USING REMOTE SENSING DATA TO IMPROVE SIMULATION MODELING FOR PRECISION AGRICULTURE

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ABSTRACT

Simulation modeling is an indispensable tool in forward-looking decision support for precision farming. Inadequate parameterization and lack of controlling variables have limited the wide scale application of such models in decision support tools for precision farming to a large extent. In this study high resolution multi-temporal remote sensing images were used to derive spatially variable crop characteristics that can be used as input variables in deterministic crop growth simulation models. Such an input parameter is the crop coefficient (K_c), which expresses the ratio between crop evapotranspiration and reference evapotranspiration (obtained from weather stations). It can be calculated from weather data and remote sensing based values of LAI (Leaf area index), crop albedo and crop height. This procedure allows accurate estimation of spatial and temporal variation of K_c and can, therefore, give much better control of simulation models that use this characteristic as input variable. On the Van Bergeijk farm in the Southwest of the Netherlands in 1999 three remote sensing images, with bands in the green, red, and near infrared, were taken and used to derive maps of LAI, and crop height. These maps where used in combination with weather data to derive a map of the crop factor K_c. The simulation model WAVE was used to execute simulations with and without the spatial variable K_c-factors. Model responses such as actual transpiration and the flux from the root zone were compared with the standard methodology using a homogeneous K_c-factor for the entire field. Simulated actual crop transpiration varied between 59 and 330-mm yr^{-1}, compared to 270-mm yr^{-1} for homogeneous K_c-values. Simulated water flux from the root zone strongly related to leaching of nutrients varied between 273 and 624-mm yr^{-1} for spatial variable K_c-values; to 319 and 416 mm yr^{-1} for simulations with homogeneous K_c-values. This study demonstrates that remote sensing information can be used as model input variable to better and more accurately parameterize simulation models for decision support in precision farming.

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INTRODUCTION

When reviewing literature on precision farming (*e.g.* Robert *et al.*, 1993, 1995, 1997, 1999; Stafford 1997, 1999) two main types of decision support systems can be distinguished: (i) decision making tools based on sensors, measuring the actual status of properties such as electrical conductivity or soil nitrogen status *on-the-go* (*e.g* Suduth *et al.*, 1998; Broughton *et al.*, 1999; Colburn, 1998) translating this information in, for example, a fertilizer recommendation, (ii) decision support systems based on simulation modeling (Sadler and G. Russell, 1996; Booltink and Verhagen 1996, Van Alphen and Stoorvogel 2000). Using actual weather, management and soil information, crop responses, nitrogen demands and losses are calculated and transformed into a fertilizer recommendation. Both approaches have advantages and disadvantages. In case of decision support systems based on remote or proximal sensing, the predictive power is limited and forward-looking approaches are difficult and highly uncertain. Attractive, however, is the relative low effort in collecting the necessary data. Simulation models on the contrary, if well calibrated and validated, can fairly easily be used to make predictions and explore scenario studies. Disadvantage of especially complex simulation models is that parameterization and appropriate calibration of those models can only be done by experts. Studies trying to integrate both methods are rare, mostly focussing on the comparison of simulated model responses with yield maps or remote sensing images, which can be called *a-posteriori* integration. This study focuses on the integration of remote sensing information in simulation modeling, using remote sensing based crop characteristics as inputs in simulation models. By doing so remote sensing information is used to control the model and can therefor be considered as an *a-priori* integration.

On the Van Bergeijk farm in the south west of the Netherlands Van Alphen and Stoorvogel (2000) applied the WAVE-model (Vanclooster *et al.*, 1994) to simulate soil nitrogen status and crop responses with the aim to derive nitrogen fertilizer recommendations. Parameterization of this model in terms of soil physical and chemical characteristics was carried out with great care, including soil spatial variability (Van Alphen and Stoorvogel 2000; Van Alphen and Booltink 2000). However, spatial variable crop characteristics were not considered.

