schott, 2003; Barsi, Schott, Palluconi, & Hook, 2005). The atmospherically corrected radiance in the optical and infrared bands were then converted to top-of-atmosphere reflectance following the methods shown by Chander and Markham, (2003). The atmospherically corrected radiance of the thermal band is converted to temperature in Kelvin (K). Finally, NDVI is calculated for each date from the red and near-infrared atmosphere-corrected reflectance.

Kaufmann et al. (2003) show that the dynamics of NDVI and surface temperature were closely related. Typically, high values of NDVI correspond to lower surface temperature. A preliminary assessment of

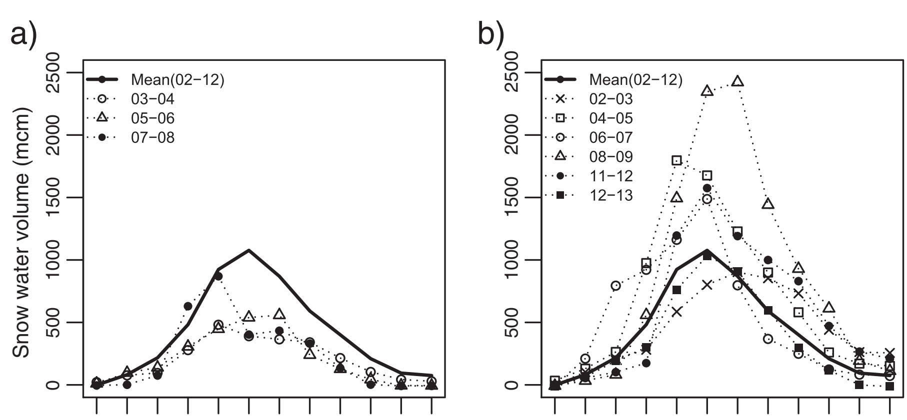

Fig. 4. Average monthly snow water volume (SWV) over Afghanistan for a) drier years which were defined if the SWV of that year was below the long term (2002–2012) mean SWV, and b) wetter years which were defined if the SWV of that year was above the long term (2002–2012) mean SWV. The basin-specific SWVs were summarized together to create average SWVs for the entire country.

Table 1
List of Landsat images during the first and second growing seasons that were used to identify irrigated areas in Afghanistan, showing path/row and acquisition dates.

WRS2 Path/Row	Year	First growing season	Second growing season
p155 r38	2000	Mar 21, May 08	Sep 13, Sep 29
	2009	Mar 14, May 17	Aug 21
	2010	Mar 01, Apr 02, Apr 18	Sep 09
	2011	Mar 20, May 07	
p155 r34	2000	May 08	Aug 12, Aug 28
	2010		Jul 07, Sep 09
p153 r35	2000		Jun 11, Jun 27, Sep 15
	2009		Aug 07, Aug 23
	2010		Jul 09, Jul 25, Aug 26
	2011	Apr 23	Aug 13
p157 r36	2000	Apr 20, May 06	Sep 11
	2009	Mar 12, May 15	
	2010	Mar 31, Jun 19	Aug 06
	2011	Apr 19, May 06	

three Landsat scene areas, located in the arid region of Afghanistan, indicated that surface temperatures in the irrigated areas were generally 3–10 K lower than the temperatures in non-irrigated areas. It was also observed that by early May an irrigated cell has an NDVI of >0.45 and a temperature of <311 K. Therefore, a combination of these two indicators provided a good basis for identification of irrigated areas. Subsequently, we applied Eq. 2 to NDVI and surface temperature to identify irrigated areas for each scene.

$$Irrigated = (NDVI>0.45) AND (K<311) \quad (2)$$

The threshold of NDVI and temperature were adjusted slightly depending on the acquisition date of the image. Finally, the resultant maps were combined to create a single map of irrigated areas by year. Landsat-derived irrigation maps (at 30 m spatial resolution) were compared with the irrigated areas from MODIS (at 250-m spatial resolution). Due to the inherent difference in spatial resolutions, per pixel comparisons were not practical. Therefore, areal estimates of irrigated areas from both Landsat and MODIS-derived maps over the same geographic locations were compared instead of pixel-by-pixel comparison.

