Field size precision water management based on time series analysis of satellite images

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SUMMARY

As a result of climatic variability, extreme local meteorological phenomena will more likely significantly affect the agriculture in the near future. Space-based remote sensing provides an opportunity for continuous tracking the biomass growth of plants. A basic input of farm level irrigation models is the crop coefficient (K_c), which was defined by the leaf area and by which the transpirating area can be connect to the phenological changes in time. The widely used FAO CROPWAT irrigation model estimated K_c for a given place with large error by 3 point. In our research, NDVI time series – which were calculated from Landsat TM remote sensed images – were used on the 19 hectare sample plot of sugar beet test plant to determinate K_c values which indicate the phenological state with higher accuracy. K_c values were calibrated by field measurements. Digital Elevation Model (DEM) and water management soil-cartogram of the area were also created and used for calibration. We computed and evaluated heterogeneity by running principal components analysis that was performed on the time-series of the biomass. The results assisted and enabled the precision water management planning of the sample plot, as well as the calculation of different water management scenarios and finally the sustainable water management by timely dynamic data exchange of GIS and CROPWAT input/output.

KEYWORDS: Remote sensing, precision farming, NDVI, water management

INTRODUCTION

Under the continental climatic conditions of the Carpathian-basin, low or high temperature, as well as extreme agrohydrological conditions, like water shortage or water surplus are the most problematic environmental factors (Veisz & Sellyei, 2004). The extremities in the amount and distribution of rain are showing an increasing tendency in Hungary, which often causes problems in crop production (Nagy, 1995; Várallyay, 2005). The test crop we applied was sugar beet. Sugar beet and its production technology in EU will face a critical situation based on the cut off farm subsidiary, therefore it is a great importance to develop and use cost effective methods in crop production (European Commission, 2004).

Water management and especially pressurized irrigation are less introduced into GPS-based precision agricultural technology (Marques da Silva & Alexandre, 2003). There are several reasons for this, but we could emphasize the missing dynamically changing input model parameters for example timing of the crop and climatic conditions. Satellite, airborne and near field remote sensing data sources can provide a good solution to fill the gap of this data shortage.

A major disadvantage of widely used robust point-based practical water management models (WMM) is that they unable to provide proper information for farmers about those parameters that change dynamically in time and field level, so as they could not efficiently adjust several elements of the integrated small scale water management (Kovar & Nachtnebel, 1996). This management practice is not only includes irrigation, but also other more important technological parameters such as water stress tolerant crops, cultivation or nutrition management. In this study the authors present a GPS-RS-WMM model integration, as a possible solution for making farm management more effective.

MATERIALS AND METHODS

In our research we analyzed the water management system of a 19 hectare sugar beet field in Northeast-Hungary. On this field, detailed research work was carried out. Plant agro-technological data was prepared in ArcGIS environment. GPS registered samples were collected on the field on the plant evaporation surface with ACD type leaf area scanner in different phenological phases, and parallel sampled and measured the actual soil water content by TDR method in every 0.2 m layers till 1.5 m depth to prepare available water content profile of root zone (Rajkai & Rydén, 1992). The soil type on site is chernozem. The major parameters of the experimental field are shown in table 1.

Soil horizon	pH	Flexibility index	Cum. salt%	AL soluble K_2O ppm	AL soluble P_2O_5 ppm
Aa	6.7-7.3	38-39	0,03-0,04	202-214	27-29
A_1	7,6-8,3	39-41	0,04-0,05		
B	7,8-8,4	37-39	0,03-0,04		
C_1	8,4-8,8	36-40	0,05-0,06		
C_2	8,6-8,9	33-36	0,06-0,07		

Table 1: Typical soil parameters of the sample plot

Sample points were selected by geostatistical evaluation, which was based on 1:10000 scale digital elevation TIN model and digital soil maps (Isaaks & Srivastava, 1989; Cressie, 1993). The time-series were calculated from nine different Landsat images that cover the sample plot and the full phenological period (Image source: FÖMI, 2005[28]). Vegetation indices are mainly derived from reflectance data from discrete red (R) and near-infrared (NIR) bands. They operate by contrasting intense chlorophyll pigment absorption in the R against the high reflectance of plant materials in the NIR. Such is the case of the normalized difference vegetation index NDVI=(NIR-R)/(NIR+R) (Rouse et al., 1973), which is the most widely used index, especially when analyzing data taken from satellite platforms. In our research NDVI was calculated from the Landsat images.