Studies of Diels (1994) and Vanclooster (1995) showed that the factor expressing the ratio between crop evapotranspiration and the reference evapotranspiration, the so-called K_c-factor, was one of the most critical parameters in terms of sensitivity. Accurate determination of this K_c-factor is, therefore, necessary to obtain reliable modeling results.

D'Urso and Menenti (1995) and D'Urso and Santini (1996) developed a method in which they derive the K_c factor by combining, meteorological data and crop characteristics obtained from remotely sensed data. The theoretical framework for the application within precision farming was described by Booltink *et al.* (1999) and Booltink (2000). This method allows the determination of spatially variable K_c factors and thus the inclusion of spatial variable crop characteristics as *a-priori* inputs in simulation models.

The objective of this study is to apply this method within the framework of a decision support system for precision agriculture with the aim to integrate sensing-based tools with model-based tools.

STUDY AREA

The van Bergeijk farm, located in the Southwest of the Netherlands, is a commercial farm of approximately one hundred hectares. Winter wheat, consumption potatoes and sugar beets dominate the intensive 4-year crop rotation. The soils consist of marine deposits, which are generally calcareous and have textures ranging from sandy loam to heavy clay-loam. Peat residues are incidentally found resulting in relatively high organic matter contents. With the excellent drainage system, controlled by a dense system of tile drains, these soils are considered to be prime agricultural land. (Booltink *et al.*, 1999).

A detailed soil survey was conducted at the Van Bergeijk farm in the spring of 1997. Approximately 600 augurings were done, 300 sampling points were located according to a regular grid and the other 300 on places where highest variability was expected, based on information obtained from aerial photography. Most soil properties, needed as input for a simulation modeling, were determined directly. Others could be derived indirectly using pedotransfer functions (Wösten *et al.*, 1998; Wösten and Van Genuchten, 1988). Soil layers were classified into a total of 16 taxonomic classes defined by the Dutch 'Staring series'. This classification distinguishes between topsoil and subsoil layers, which are further, differentiated towards texture and SOM-content. Each taxonomic class was sampled in the field to determine average soil physical characteristics using the crust infiltrometer (Booltink *et al.*, 1991) and multi-step outflow methods (Van Dam *et al.*, 1990). Van Alphen and Booltink (2000) showed that hydraulic characteristics derived through a combination of pedotransfer estimates and simple on-site physical measurements (*i.e.* saturated moisture content and bulk density) gave best results when simulating soil moisture regimes in the study area.

For this study a 15 ha field, 81 augurings with soil physical and chemical characteristics were taken. Interpolated maps in this study were based on these 81 points. To verify remote sensing information, detailed crop observations were made during the three flights on 8 plots within the study field.

REMOTE SENSING

Remote sensing images of the van Bergeijk farm were taken on May 27, June 25, and July 31 1999. The latter was not used in this study since the crop had reached full maturity at that time and was ready for harvest. Images were made with a Kodak DCS240 monochrome matrix-CCD camera mounted on a CESSNA. Different filters were applied during the flight, resulting in one image for each of the green (550 nm), red (650 nm) and near infrared (850 nm) spectral bands. A spatial resolution of 0.50 m was reached on the ground. Due to positing problems during the first flight the first image did not cover the complete field.

An image taken on 1 April 1997 with the Dutch multi-spectral airborne imaging scanner CAESAR (Charge-Coupled Device Airborne Experimental Scanner for Applications in Remote Sensing) was used to quantify bare soil reflections. Reflectance of the CAESAR scanner was measured at 550±15 nm, 670±15 nm and 870±25 nm over the whole farm at a spatial resolution of 75 cm.

Radiometric corrections, necessary to convert digital numbers into reflection percentages, were carried out by the National Aerospace Laboratory (NLR) using a series of reflection panels and a limited set of crop reflections on the 8 control plots in the field, measured with a 8 channel CROPSCAN. Geometrical corrections were carried out using a data set of ground control points measured with a high accuracy differential GPS.