3. Results and discussion

Implementation of the threshold-dependent decision tree classifier model for each study year resulted in 14 maps showing the spatial distribution of irrigated areas across Afghanistan. The spatial distributions of irrigated areas derived from MODIS seasonal peak NDVI for 2000, 2004, 2009, and 2011 are presented in Fig. 5. The maps identified the spatial distribution of irrigated areas across the country. High concentrations of irrigated land were mostly found in Kunduz in the northeast, Faryab and Balkh in the north, Hirat in the west, Helmand in the southwest, and Parwan, Kapisa, Kabul, Nangarhar, Ghazni, and Logar provinces in the east/southeast. Some small patches of irrigated lands were also identified along the valley and river plains of the central highland provinces.

The 14-year (2000–2013) national average irrigated area was found to be 2 million hectares in Afghanistan. The irrigated area estimates for Afghanistan vary substantially between sources (Table 2). While the 14-year average irrigated area found in this study resembles irrigated area estimates provided by U.S. Department of Agriculture Foreign Agriculture Service, it is below the estimates provided by other sources except Global Irrigated Area Map (GIAM) and GLCC. FAO estimates were among the highest estimates of irrigated area for Afghanistan. The FAO estimate of irrigated area for 1993 equals the area equipped for irrigation, and the 2010 estimate by FAO was more than the area equipped for irrigation provided by Kassel digital global map of irrigated areas (Table 2). The area equipped for irrigation means area equipped to provide water to crops, which is not necessarily the same as actual

