5 - REMOTE SENSING APPLIED TO IRRIGATION

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Abstract: The series of 10-day SPOT Vegetation NDVI images for 1999 – 2002 were used for: land use classification, mainly to improve the accuracy of irrigated areas delineation; analysis of variations of the 10-day NDVI average values for different units of aggregation (irrigation zones of Fergana Valley, administrative districts of Fergana province, and collective farms of Kuva district). Additionally, two Landsat-7 ETM+ satellite images on 28/04/2001 and 02/08/2001 were used for: main crops (winter wheat and cotton) classification, based on NDVI values analysis; soil salinity recognition by calculation of NDVI heterogeneity index (coefficient of NDVI variations) inside of each parcel for two selected areas. The joint use of the images from both satellites (SPOT Vegetation and Landsat-7), together with GIS layer of parcels polygons, were used to model 10-day crop coefficients (Kc) from NDVI values. Results may be used to adjust for local conditions the Kc values recommended by FAO-56 publication for calculation of crop water requirements in alternative to other procedures adopted in this project.

Keywords: Remote Sensing, SPOT Vegetation Products, Landsat-7 ETM+ images, NDVI, Crops classification, Soil salinity recognition, Crops coefficients modelling.

Introduction

The use of satellite images to support land and water management is technically possible since the end of the seventies. The multi-spectral images of low spatial resolution (1100 m) from NOAA AVHRR satellites were used in land use/land cover classification and for monitoring of irrigation and drainage processes across large (Bastiaanssen, 1998) and small areas (Chemin *et al.*, 2004).

The recently (in 2000) launched TERRA satellite, equipped with a MODIS sensor, has an improved spectral (36 bands) and spatial (250 m – 1000 m) resolution, raises new opportunities for further investigations (Gitelson and Kaufman, 1998; Milne and Cohen, 1999; Zhan *et al.*, 2002). The SPOT Vegetation (from 1998) 4 bands data, and their products (NDVI, DMP) of the

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global coverage, have a spatial and temporal resolution of 1000 m and ten days, respectively. Those images have been used for crop monitoring and yield forecasting (Eerens *et al.*, 2001). The main advantage of the low spatial resolution images is a high temporal resolution as the repetitive image is collected twice a day (for MODIS) and free of charge via the Internet.

The series of Landsat satellites with different sensors (MSS, TM, ETM+) have been used very widely. The spatial resolution of multi-spectral images varied from (56 m*89 m) for MSS to 28.5 m for TM and ETM+ sensors. The temporal resolution is 16 days, but taking the cloud presence into account, there are usually available up to 3-4 cloud free images per year. The Landsat images are the main investigation data sources from regional to field scales and for different tasks (Bastiaanssen, 1998; Vincent *et al.*, 1996; Metternicht and Zinck, 2003).

Besides Landsat, there are other sources of images from France (SPOT HRV), India (IRS LISS), Russia (RESURS), but their prices are much higher than the Landsat ones. More cheap are the images from ASTER sensor, which is located on the same satellite (TERRA) as MODIS. The multi-spectral (15 bands) ASTER images have a spatial resolution of 15 to 60 m. The EO-1 ALI data is the next generation of Landsat satellites, with improved spectral resolution (9 bands).

Fine spatial resolution (0.6 m – 4 m) multi-spectral images are available from the IKONOS (4 bands) and Quickbird (4 bands) satellites, and their prices are very high. The images can be used effectively for precision farming (Staenz and Williams, 1997; Pacheco *et al.*, 2001).

The Hyperion images from the EO-1 satellite are the first hyper-spectral (220 bands) data on space. The images have the spatial resolution of 30 m and are the excellent source for soil salinity recognition (Metternicht and Zinck, 2003) and other tasks (McNairn *et al.*, 2001).

The radar data (JERS SAR and Radarsat) is the family of active satellite sensors. Because of their ability to penetrate the clouds, the radar images are usually used in the tropics or in any other cloud conditioned situations. The images are often used for analysis of the soil wetness spatial distribution at the shallow depth.

Source data

For the purpose of investigation, was used the 10-day period (each ten days for each year) SPOT Vegetation Products (NDVI) images for 1999, 2000, 2001 and 2002; and two multi-spectral Landsat-7 ETM+ images on 28/04/2001 and 02/08/2001.

For spatial analysis were used the GIS layers:

- Main irrigation zones for the Uzbek part of Fergana Valley;

- Administrative districts for the Fergana province of Uzbekistan;
- Collective farms for the Kuva district in the Fergana province;
- Parcels of one collective farm for the Kuva district of the Fergana province;
- Parcels of 3 collective farms for the Akhunbabaev district of the Fergana province.

The available satellite images were used for investigations in the following directions:

1. Land use classification by using of multi-temporal (10-day period) SPOT Vegetation NDVI profiles.
2. Analysis of the SPOT Vegetation NDVI 10-day period values, averaged for the different units of area (irrigation zones, administrative districts, collective farms) for the years 1999 to 2002.
3. Main crops (cotton and winter wheat) classification on the basis of calculated average NDVI values for each parcel from two Landsat-7 ETM+ images on 2001 year.
4. Soil salinity recognition from the analysis of NDVI values heterogeneity index for each parcel.
5. Modeling of 10-day period values of crop coefficients (Kc) for main crops derived from the NDVI values for each parcel.

Land use classification

For each 10-day period NDVI image from SPOT Vegetation, on the 1999-2002 years, was made a subset for the Fergana Valley area, and the 10-day period subsets were stacked for each year. As a result, four (for each year) 36 canals images (each canal consists from the NDVI values for one decade) were created.