DERIVATION OF CROP CHARACTERISTICS

The crop coefficient K_c

One attractive option of linking remote sensing data with simulation models is that remote sensing data can be used to derive model input parameters. Remote sensing in this mode can easily take into account spatial variable crop responses. The crop coefficient (K_c) expresses the ratio between crop evapotranspiration (Et_c) and the reference evapotranspiration (ET_0) as obtained from climatic data (Monteith and Unsworth, 1990) (Equation 1). D'Urso and Menenti (1995) and D'Urso and Santini (1996) developed a method in which they derived the K_c factor by combining, meteorological data with crop characteristics obtained from remotely sensed data. This method is be briefly described below and is fully described in Booltink *et al.* (1999) and Booltink (2000).

Equation 1 $$K_c = \frac{ET_c(r_c = r_{c,\min})}{ET_0}$$

Where the canopy resistance r_c for the considered crop is set to the corresponding minimum value ($R_{c,min}$) as calculated in Equation 2

Equation 2 $$r_{c,\min} = \frac{R_l}{0.5LAI}, \qquad 0 < \mathrm{LAI} \leq 5$$
$$r_{c,min} = 40, \qquad \mathrm{LAI} > 5$$

Where R_l is the average daily stomatal resistance of a single leaf. For most crops under non- stressed conditions R_l is set equal to 100-s m^{-1}.

The K_c-factor can then be calculated using Equation 3:

Equation 3

$$K_c = \frac{1}{\lambda}\frac{\Delta(R_{ns} - R_{nl} - G) + 1.013\rho 86.4 D_E / r_a}{\Delta + \gamma(1 + r_{c,\min}/r_a)} \frac{\Delta + \gamma(1 + 0.34U)}{0.408\Delta(0.77S_t - R_{nl} - G) + \gamma\frac{900}{T+273}UD_E}$$

R_{ns} represents the net incoming short wave radiation that can be derived using Equation 4 (Smith, 1990) using the albedo α and the total incoming radiation S_t (MJ m^{-2} d^{-1})

Equation 4 $$R_{ns} = (1-\alpha)S_t$$

r_a can be calculated with Equation 5:

Equation 5
$$r_a = \frac{\ln\left(\frac{z_U - \frac{2}{3}h}{0.123h}\right)\ln\left(\frac{z_T - \frac{2}{3}h}{0.0123h}\right)}{0.168U}$$

with z_U, z_T for the measurement heights (m) for wind and temperature respectively (Monteith and Unsworth, 1990), h for the crop height (m), and U (m s^{-1}) the wind speed at 2 m.

The other basic weather data needed for the application of Equation 3 are the air temperature, T (°C) and the relative humidity, RH (%).

From Equation 3 it results that for a given set of climatic parameters $[S_t, T, RH_{\%}, U]$, the value of K_c depends only on the canopy characteristics α, LAI and h. Therefore, K_c can be written as (D'Urso and Menenti, 1995; D'Urso and Santini, 1996):

Equation 6
$$K_c = f(S_t, T, RH\%, U; \alpha, LAI, h)$$

Spatial variability of S_t, T, $RH_{\%}$, U on field scale is generally considered to be small, crop albedo values for a crop in vegetative stadium vary between 0.23 - 0.25 (Monteith and Unsworth, 1990), therefore spatial variability of K_c depends on the variability of LAI and crop height h only.

Weighted Difference Vegetation Index (WDVI)

The Weighted Difference Vegetation Index is defined as follows:

Equation 7
$$WDVI = NIR - \frac{NIR_s}{R_s} \cdot R$$

Where NIR and R are the reflectances in the near infrared and red, respectively. The subscript s indicates reflectances of the bare soil.

As no bare soil image was available for the study area, the $NIRs/Rs$ ratio was derived from a neighboring field with similar soil characteristics whose soil reflectance was measured in 1997 with CAESAR. The average $NIRs/Rs$ ratio of the adjacent field (1.298) was used to estimate WDVI on the experimental field at both dates. The value 0 was attributed to WDVI when NIR/R was lower than $NIRs/Rs$. Although an error is made here, the effect of that will negligible as long as crop cover is close to 100% since red reflectance of a crop at full coverage is close to zero (see Equation 7). This assumption is valid for approximately 90 % of the field.