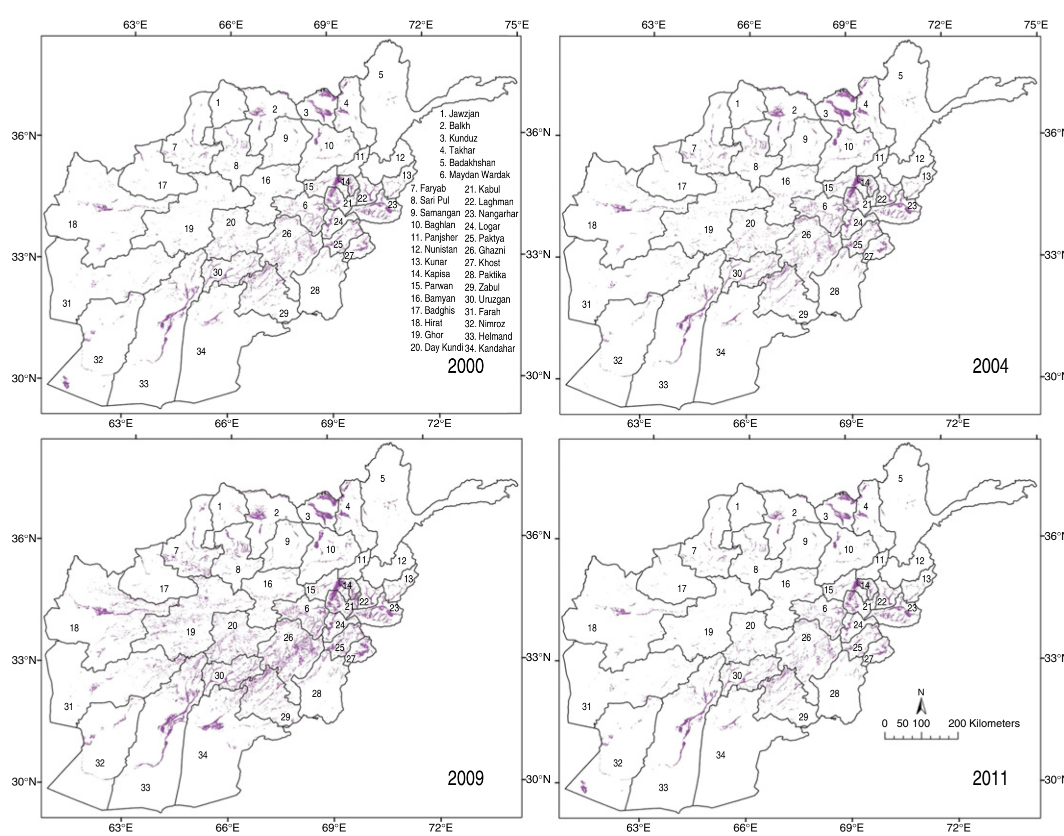

Fig. 5. Spatial distributions of irrigated areas in Afghanistan derived from MODIS seasonal peak NDVI. The years 2000 and 2004 were water-deficit years, and the years 2009 and 2011 were water-surplus years.

Table 2
Comparison of estimated irrigated areas in Afghanistan by different sources and methods.

Sources	Irrigated areas (million ha.)	Time period	Method	Resolution	Frequency	Description	Input data
This study	1.6	Dry year avg.	Remote sensing	250 m	Yearly	Irrigated area	250 m MODIS NDVI
	2.3	Wet year avg.					
	2.0	2000-2013 avg.					
Ward 2010	2.7	2003	Statistics	-	Once	Irrigated area	World fact book
Qureshi, 2002	2.6	1978	Statistics	-	Once		-
USDA-FAS	2.0	2011	Statistics	-			
1993 land cover map of Afghanistan by FAO	3.2	1988–1993	Remote sensing	Vector polygons	Once	Irrigated area	Satellite images and space photographs
2010 land cover map of Afghanistan by FAO	3.4	2010	Remote sensing	Vector polygons	Once	Irrigated area	SPOT satellite images
GIAM	1.7	1999	Remote sensing	10 km	Once	Irrigated area	AVHRR, SPOT, Rainfall, GTOPO30, SAR, Global tree cover.
Kassel digital global map of irrigated areas	3.2	2005	Statistics and digital mapping	5 minute	Once (multiple versions)	Area equipped for irrigation	Statistics, printed maps and digital data
GLCC	1.5	1992–1993	Remote sensing	1 km	Once	Irrigated cropland and pasture	AVHRR satellite images

irrigated area. Often part of the equipped area is not irrigated for various reasons such as lack of water, absence of farmers, land degradation, conflict, damage and organizational problems. Furthermore, the FAO estimates were over 85% of the total 3.7 million hectares of cultivable land, which includes 1.3–1.7 million hectares of rainfed land (Qureshi, 2002; USDA-FAS, 2011). The FAO 1993 and 2010 land cover maps were derived from satellite images and space photographs. A qualitative assessment (in this study) of these two maps (1993 and 2010), with the help of 3.2 m spatial resolution Google Earth images provided by Digital Globe concluded that while the FAO maps identified irrigated areas comprehensively across the country, their image interpretation processes appear to overestimate irrigated areas at the national scale. On the other hand, GIAM and GLCC not only show lower irrigated area estimates compared to estimates by other sources, but also fall short identifying spatial distribution of irrigated areas as they only identified major irrigated areas in the north and southwestern parts of the country. Because the smaller farm sizes and sparsely irrigated areas were not well resolved in the coarse resolution satellite images used to produce GIAM and GLCC maps, and due to a lack of training and lack of climate datasets for Afghanistan, irrigated area is underrepresented by these two sources. While the mapping methods and description of input data were provided for remote sensing based estimates, the same level of details were not available for the sources of statistical estimates of irrigated areas in Afghanistan from Table 2.