Afterward, the unsupervised land use classification (with assigned 12 classes) was made, using the stack of 10-day period NDVI images for each year. The 2002 year classification results are shown on Fig. 1.

The profiles for the 10-day period NDVI values, for typical pixels inside of dark green areas (which have a good vegetation conditions), and the pixel from bare soil, are shown on Fig. 2. The typical two peaks of NDVI temporal profile for the irrigated area correspond to two main crops (winter wheat and cotton), sown in the area. The March - main rainy season - NDVI peak for the non-irrigated areas, is linked to the rainfed pastures.

As there was no available ground truth data to make an accurate land use classification, the main activity was made for the irrigated areas classification for the GIS layer accuracy improving of the irrigation zones delineation for Fergana Valley.

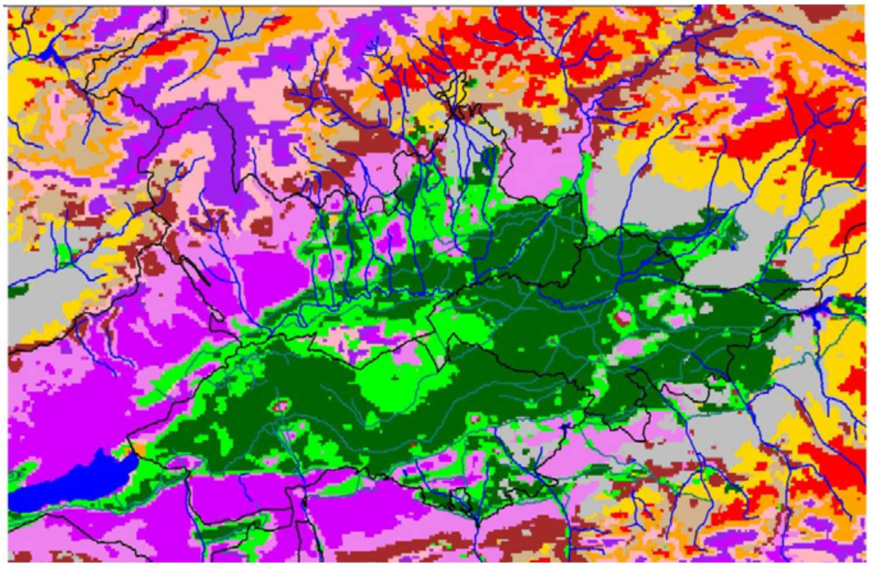


Fig. 1. Result of land use classification for Fergana Valley on 2002.

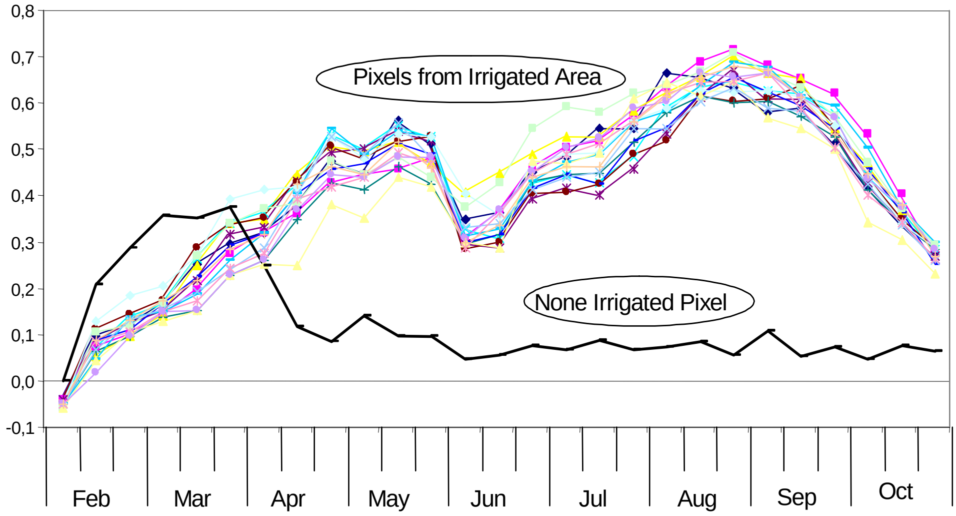
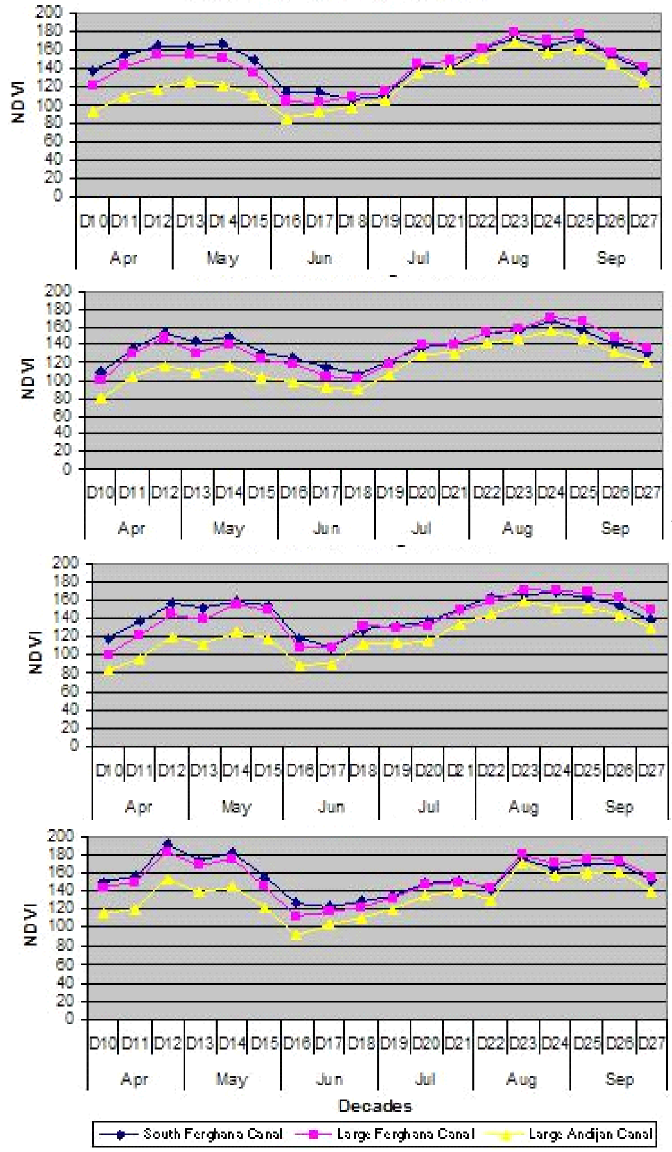