Leaf Area Index (LAI)

Leaf area index was derived from WDVI according to the semi-empirical method of Clevers (1988, 1989):

Equation 8
$$LAI = -\frac{1}{\eta} \cdot \ln\left(1 - \frac{WDVI}{WDVI_\infty}\right)$$

This relation is valid for one cropping season. As leaf area measurements were made at the same locations at both survey dates, these observations may present some dependence. Therefore, use was made of a mixed effects-model for non-linear regression (S-Plus, 1999) to estimate the 2 parameters: $\eta = 0.181$ and $WDVI_{\infty} = 83.7$.

If no ground control information is available Uenk *et al.* (1992) have derived some general relations between the WDVI, LAI, and the crop cover percentages. These general relations can be used instead of Equation 8.

Crop height

One of the variables necessary to calculate the K_c-factor is crop height. Crop height was measured during the remote sensing flights on several places within the experimental field. The correlation of crop height with the WDVI was statistically explored to obtain a spatial variable map of crop height.

SIMULATION MODELING

Dynamic simulations of soil-water-plant interaction were conducted with the mechanistic-deterministic simulation model 'WAVE' (Water and Agrochemicals in soil and Vadose Environment) (Vanclooster *et al.*, 1994). WAVE integrates four existing models describing:

1. One-dimensional soil water flow: SWATRER (Dierckx *et al.*, 1986),
2. Heat and solute transport: LEACHN (Hutson and Wagenet, 1992),
3. Nitrogen cycling: SOILN (Bergström *et al.*, 1991) and,
4. Crop growth: SUCROS (Spitters *et al.*, 1988).

Differential equations governing water movement (Richards' equation) and solute transport (convection-dispersion equation) are solved with a finite difference calculation scheme. For this purpose soil profiles were divided into one-centimeter compartments.

Water stress is calculated according to Feddes *et al.* (1978). Maximum uptake rates are defined by a sink term, which is considered constant with depth. Water uptake is reduced at high and low-pressure head values, according to crop-specific thresholds. Van Alphen and Stoorvogel (2000) presented a detailed description of modeling procedures. Van Alphen and Booltink (2000) described validation

Sensitivity analyses of Vanclooster (1995) and Diels (1994) on the WAVE model showed that the K_c -factor was one of the most sensitive parameters in determining the water balance, especially actual crop transpiration. In this study we, therefore, focus primarily on model predictions of actual crop transpiration and leaching of water below the crop root zone. Simulations for all 81 soil profiles within the field were carried out with the standard K_c -factor s, homogeneous over the field (Feddes *et al.,* 1978) and with "*site-specific*" K_c –factors.

When the Penman equation is used to calculate potential evapotranspiration with grass as a reference surface, the K_c-factors of Doorenbos and Pruitt (1977) can be used to estimate the crop evapotranspiration. In the approach of Doorenbos and Pruitt, the growing season is subdivided into 4 stages: the initial, the crop development, the mid-season and the late season. For bare soil

Table 1. Summary of the reflectances of the experimental field for the 3 bands on the flights of May 27 and June 25.

Date	Spectral band	Minimum	Maximum	Mean	Standard deviation
27-05-99	Green	0.39	55.30	5.75	3.31
	Red	0.99	38.55	5.99	3.86
	Near infra-red	0.12	82.09	48.57	8.21
25-06-99	Green	1.14	52.66	7.36	2.35
	Red	0.42	35.48	5.93	3.46
	Near infra-red	1.90	80.63	54.27	7.22