The observed temporal dynamics of MODIS-derived irrigated areas revealed that the extent of total irrigated area diminished in dry years and increased in wet years. The average irrigated area in dry years was about 1.6 million hectares and approximately 2.3 million hectares in wet years. The extent of irrigated area may vary by about 30% between water deficit and water surplus years, which can be an indication of subsequent food production and food security situations for the country. Consistent with prevailing successive years of drought from 1999 through 2001 (FAO, 2004), the lowest irrigated area of 1.3 million hectares was estimated for 2001, whereas the record setting snowpack in the highlands in 2012/2013 (USGS, 2013) contributed to the estimation of the highest irrigated area of over 2.5 million hectares in 2012 and 2013. The threshold-dependent decision tree classifier model was implemented to map irrigated areas for 2013 in mid-September. With above average snow water volume available in 2013, the year was identified as a water surplus year; successively the model tuned for wet years was implemented. The estimated irrigated area for 2013 was found to be 2.62 million hectares – a 1.95% increase over 2012 estimates.

Analysis of interannual variability in irrigated areas reveals that irrigated areas of the southeastern provinces (Parwan, Laghman, Kapisa, Kabul, Nangarhar, Maydan Wardak, Logar, Ghazni, Paktya, and Khost) change the least. These are also the provinces that receive the highest rainfall in the country (Qureshi, 2002), which implies that irrigation in these provinces could be supplemental and less dependent upon seasonal snowmelt. On the other hand, most of the interannual variance is observed in the northeast (Takhar, Kunduz, Baghlan), north (Bulkh, Faryab), west (Hirat), and southwest (Kandahar, Uruzgan, Helmand) provinces, which means irrigation in these provinces is highly dependent upon seasonal snowmelt.

Fig. 6 a shows that 2000, 2001, 2004, and 2008 were among the lowest irrigated area years, whereas irrigated area was high in 2005, 2007, 2009, 2012, and 2013. The 2013 irrigated area estimate exceeded all previous records of the last decade. Despite reductions in irrigated areas during dry years, an overall increasing trend in irrigated areas has been observed during the last 14-year period (Fig. 6a). While irrigated areas are increasing nationally, there are provincial differences in the magnitude of increasing irrigated area extent. Fig. 6b shows that among the dominant irrigated provinces, irrigated area increases marginally for most except Helmand, where irrigated areas more than doubled during the last decade. Perhaps the most dramatic increase in irrigated areas was observed in the Nimroz province. The average irrigated area in this province was about 44,000 hectares prior to 2012,

but in 2012, that number increased to 140,000 hectares – over a three-fold increase. These newly irrigated areas were located in the northern part of the province along the border with the Farah province.

4. Quality assessment of irrigation maps

The reliability of any map derived from remote sensing depends on quantitative quality assessment compared to ground reference information. Although ground reference information is the optimal source for validation of remotely sensed products, it may not always be available in a data sparse environment such as Afghanistan. However, high resolution satellite imagery shows potential to fill the gaps by providing land cover/land use information as a proxy to ground reference.

4.1. Quantitative assessment

Fig. 7 shows a false-color composite of an April 1, 2010, Landsat 5 image over Helmand and Kandahar provinces, along with the areas classified as irrigated for 2010 from multiple Landsat 5 images for the same region. Visual interpretation of these classified results suggests that the threshold-dependent classifier produced reasonably good results. The sparsely vegetated landscape in contrast to agricultural crop areas, in the sampling locations, was beneficial in identifying the irrigated areas from Landsat.

Irrigated areas were identified using Landsat imagery for 2000, 2009, 2010, and 2011. Estimates of irrigated area for these years were extracted from both Landsat- and MODIS-derived maps for the same geographic locations and are presented in Fig. 8. The area estimates compared well for all four years with an average goodness of fit of $r^2 = 0.91$. However, a positive bias toward Landsat-derived estimates was observed for the early years, e.g., 2000. The bias gradually moved toward MODIS-derived estimates for the later years. The difference in spatial resolution between Landsat and MODIS may have contributed to this bias. As irrigated area gradually increased, the amount of mixed pixel (Busetto, Meroni, & Colombo, 2008) problems grew, resulting in additional areas being identified as irrigated in the MODIS-derived maps. Overall, the good agreement between Landsat and MODIS-derived irrigated area estimates suggests that the MODIS-derived irrigated area maps were reasonably accurate.