Fig. 2. 10-day NDVI values for pixels from the irrigated area and rainfed land of Fergana Valley.

Analysis of the SPOT Vegetation 10-day NDVI values

Through spatial overlay of the GIS polygon layers of the Fergana Valley's irrigation zones, the Fergana province's administrative districts and Kuva district's collective farms the average NDVI values, for different units of area, was calculated for each decade. The original values of the SPOT Vegetation images, stretched to (0-255) were used for the analysis. The temporal profiles of the average NDVI values for the main irrigation zones of the Fergana Valley (for the 1999-2002 years) are shown on Fig. 3.



a) b) c) d)

Fig. 3. 10-day NDVI values for main irrigation zones in Fergana Valley: a) 1999, b) 2000, c) 2001 and d) 2002.

The temporal profiles of the average NDVI values for administrative districts of Fergana province on 2002 year are shown on Fig. 4 and those for some collective farms of Kuva district on 2002 year are shown on Fig. 5.

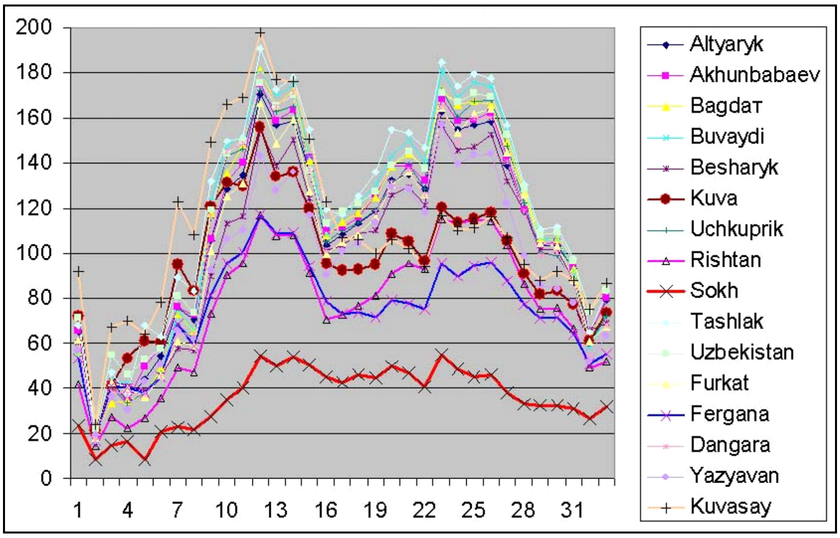


Fig. 4. 10-day NDVI values on 2002 year for administrative districts of Fergana province.

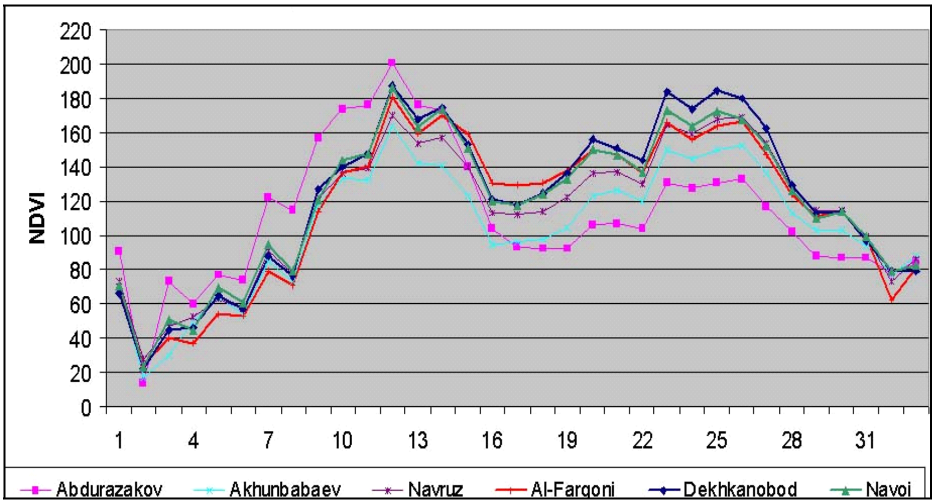


Fig. 5. 10-day NDVI values on 2002 year for collective farms of Kuva district.