conditions, or if the crop ground cover is less than 10 %, evapotranspiration is mainly controlled by the moisture content in the top soil. The soil evaporation decreases as the soil dries. This effect is accounted for in the approach of Doorenbos and Pruitt by assuming a small value for K_c. Since the reduction of the evaporation is accounted for when solving the water flow equation, a K_c-factor of 1 is used during the crop initial stages (from germination until the ground cover is equal to 10%). During mid-season (from effective full ground cover until start of maturing) and at maturity K_c-values of 1.2 were used to calculate the potential crop evapotranspiration, if grass is the reference surface. The value of the K_c-factor for the crop development phase (end of initial stage until attainment of effective full ground cover) is obtained by linear interpolation between the K_c-factor of the initial stage (which is mostly equal to 1.0) and the K_c-factor of the crop mid-season stage. The K_c-factor of the late-season stage (end of mid-season, until attainment of crop maturity) is obtained by linear interpolation between the mid-season and maturity K_c-value.

DISCUSSION AND RESULTS

Remote sensing and crop characteristics

In Table 1 crop reflections of the 2 flights are summarized. High green and red reflectances correspond with areas of bad crop development whereas as high near infrared values correspond with a well-developed crop. When comparing the mean and standard deviation of the reflectances in the various bands with the maximum and minimum values it can be concluded that the above mentioned extremes where exceptional and the crop was generally well developed.

In Figure 1, WDVI values for the flight of June 25 are presented. Dark grey-tones correspond with parts of the field with a badly developed crop, resulting in low WDVI values. Light grey-tones indicate a well-developed crop. Table 2 presents the summary statistics of the remote sensing derived crop characteristics.

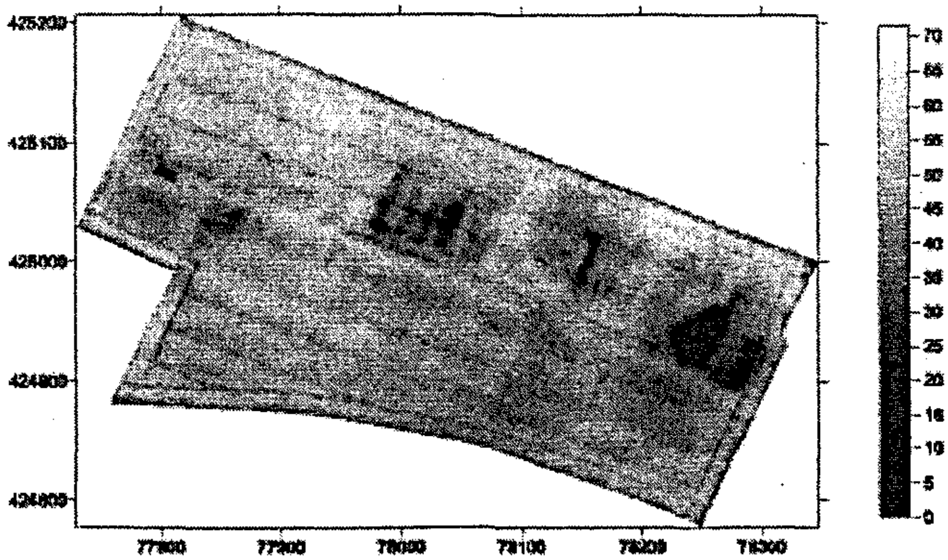

Figure 1. WDVI map for June 25 1999 of the experimental farm at the Van Bergeijk farm