4.2. Qualitative assessment

Cereals (mostly wheat, rice, maize, and barley) are the most commonly grown crops in Afghanistan (MAIL, 2011) and accounted for 77% of the agricultural Gross Domestic Product in 2010-2011 (MAIL, 2012). Because of the cereals' large proportion of agricultural production and high dependence on weather, we expected good agreement between total irrigated area and total cereal production annually. Total cereal production includes both irrigated and rainfed areas, as separate irrigated figures were not available for earlier years. Cereal production and irrigated area estimates are presented in Fig. 9 a and b. The figures show that annual cereal production tracks the interannual variability of irrigated areas remarkably well, with a goodness of fit $r^2 = 0.9$. The annual cereal production totals for 2001, 2004, and 2008 were among the lowest and corresponded to less irrigated area for those same years (Table 3). We compared model outputs of irrigated area against those reported by Ministry of Agriculture, Irrigation and Livestock (MAIL) Agricultural Prospects Reports (MAIL, 2012), and found general agreement in annual trends. However, the reports were only available for 2005–12 and were crop specific for wheat only, owing to potential differences. The 2012 total cereal production was estimated to be 21% greater than the 5-year average from 2005 to 2009 (MAIL, 2012), while 2012 wheat production alone was expected to be 36% more than the wheat production of 2011 (USDA-FAS, 2012). The national irrigated area estimate for 2012 was 26% above the mean and 23% greater than the 2011 estimate. These increases agree well with the cereal production estimates for the country. The 2012 grain harvest was reported to be the second highest on record for the past 35 years (FEWS NET, 2013). For 2013, the irrigated areas increased by 1.95% from the irrigated areas in 2012. Since the historical national irrigated area estimates show close agreement with national cereal production, the national cereal production was estimated to be 6.46 million MT based on a regression analysis between historical irrigated area estimates and cereal productions for the country. The 2013 estimated cereal production is 2.2% higher than the cereal production of 2012 at the national level. Although the estimated increase in cereal production is marginal, it implies improved food security conditions for 2013 in Afghanistan. However, the food security conditions need to be validated using actual crop production information for 2013.

4.3. Accuracy, errors, and uncertainty

The primary objective of accuracy assessment for geospatial maps is to promote understanding of the validity of the land use information, both categorically and across the spatial domain of the map. In the absence of irrigated area information for Afghanistan, high resolution Landsat satellite images were used to provide the reference irrigated area information for accuracy assessment of MODIS-derived irrigated area maps. Although the MODIS-derived irrigated area estimates agreed well, $r^2 = 0.91$, with irrigated area estimates derived from Landsat

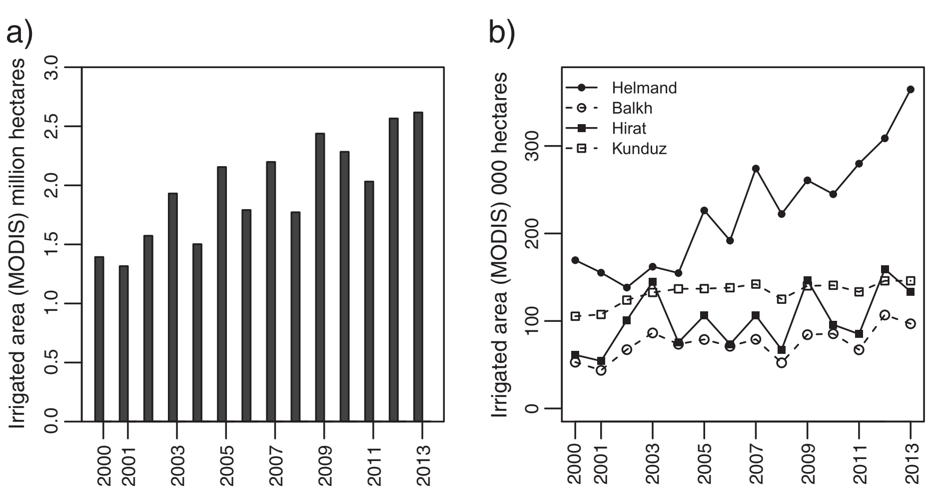

Fig. 6. a) The national interannual variability of irrigated area, b) the interannual variability of irrigated area in four irrigation dominated provinces in Afghanistan.