The CROPWAT irrigation planning and managing software was applied by using the climatic, soil characteristics and water management attributes and data of the field. FAO CROPWAT 5.7 version developed by Smith (1992) is a software to calculate crop water requirement and irrigation requirements from climatic, soil and crop data. The program allows the development of irrigation schedules for different management conditions and the calculation of water supply schemes for varying cropping patterns. The results of Hungarian CROPWAT model testing was published by Tamás & Nagy (1996), and more soil physical comparative model evaluation were made by Várallyay & Rajkai (1989). The program based on the following conceptual model (as illustrated by figure 1) (FAO series No. 56.)

With the help of the software and the utilisation of Penman-Monteith equation, reference crop evapotranspiration (ET_o) can be calculated. For the equation the following variables are required: minimum-maximum temperatrure, air humidity, windspeed and daily sunshine. The data used were collected from the weather station of Debrecen (Lat. 45°N, 21°E).

[28] FÖMI: Institute of Geodesy, Cartography and Remote Sensing

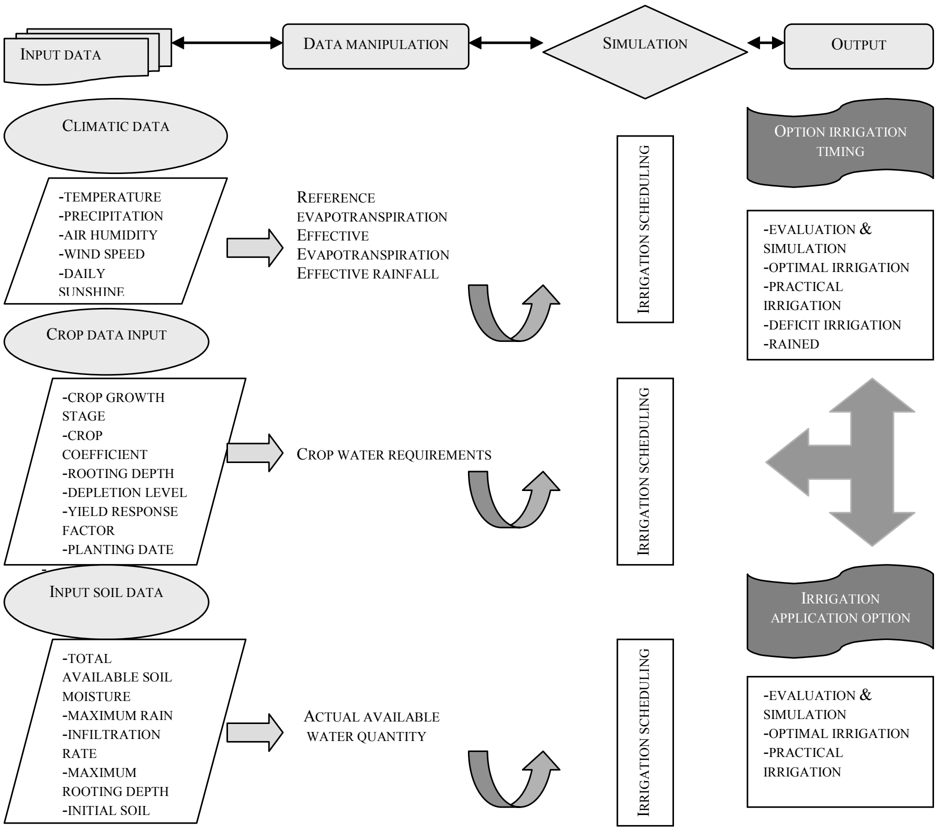

Figure 1: Dataflow model of CROPWAT

Actually, evapotranspiration of different crops depends on more complex plant physiological properties. Several authors published the results of studies on such properties (Petrasovits, 1988). Using the calculation of water balance regime this value can be determine indirectly with the following equation (FAO series No. 56.):