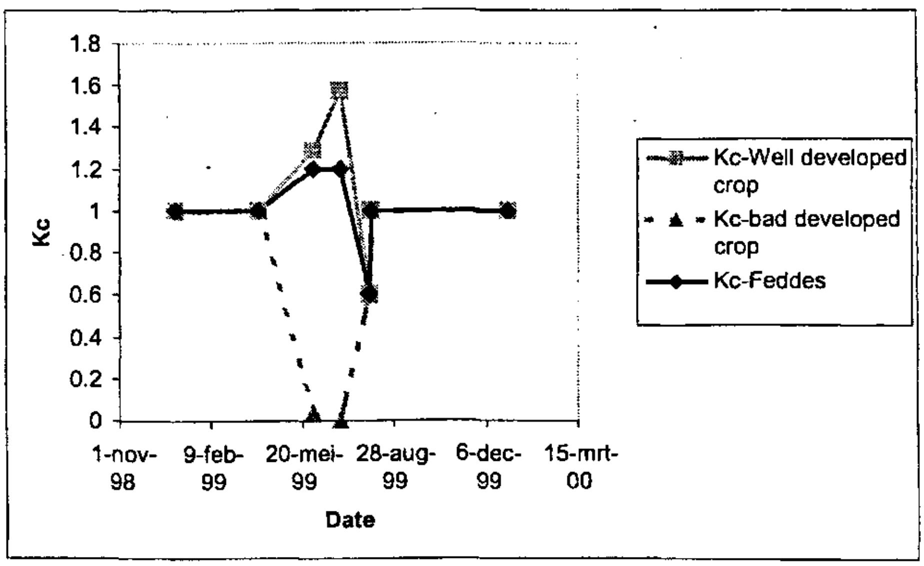

Figure 2. Some typical examples of the *"site-specific"* K_c-values compared to the standard Feddes curve.

The relation between crop height and field characteristics (organic matter and clay content of the topsoil, absolute and relative elevation of the field) was explored at each date with a linear regression using the 8 field measurement locations. No strong correlation was found. However, linear regression with WDVI as explanatory variable gave on May 27 a R^2 of 0.728 (p=0.007), and on June 25 a R^2 of 0.776 (p=0.004). Consequently, the following relations were used:

Equation 9 $$height_1 = (0.701 \cdot WDVI_1 + 17.348)/100$$

Equation 10 $$height_2 = (0.483 \cdot WDVI_2 + 56.620)/100$$

Where $height_1$ and $height_2$ are expressed in m and subscripts *1* and *2* represent the images taken on May 27 and June 25 respectively.

The K_c –values are presented in Table 3 the range of the "*site-specific*" K_c –factors are presented. Since only two of the three remote sensing images fell within the growing season of winter wheat, the standard set of Feddes was scaled with K_c–values obtained at these two dates.

Table 2. Summary statistics of images of crop characteristics

Date	Characteristic	Minimum	Maximum	Mean	Standard deviation
27-05-99	WDVI	0.010	75.629	41.100	10.892
	LAI	0.001	12.931	3.911	1.423
	Crop height	0.174	0.704	0.462	0.076
	Kc	0.000	1.665	0.601	0.634
25-06-99	WDVI	0.000	71.215	47.069	8.611
	LAI	0.000	10.515	4.702	1.212
	Crop height	0.566	0.910	0.794	0.042
	Kc	0.000	1.627	0.811	0.744

Table 3. Overview of the K_c-factors used in this study. The homogeneous set of K_c-factors was obtained from Feddes *et al.* (1978).

Date	Homogeneous	Site-specific			
		Average	Standard deviation	Minimum	Maximum
01-01-99	1.00	1.00	-	-	-
01-04-99	1.00	1.00	-	-	-
01-06-99	1.20	1.10	0.43	0.00	1.46
30-06-99	1.20	1.46	0.21	0.01	1.60
01-08-99	0.60	0.60	-	-	-
02-08-99	1.00	1.00	-	-	-
31-12-99	1.00	1.00	-	-	-

In Figure 2 a few typical examples of these *"site-specific"* K_c-factors are compared with the standard Feddes curve. For the parts at the field were winter wheat is developed well, the K_e-value at June 25 shows a strong deviation with the standard, Feddes-curve. The effect of low crop development is indicated with the set showing K_c-values close to zero. This point is located in one of the dark areas in Figure 1where crop development was bad due to long periods of water ponding in the winter season.

Comparison of spatial variable and homogeneous K_c-factors

In Figure 3a kriged map of the simulated actual crop transpiration on the 81 sampling points is presented. Actual crop transpiration varies from 59 mm yr^{-1} on places with bad crop development to 330 mm yr^{-1} on parts of the field where winter wheat was growing well (Figure 1). Soil properties have little effect on simulated transpiration since simulation of the 81 points using the standard Feddes-set of K_c-factors produced identical values (270 mm yr^{-1}) for 1999 for all sites. Compared to this single value of 270-mm yr^{-1}, the site-specific approach adds significant spatial information.