The results of SPOT Vegetation NDVI images processing demonstrate that different units of area (pixels, irrigation zones of main canals, irrigated areas of administrative districts and farms) have variations in 10-day period NDVI profile that can be explained by differences in land productivity, spatial and temporal variations of irrigation water availability, etc. It makes sense to continue the investigations to separate the factors influencing the vegetation condition.

The results can be used by decision makers at regional scale to locate the places where vegetation conditions regularly have a high, moderate or low NDVI values and to manage the water and land resources more effectively, especially in conditions of irrigation water scarcity.

Main crops classification

It is known that the Normalized Difference Vegetation Index (NDVI) value is the quantitative measure of the vegetation conditions. The Landsat images are calculated by the following formula:

$$NDVI = (Band4 - Band3) / (Band4 + Band3) \quad [1]$$

where: Band4 and Band3 are the digital numbers (values of pixels) in infra-red (Band4) and red (Band3) canals.

By spatial overlaying of the created NDVI raster layers from Landsat-7 ETM images were calculated the average NDVI values on two dates for each parcel of the project area. The calculated values were filled in two fields (NDVI_0428 and NDVI_0802) of the parcels GIS layer attribute table.

For all records of the GIS attribute table, four spatial filters were applied by using the decision rules, demonstrated on Fig. 6. For selected records by each filter were filled in the values of the created attribute field (C2001) – the code of classified main crops ("B"- bare soil during a year; "C" – cotton; "WM" – maize after winter wheat; "W" – winter wheat).

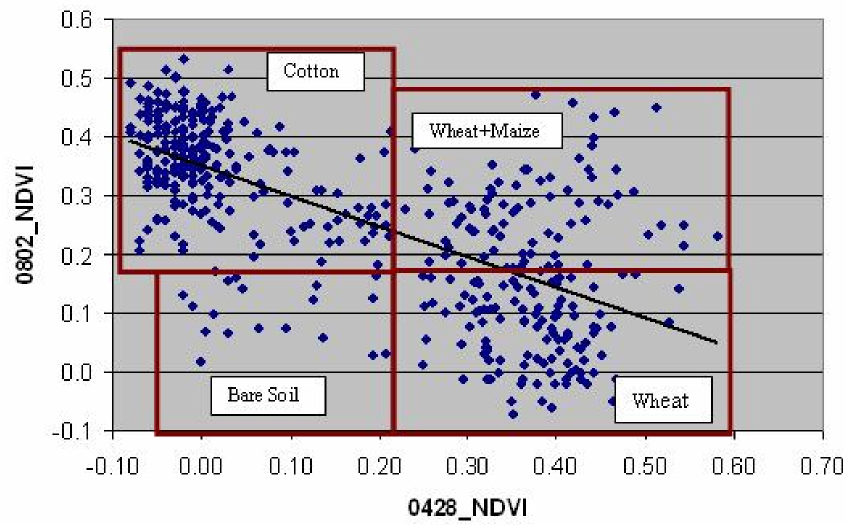


Fig. 6. Decision rules for main crops classification.

The important issue here is the threshold NDVI value for vegetation presence, after a numerous iterations was selected the NDVI value, close to 0.2.

All cities and villages polygons were classified as “WM”, so it requires the visual analysis of such polygons by using the Landsat-7 images as a background. By visual interpretation, the villages are very clearly discriminated, and for each their polygon was assigned with a special value of the new attribute field (LUC) – the land use code. On Fig. 7 is shown the result of main crops classification for each parcel of the project area. Unfortunately, there was no any solid ground truth data to make an assessment of the crops classification accuracy. The available data for the sown crops on the 16 parcels of the private “Azizbek-1” farm fully corresponds to the results of main crops classification from satellite images (100% of accuracy).

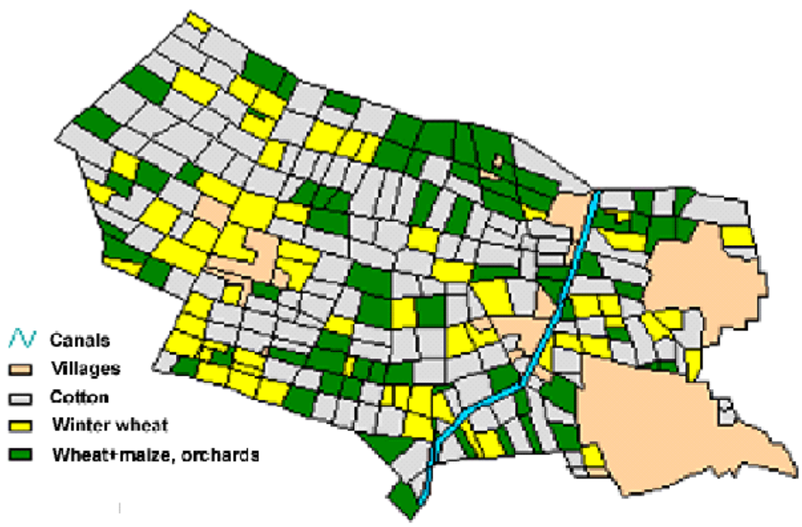


Fig. 7. Results of main crops classification for the project area.

Soil salinity recognition

There are different methods of soil salinity recognition from Remote Sensing. The typical one is based on analysis of pixel values from different spectral canals. But the accuracy of recognition depends very from the size of soil salinity spots inside of each parcel. Considering the spatial resolution of Landsat-7 multi-spectral images (30 m*30 m or 0.09 ha), the cases of soil salinity spots, less than the pixel size, will be impossible to recognize. The only way is to use the satellite images of finer spatial resolution, data from such satellite as: IRS, IKONOS or QuickBird.