$$D_{r,\,i} = D_{r,\,i-1} - (P - RO)_i - I_i - CR_i + ET_{c,\,i} + DP_i$$

where

$D_{r,\,i}$ root zone depletion at the end of day i [mm],
$D_{r,\,i-1}$ water content in the root zone at the end of the previous day, i-1 [mm],
P_i precipitation on day i [mm],
RO_i runoff from the soil surface on day i [mm],
I_i net irrigation depth on day i that infiltrates the soil [mm],
CR_i capillary rise from the groundwater table on day i [mm],
$ET_{c,\,i}$ crop evapotranspiration on day i [mm],
DP_i water loss out of the root zone by deep percolation on day i [mm].

In the crop coefficient approach the crop evapotranspiration, ET_c, is calculated by multiplying the reference crop evapotranspiration, ET_o, by a crop coefficient, K_c:

$$ET_c = K_c * ET_o$$

where

ET_c crop evapotranspiration [mm d^{-1}],
K_c crop coefficient [dimensionless],
ET_o reference crop evapotranspiration [mm d^{-1}].

Crop coefficient is computed for the following crop growing stages:

- initial stage,
- crop development stage,
- mid-season,
- late season.

The value of the crop coefficient is between 0,3-1,2 depending on crop varieties, so its average estimation error can reach the 200-300 %. Since the value of the actual crop water requirement based on model sensitivity analyses depends on the actual value of K_c significantly, the error propagation influences the reliability of the whole model. One of the aims of our searches is the rise of the accuracy of this parameter using remote sensing data source.

Considering runoff direction, the amount of effective rain was calculated by D8 runoff algorithm (published by Moore et al. (1993)) from the digital elevation model. Statistical and image analyses were performed by different software packages. We carried out principal components analysis by SPSS 12., and we made spatial statistic evaluation by clustering by IDRISI Kilimanjaro and ENVI 4.2.

RESULTS

Crop coefficient which belongs to the crop growing stages was estimated by the Normalized Difference Vegetation Index (NDVI) from the Landsat TM time series images. Leaf Area Index (LAI) was also measured and it has a strong correlation with NDVI, as written by Burai & Tamás (2004), who measured LAI of sugar beets in Látókép and compared with the NDVI, which was computed from images taken from 3 m high. The images were taken by TETRACAM ADC digital multispectral camera, which has three channels (green: 520-600nm, red: 620-750nm, near infra: 750-950nm). A near field image is shown in figure 2. NDVI, computed from the reflectance values of near infra and red channels was used for the biomass monitoring. They measured the green, photosynthetically active leaf area (LAI_Z) by leaf area measurement. They computed close correlation between NDVI and LAI, then they performed the fitting of linear function (as illustrated in figure 3).

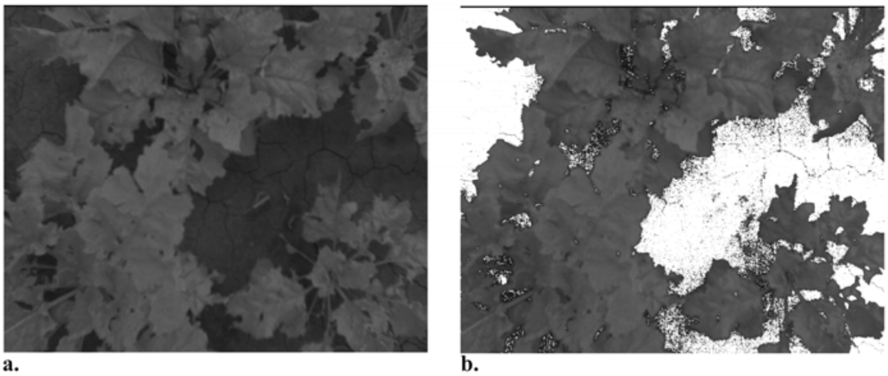

Figure 2: Near-field, multi-broad channel image of sugar beet; a., false-colour image (r: near-infrared, g: red, b: green channel); b., computed surface overlay (canopy = 74,8%)