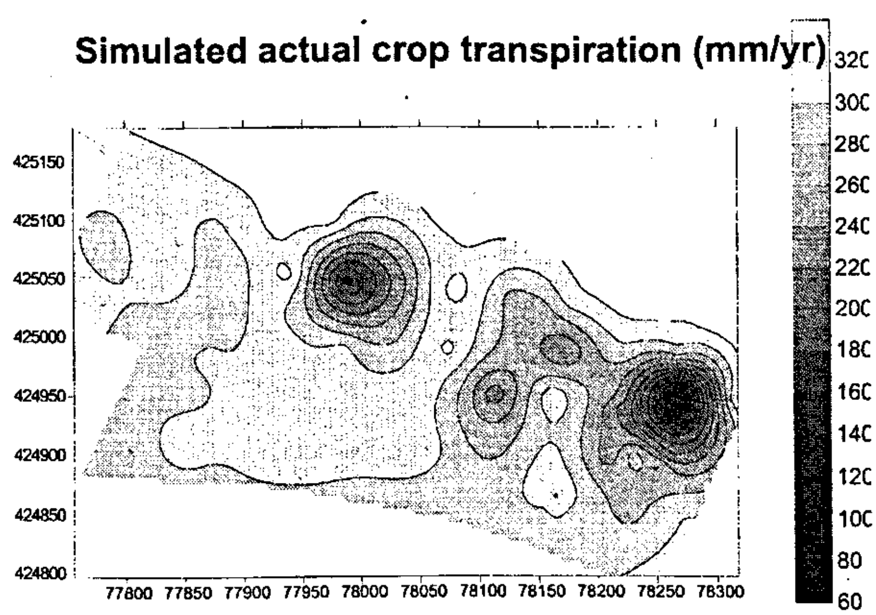

Figure 3. Interpolated map (kriging) of simulated actual crop transpiration using *"site-specific"* K_c-values.

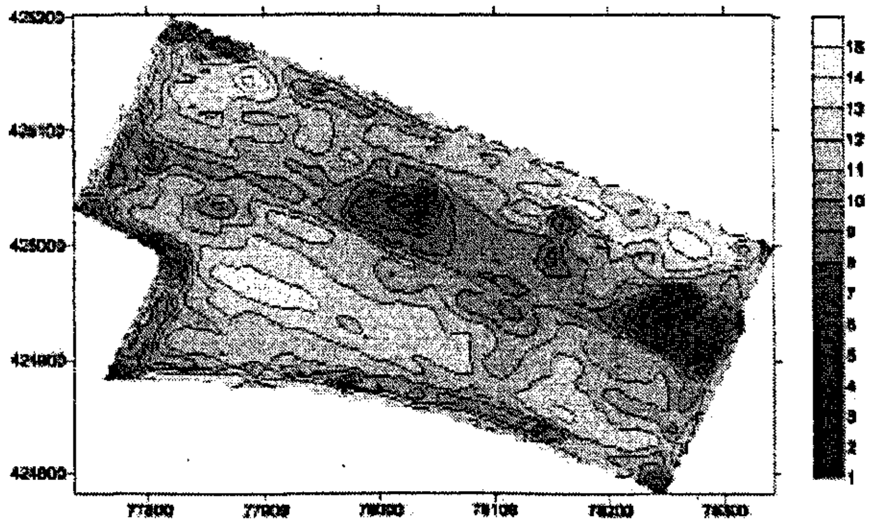

Figure 4. Winter wheat yield map of the experimental field at Van Bergeijk farm for 1999.

In Figure 4 a yield map for the field at the van Bergeijk farm is presented. Patterns within the yield map can easily be recognized in the interpolated transpiration map (Figure 3) indicating that crop transpiration and crop yield are closely related. The spatial variable actual transpiration will also have an effect on simulated water fluxes below the root zone.