The Fergana Valley is not the best area for soil salinity recognition, because there are no vast, salt affected areas, especially with salt crusts, as was confirmed during the ground truth assessment mission. During the mission, only a few places inside of Kuva district were found, which have a soil salinity problem. That is why it was made a decision of two areas using for comparative investigation: the project zone in the Akhunbabaev district and the sample zone in the Kuva district.

The soil salinity recognition used in this study is based on the vegetation cover spatial heterogeneity analysis for each parcel. An assumption was made so that the parcels having high values of NDVI spatial heterogeneity can have the soil salinity problems. It is clear, that there are other reasons that can be related to this problem, such as the irrigation water availability, bad field leveling, shortage of fertilizers; in fact, by processing of the images for one year, it is impossible to distinguish the reasons of vegetation spatial heterogeneity. This is only achievable by analyzing seasonal images for many (2-3) years and by creating spatial filters for selection of the parcels that regularly have high values of NDVI heterogeneity.

Fig. 8 shows the results of the frequency analysis of the NDVI heterogeneity index for the day 28/04/2001 for the project zone in the Akhunbabaev district and a sample zone in the Kuva district. The corresponding trend equations are respectively

$y = 0.1352\ e^{0,0092\ x}$ with $R^2 = 0.9398$, and

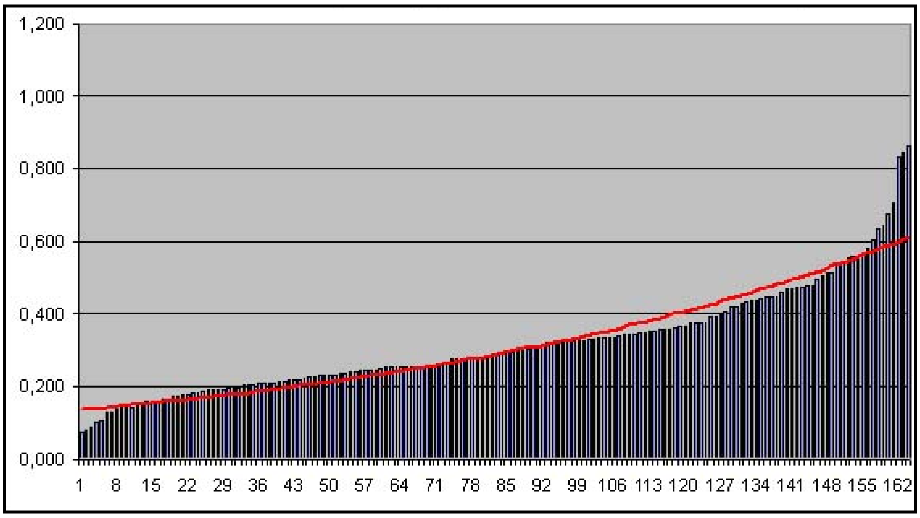
$y = 0,1748\ e^{0,014\ x}$ with $R^2 = 0.908$,

thus indicating a good data fitting.

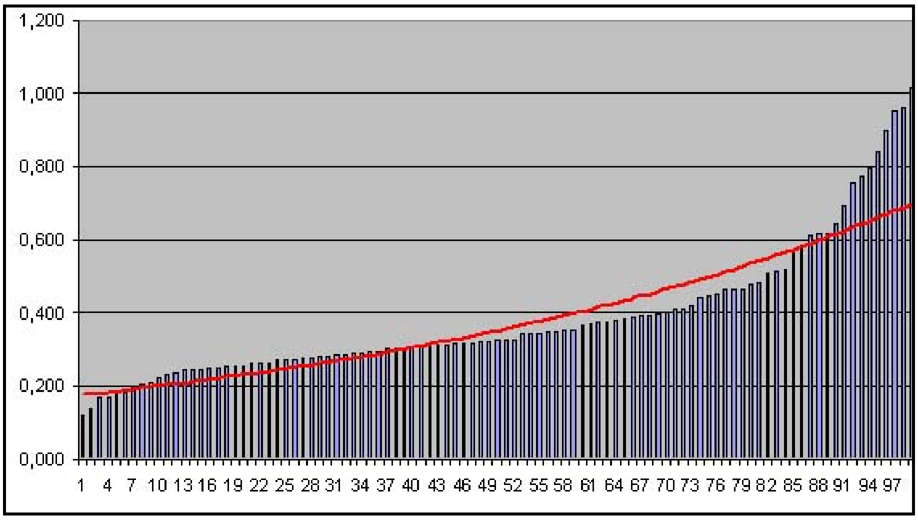
In comparison with the project zone in Akhunbabaev district, the Kuva sample area has more parcels; with higher vegetation heterogeneity index values (between 0.6 and 1.0) that can be linked to the soil properties, particularly, to the soil salinity.

Although, it will require further information to use the multi-annual Landsat-7 satellite images to verify the spatial stability of the calculated heterogeneity indexes for different years and seasons, for the areas under investigation. The parcels with regularly high HI and low NDVI are the first candidates for collecting detailed ground data on soil salinity measurements.