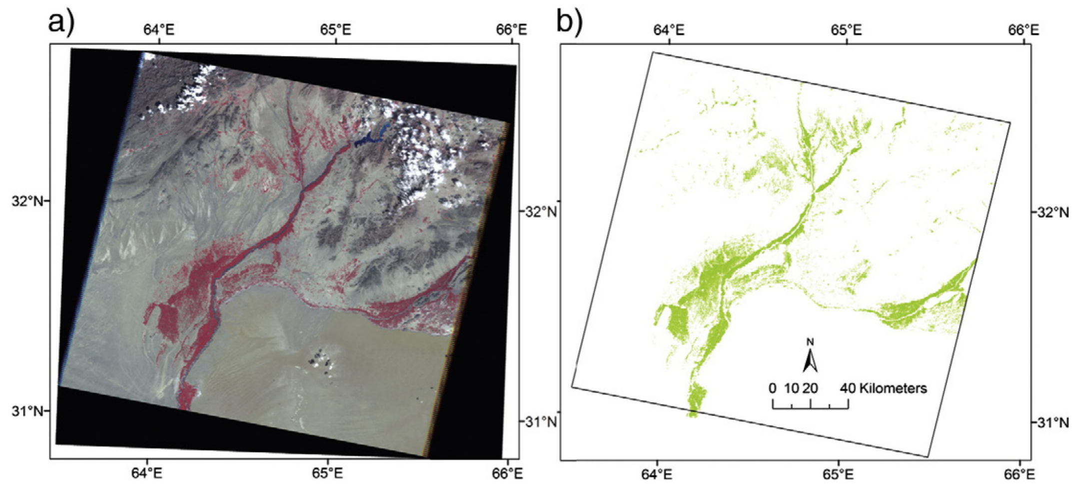

Fig. 7. a) April 1, 2010, false-color composite of Landsat Thematic Mapper image (p155r38) over Helmand and Kandahar provinces. b) Irrigated areas derived from multi-temporal Landsat NDVI and surface temperature for 2010.

images, the derived estimates were spatially and temporally restricted because of image availability, and hence somewhat limited and may be considered as a limitation of this study.

Uncertainties are inherent in most geospatial data, hence it is important to communicate to the user the underlying uncertainties of input data and the final product. The main source of uncertainty for the MODIS-derived irrigated area maps is the selection of NDVI thresholds to differentiate irrigated areas from non-irrigated area. The NDVI thresholds were selected empirically on a trial and error basis, and thus are somewhat subjective and may have uncertainty associated with them. Although the selected thresholds were effective in differentiating irrigated areas for the past 14 years, they need to be evaluated carefully with respect to environmental conditions, and adjustments in the NDVI threshold values may be necessary before applying the model for any future year. Permanent pasture/range land and forest were two of the key inputs to the non-irrigated area mask. These land covers were identified using SAM, which is known to perform well in the areas of homogeneous land cover types. Although the pasture/range land and forest areas are concentrated in northern and northeastern Afghanistan, the classified maps of permanent pasture/range land and forest were not independently validated. The potential misclassification error in these land cover types may introduce positional uncertainties in the non-irrigated area mask used by the model.