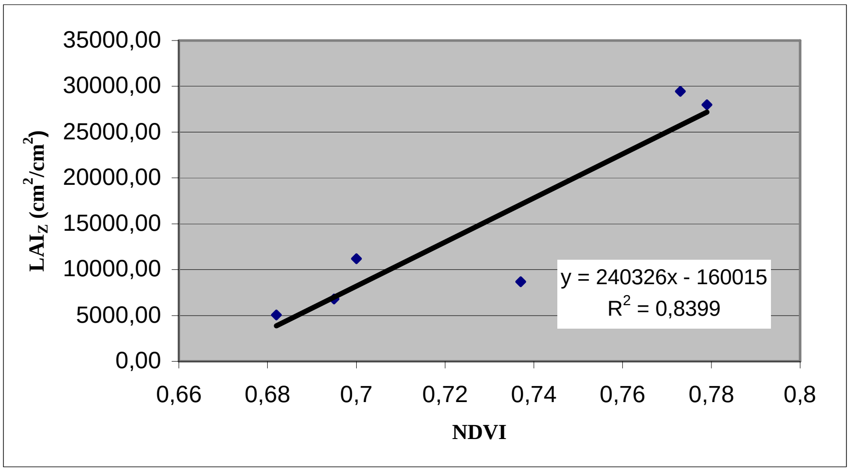

Figure 3: Regression between normalized difference vegetation index (NDVI) and leaf area index (LAI) in sugar beet searches

After preparing time-series from the Landsat images, principal components analysis was carried out from them by using the IDRISI GIS software. Computed mean and standard deviation values for the 9 different dates are summarized in table 2.

Date	04. 04.	22. 05.	16. 06.	23. 06.	18. 07.	25. 07.	03. 08.	10. 08.	04. 09.
Mean	0,0206	0,1354	0,5223	0,6223	0,6929	0,6768	0,6024	0,7181	0,6819
Standard deviation	0,053	0,063	0,065	0,065	0,064	0,073	0,074	0,063	0,058

Table 2: Results of the principal components analysis of the 19 ha experimental field according to 9 different dates

Principal components analysis showed the variances for the test area. As a next step, clustering was made from the first principal components image, and 5 parts of the plot that considered homogeneous were selected by this. As a result of clustering the area of the first site became 1,5 ha, the second site is 0,5 ha, the third is 1,8 ha, the fourth is 7,1 ha and the fifth is 8,1 ha. We created ROI (Region Of Interest), so the 5 ROI covered the 5 sites. The average NDVI values that are covered by these ROI were calculated from the 9 time steps. A single site has 9 average NDVI values. Regression equation was fitted for these average values, determining the parameters, and strength of the correlation.

We also illustrated the crop coefficient values, which are given for sugar beet in CROPWAT-model (as illustrated in figure 4).

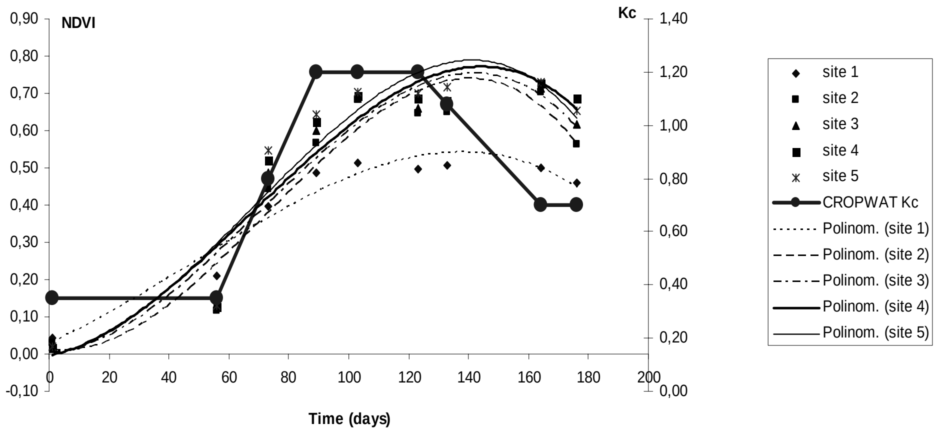

Figure 4 : Relationship between crop coefficient (K_c) and normalized difference vegetation index (NDVI) values and tertiary equations for the 5 selected sites