The correlation between vegetation heterogeneity index (HI) and NDVI values, averaged for each parcel, can be used as a performance indicator of the irrigated land productivity (Fig. 9). On the right side of the graph are shown higher NDVI values with lower heterogeneity (well performing crops), and on the left side, lower NDVI values with highest heterogeneities (performance to be improved) can be seen.



a)



b)

Fig. 8. Frequency analysis of NDVI heterogeneity index for the a) Akhunbabaev district and b) Kuva sample area.

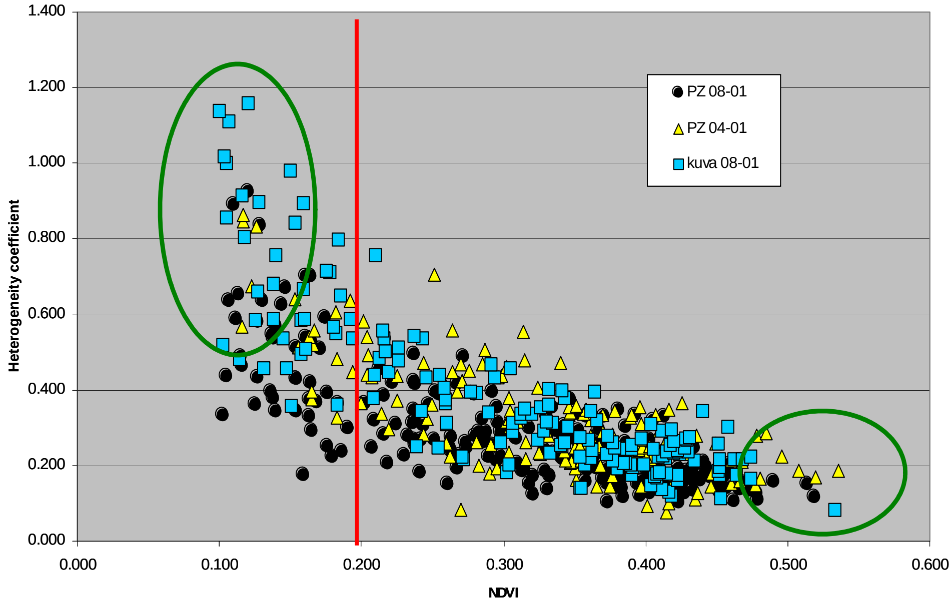


Fig. 9. NDVI Heterogeneity index (HI) versus NDVI at the plot scale.

Modeling 10-day crop coefficients (Kc) for main crops

As all pixels of the SPOT Vegetation images have an "at ground" size of 100 ha and the common size of each parcel is 4 up to 10 ha, it is impossible to find a "pure" pixel with the unique crop inside the area of Fergana Valley. So, by using SPOT Vegetation images, "mixed" pixels which content data from the vegetation and bare soil are always obtained.

When modelling 10-day crop coefficient (Kc) for main crops, it is advisable to combine the data from three sources:

1. The 10-day period SPOT Vegetation NDVI images;
2. The Landsat-7 ETM+ images, regarding the maximum vegetation conditions of main crops dates (in our case: winter wheat and cotton); and
3. The GIS layer of parcel polygons.

The first task was to analyze the compatibility of data from these sources, as it was planned to use simultaneously the NDVI values from different satellite sensors of various spatial resolution. For that purpose, the analysis of correlation between the degradated (to 600 m) NDVI values from the original Landsat-7 images (30 m) and calculated weighted average NDVI for each parcel inside the degradated pixel was provided.

The boundaries of degradated Landsat-7 pixels (red lines) and the thematic raster layer of NDVI gradation, created from Landsat-7 image, are shown on Fig. 10.

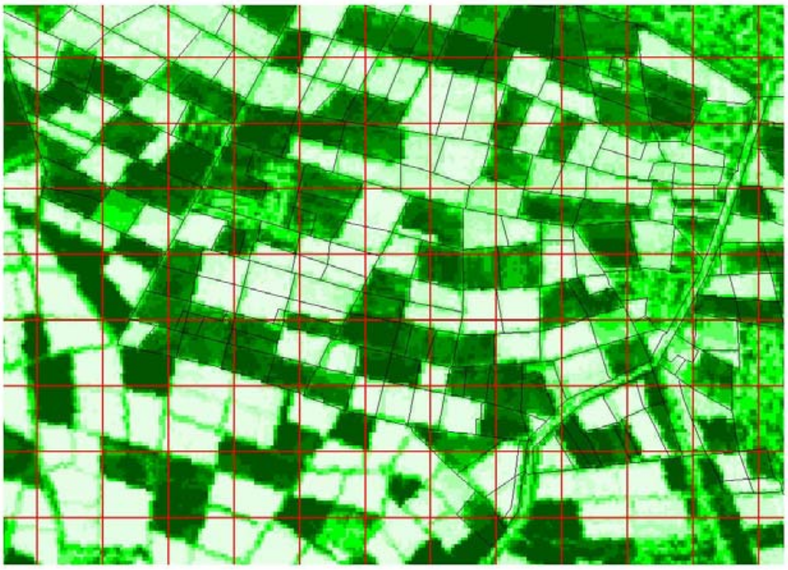


Fig. 10. Thematic raster of NDVI gradation from the Landsat image with the boundaries of pixels, degradated to 600 m.