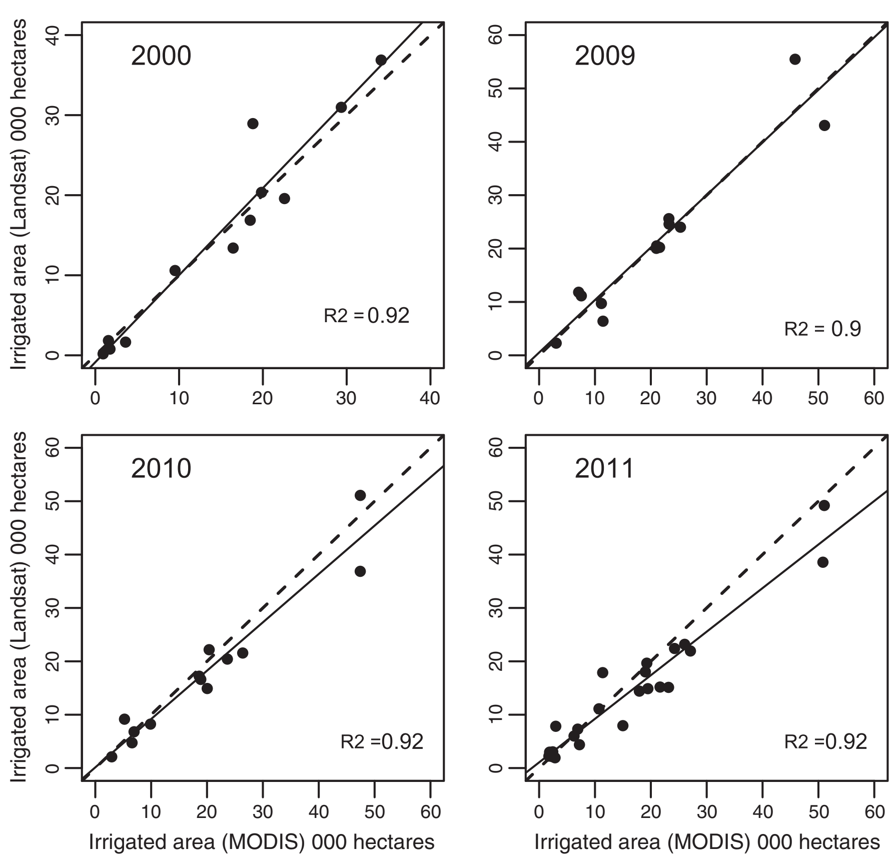

Fig. 8. Comparison of MODIS-derived irrigated areas and Landsat-derived irrigated areas for 2000, 2009, 2010, and 2011.

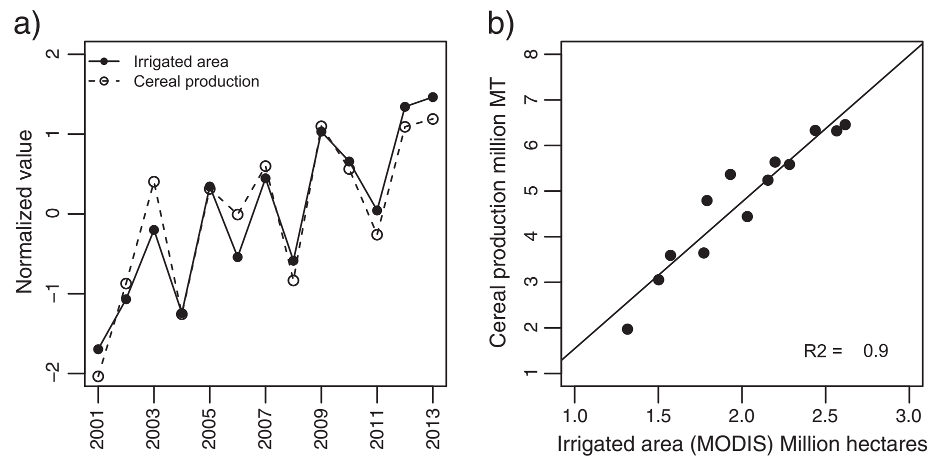

Fig. 9. a) Irrigated area and cereal production for Afghanistan. Both irrigated area and cereal production time series have been normalized by their standard deviations. b) Goodness of fit between irrigated areas and cereal production for Afghanistan. Note: source of the cereal production data: 2001, MAIL, 2011; 2002–2012, MAIL, 2011, 2012, estimated in this study.