We could appreciate the NDVI values which were estimated between 2 measuring dates with the help of the regression equation. As mentioned earlier, NDVI is in strong correlation with LAI, and LAI is in strong correlation with K_c, so there is strong empirical correlation between these parameters. Daily values of the tertiary equation (as shown in table 3) had to be suited for the K_c values. Since K_c=1,2 is equal with the maximum of the tertiary equation, we have NDVI value enumerated to K_c value by proportional matching.

	Polynomial equation	r^2 value
Site 1	y = -2E-07x3 + 3E-05x2 + 0,0035x + 0,0342	0,9427
Site 2	y = -6E-07x3 + 0,0001x2 - 0,0012x + 0,0139	0,9142
Site 3	y = -5E-07x3 + 0,0001x2 + 0,0004x + 0,0028	0,9079
Site 4	y = -4E-07x3 + 9E-05x2 + 0,0017x - 0,0039	0,8997
Site 5	y = -4E-07x3 + 9E-05x2 + 0,0017x - 0,0042	0,8997

Table 3: Polynomial equation for the 5 selected sites

We had the reference crop evapotranspiration (ET_o) values for the whole area, which was measured by a weather station that collected the data of an A-type evaporation pan. To extend these data for the free water surface evaporation, we had to use a *c* constant factor. The average value of this factor is 0,76. Multiplying daily pan evaporation data by this *c* factor, we got the correct data. The modified ET_o values are illustrated by figure 5.

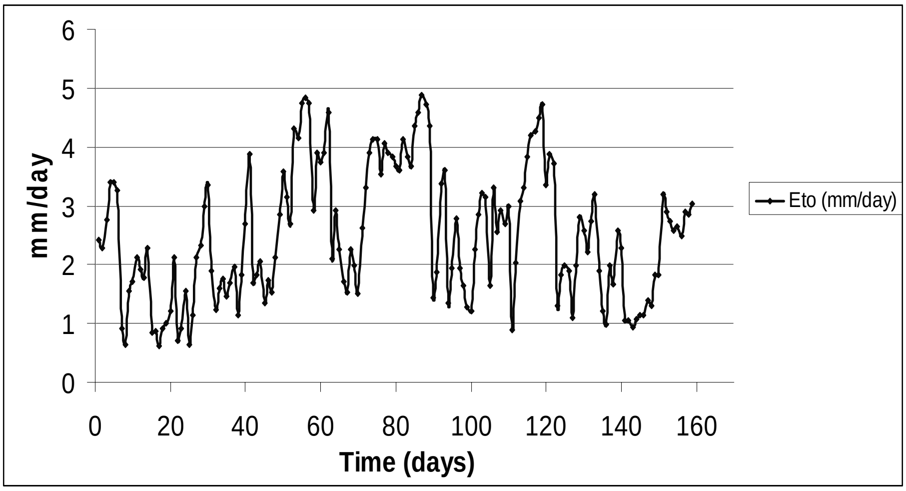

Figure 5: Reference crop evapotranspiration (ET_o) values, modified by *c* constant factor for the 19 ha experimental area

After getting the corrected values, we could calculate crop evapotranspiration (ET_c) for the 5 selected sites by multiplying the modified reference crop evapotranspiration, ET_o by the crop coefficient, K_c (illustrated by figure 6).