A good correlation between the values of degradated pixels (600 m) and calculated weighted average NDVI values for parcels, inside of each degradated pixel was found for both dates: 28/04/2001 (Fig. 11a) and 02/08/2001 (Fig. 11 b). The respective regression equations are

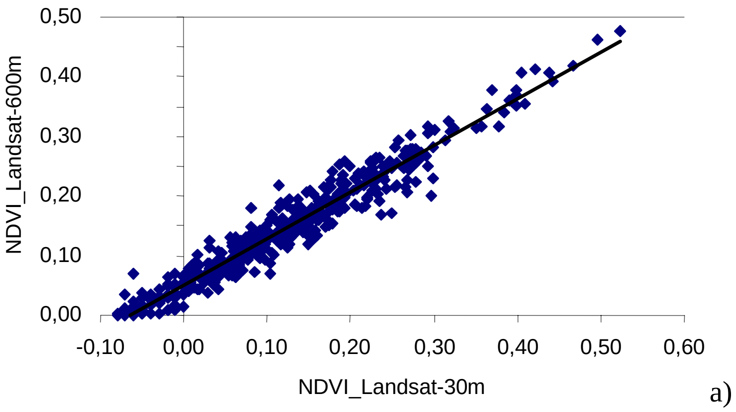
$y = 0.7788\,x + 0.0516$ with $R^2 = 0.9413$, and

$y = 0.8697\,x + 0.0345$ with $R^2 = 0.9454$.

The same type of correlation analysis was made between the weighted averaged NDVI values from Landsat-7 images (on 28/04/2001 and 02/08/2001), for the parcel's parts, inside of each SPOT Vegetation image's pixel, and NDVI values from SPOT Vegetation images on 12th and 22nd decade of 2001, correspondently. The best correlation was for parcels classified as "Wheat+Maize" on August (Fig. 12), which equation is

$y = 0.8801\,x + 0.0397$ with $R^2 = 0.8568$.

Besides, by analysis of separate pixels with poor vegetation conditions, it was found that SPOT Vegetation sensor is much more sensible to the vegetation presence, in comparison with the Lansat-7 ETM sensor.



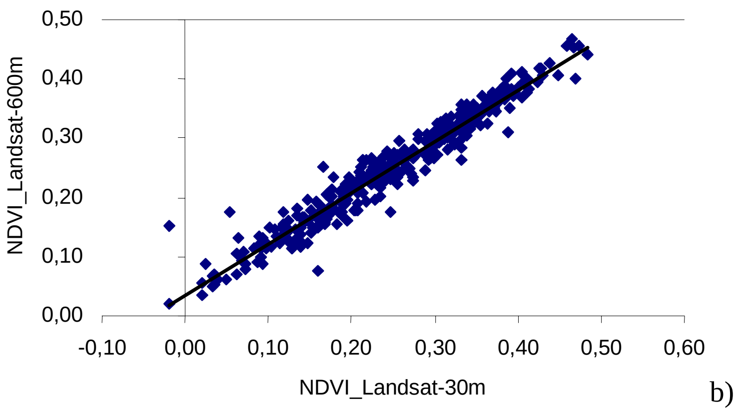


Fig. 11. Correlation between the values of degradated pixels (600 m) and the calculated weighted average NDVI values from the Landsat image (30 m) on a) 28/04/2001 and b) 02/08/2001.

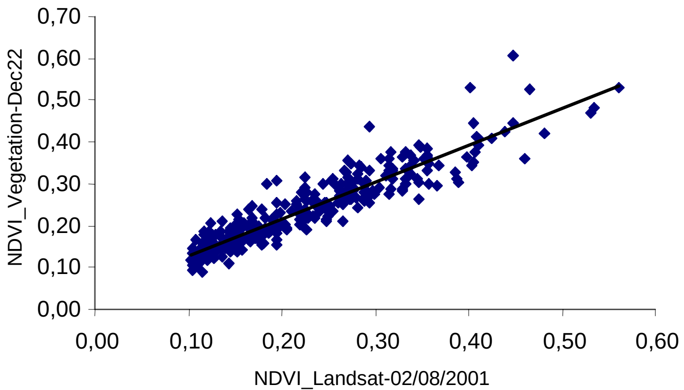


Fig. 12. Correlation between the values of SPOT Vegetation pixels (1000 m) on 22nd decade, 2001 and the calculated weighted average NDVI values from the Landsat image (30 m) on 02/08/2001.

Based on the SPOT vegetation NDVI raster layers was created the GIS vector layer, where each polygon corresponds to a pixel, and the 10-day period NDVI values for each polygon were filled in the created attribute fields. By spatial overlaying of this layer and the parcels GIS layer the new GIS layer was created, where polygons of many parcels were subdivided on parts during intersection with polygons of the SPOT Vegetation pixels boundaries.

For modeling of the 10-day period NDVI values for each parcel, an assumption was made, considering that the proportion of the cropped fields/bare soil on 28/04/2001 is representative for decade numbers from 7 to 16, and this proportion on 02/08/2001 is representative for decade numbers from 17 to 30. So, based on the parcel's parts area proportion inside each polygon of the SPOT Vegetation pixel and their NDVI values, calculated from both Landsat-7 ETM images, the 10-day period NDVI values for each parcel's parts were calculated. After that, the weighted average NDVI was calculated for each parcel from the NDVI of it parts for all decades. The statistical results of the 10-day period NDVI modelling for 206 parcels classified as "Wheat" are shown on Fig. 13 and those for 670 parcels classified as "Cotton" are shown on Fig. 14.