Another potential source of uncertainty in the MODIS-derived maps is the 250-m (6.25 hectares) binary pixel mapping unit where 100% of the pixel area is considered irrigated. The choice of appropriate scale in mapping irrigated area depends on the methods to be used to extract irrigated areas and the extent of the mapping area. Typically, finer spatial resolution satellite data provide more precisely derived irrigated areas, because fragmented areas can be better detected (Velpuri et al., 2009). On the other hand, large proportion errors can arise when landscapes are represented at increasingly coarse scales (Thenkabail et al., 2007). Although the 250-m resolution binary maps identified spatial distribution of irrigated areas across the county well, with the median irrigated farm size of 1.4 for Afghanistan (Qureshi, 2002), the fragmented small irrigated fields may not be well resolved in the MODIS-derived irrigated area maps.

5. Conclusion

We implemented a simple but effective method to use seasonal peak NDVI thresholds in a decision-tree classifier model to map annual irrigated areas in Afghanistan from 2000 through 2013. The regionally adjusted thresholds for differentiating irrigated areas from non-irrigated areas were obtained empirically, through an iterative process, by comparing the results with high resolution Google Earth imagery for the same time period. Two separate models were built to account for vegetation growth differences between water surplus and water deficit years. The maps were spatially consistent in identifying irrigated areas across the country through time, and the interannual variability in irrigated areas was well depicted. Due to a lack of ground reference information to validate these maps, we classified irrigated areas from multiple snapshots of the landscape, per growing season, using Landsat 5 optical and thermal sensor images. The irrigated areas derived from Landsat for four years agreed well with the areas derived from MODIS for the respective years, which provides confidence in our ability to map irrigated areas using the coarser resolution MODIS data.

We observed that the annual extent of irrigated areas was influenced by the availability of surface water, especially from snowmelt. The average amount of irrigated area was found to be approximately 2 million hectares in Afghanistan, but was shown to be as low as 1.3 million hectares in a high water deficit year and as high as 2.6 million hectares in a high water surplus year. In general, the amount of irrigated area varied by about 30% between water surplus and water deficit years. We found that the interannual variability of the irrigated area tracks well with the variability of total cereal production, implying that fluctuations in the irrigated area estimates may also be reflective of the country's potential food production and availability.

The proposed method allows full implementation of the model as early as mid-September (towards the end of second growing season) in Afghanistan. These results hold promise for obtaining estimates of potential food production scenarios for the country, which can further aid food security monitoring. The unique pattern of the landscape was somewhat favorable for model implementation in Afghanistan, but the model can also be applied in other geographic regions. Implementing the model for central Asian countries along with identification of irrigated areas at sub-pixel level is a potential area of future research.

Table 3
Annual estimates of cereal production and irrigated area for Afghanistan.

year	National cereal production in million metric tons	Irrigated area in million hectares	Normalized cereal production $(x-\bar{x})/\sigma$	Normalized irrigated area $(x-\bar{x})/\sigma$
2000		1.39		
2001	1.98	1.32	−2.038	−1.695
2002	3.59	1.57	−0.872	−1.069
2003	5.37	1.93	0.408	−0.200
2004	3.06	1.50	−1.257	−1.242
2005	5.24	2.16	0.317	0.344
2006	4.80	1.79	−0.005	−0.541
2007	5.64	2.20	0.603	0.447
2008	3.65	1.77	−0.834	−0.585
2009	6.33	2.44	1.103	1.032
2010	5.59	2.28	0.566	0.657
2011	4.44	2.03	−0.258	0.044
2012	6.32	2.57	1.096	1.343
2013	6.46	2.62	1.190	1.465

Data source: cereal production estimates for 2001, MAIL, 2011; 2002–2012, MAIL, 2011, 2012, this study. 2000–2013 Irrigated areas estimates, this study.

However, careful evaluation of the temporal NDVI profiles of a given landscape and adjustments in derived thresholds are needed.

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