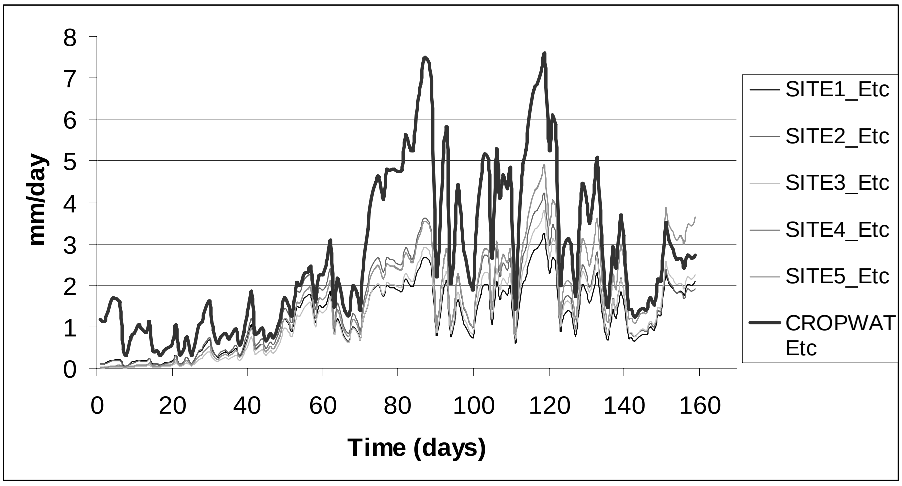

Figure 6 : Curves of calculated crop evapotranspiration (ET_c) for the 5 sites and estimated ET_c by CROPWAT

The model was fed with the actual water supply data using the soil-cartograms, and with the help of the field measurements considering rooting depth which is increasing in time. To calculate sugar beet crop water requirements was taken into account five homogenous plot size actual water regime based on rainfed water condition. The amount of total rain was modified by the value of the runoff and we calculated the maximum rain infiltration rate. Dry matter production and also the length of the individual growing stages were measured on site. The initial stage ended on the 25th day, the crop development stage was 35 day, mid-season and the late season was 50-50 day. Crops factors (K_c) and a field response factor to estimate yield reduction due to drought stress (K_y) were determined, and rooting depth measured. K_c and K_y factors have to be given for each growing stages.

We examined the difference between ET_o values estimated with the Penman-Monteith equation by CROPWAT model and calculated ET_o values based on the A-type pan evoporation measured on the weather station. We found that estimated ET_o values have exceeded calculated values with 7-12%. We also compared the difference of crop water requirement (CWR) values between the 5 sites and the CWR values estimated by CROPWAT, regarding to the daily soil moisture in the certain rooting depths. We determined that CROPWAT model is overestimates the CWR in the initial stage at about 100 % to the effectively calculated water requirement. In the crop development stage it correlates well. In the mid-season the estimated CWR values shows higher values again at about 30-50 %. In the late-season the overestimating of the CROPWAT model is lower, less than 10 %. The received values can be explained by the extreme climate in the definite periods, because the temperature was lower than the typical in the above-mentioned periods.

The aim of the project was to observe the effectiveness of irrigation and rain water. The results of this model provided practical aid for farmers on the efficient and sustainable management of natural resources in accordance with agro-environmental requirements and regulations so it can improve the effectiveness of irrigation and rain water and prepare new water management strategy in a precision farming condition.

CONCLUSION

The ET_o and the crop water requirement values estimated by CROPWAT model have exceeded the calculated values that based on measured data. Because of the gained results it is suggested to use the measured data in practice.

The model is suitable for not only the development of water management strategies based on natural moisture, but also for different irrigation variants, such as irrigation time period and technical optimization of water distribution.

As the result of the scheme we calculated the crop irrigation requirement, the net scheme irrigation requirements in mm day^{-1}, 1 s^{-1} ha and 1 s^{-1} (SQ), irrigated area as percentage of total scheme area (Ar), and irrigation requirement in 1 s^{-1} ha^{-1} for actually irrigated area (AQ). Crop water requirement was determined and it is suitable for optimization the irrigation requirement by this.

GIS-RS-WMM integration is suitable for the analysis of the effectiveness of environmental sound water management strategy, the development of irrigation schemes in Hungary as well and also to reduce costs and save water. With low inputs it is also suitable to test the water regime of different plant varieties and precision soil cultivation alternatives.

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