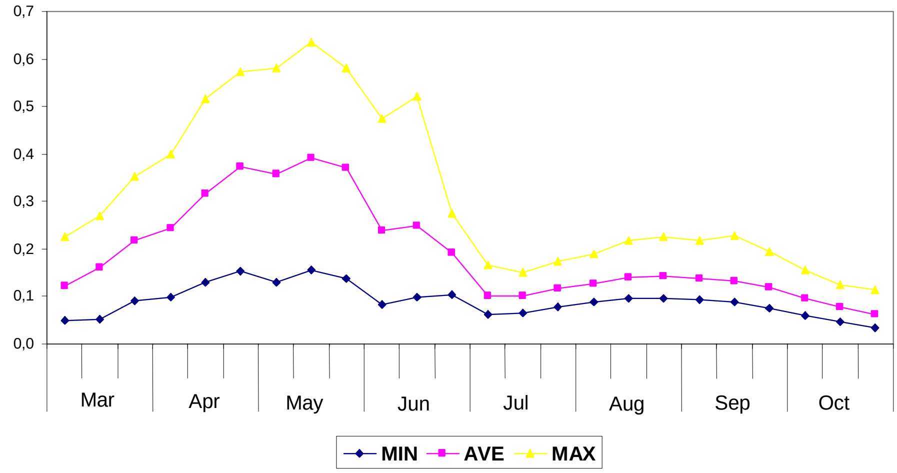


Fig. 13. The statistics of modeled 10-day NDVI values for "Wheat" parcels.

It is known that there is a strong linear correlation between the NDVI values from Landsat-7 ETM images and the crop coefficient (Kc) values. The FAO 56 publication (Allen *et al.*, 1998) recommends that the maximum Kc value should be equal 1.2 for the winter wheat and cotton crops, so, at the first approximation, the 10-day period crop coefficients values were calculated from the modeled NDVI values by simple formula:

$$Kc = 2 * \text{NDVI} \quad [2]$$

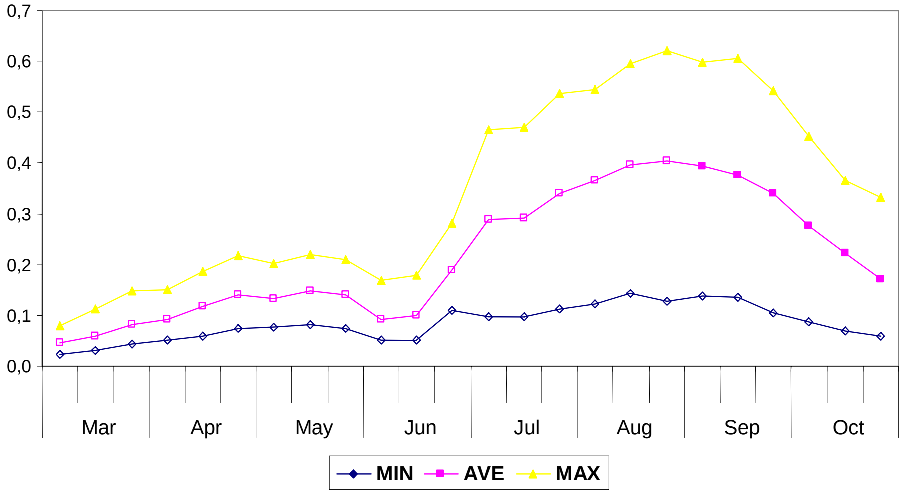


Fig. 14. The statistics of modeled 10-day NDVI values for "Cotton" parcels.

Modeled from Remote Sensing the decadal crops coefficient (Kc) values can be used for correction of the FAO recommended Kc values, more adjusted to the local conditions (Fig. 15). The results of Kc modeling from satellite images need to be further verified for different years and for other locations.

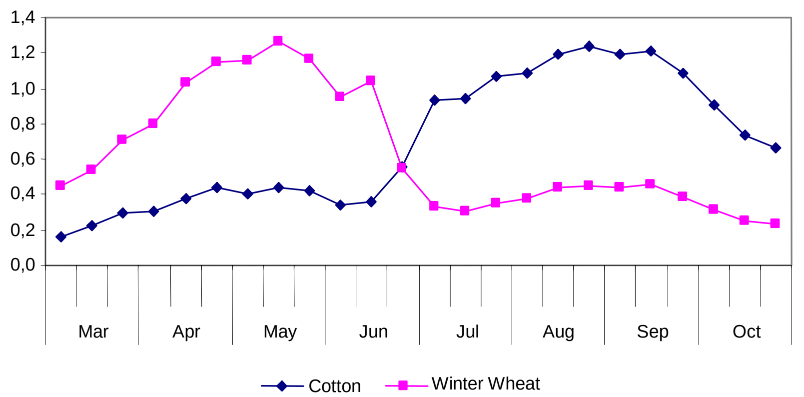


Fig. 15. Maximum 10-day Kc values for the main crops modeled from remote sensing.

Conclusions

The method based on the NDVI analysis, calculated from the multi-spectral satellite images Landsat-7 ETM, has shown rather good results regarding the main crop classification. The preliminary results of soil salinity recognition by the use of the vegetation heterogeneity index can be improved by using multi-annual (seasonal) Landsat images. The use of the hyper-spectral and high spatial resolution multi-spectral satellite images will substantially improve the accuracy of soil salinity recognition.

The combination of low spatial, but high temporal resolution images (SPOT Vegetation Products) with high spatial, but low temporal resolution images (Landsat-7 ETM), and GIS layers of parcels boundaries, gives a possibility to model the 10-day values of the crop coefficient (Kc) from NDVI. The verified Kc values can be also used for modeling of actual crop water requirements as for separate parcels, as well for any area of investigation.

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