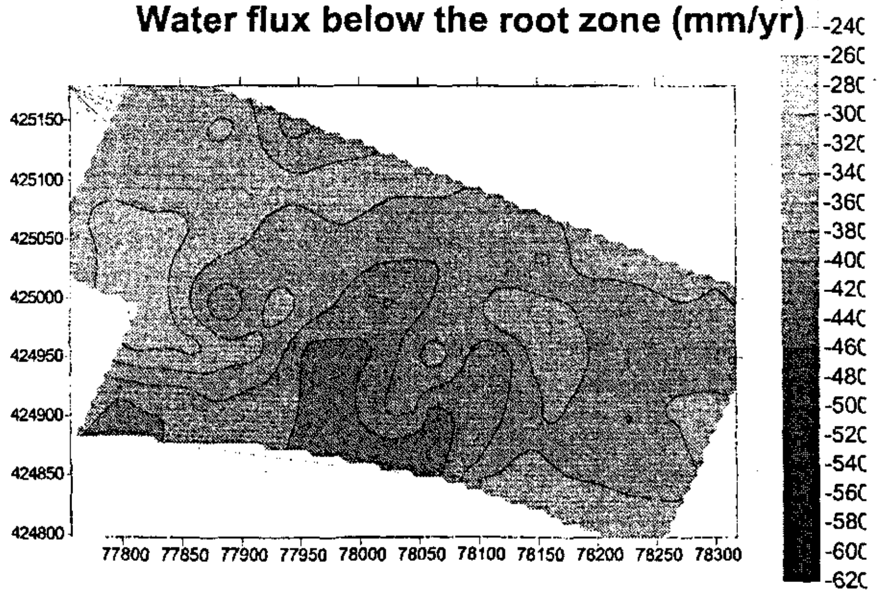

Figure 5. Interpolated map (kriging) of the simulated water flux below the root zone using the homogeneous (Feddes) K_c-values for 1999. A negative flux indicates a downward movement.

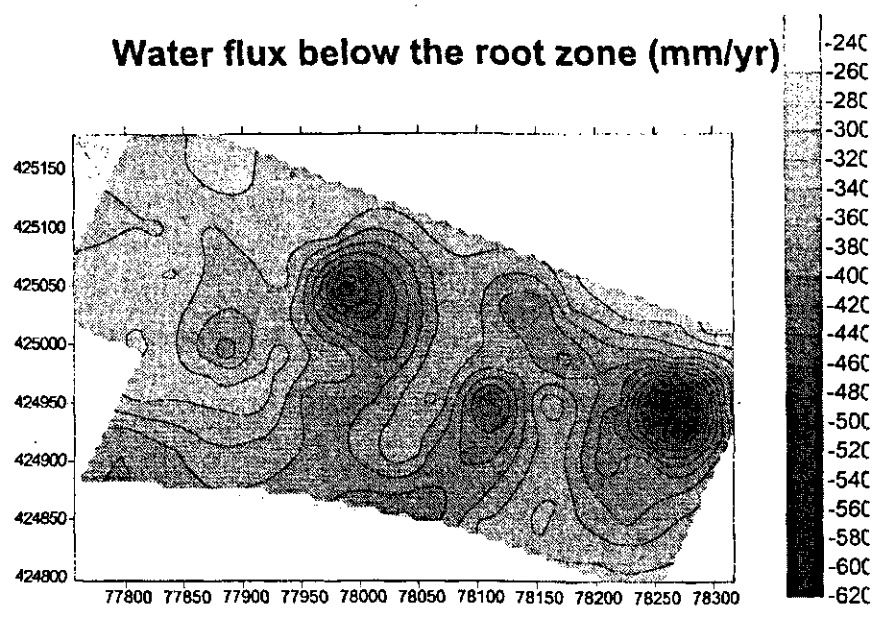

Figure 6. Interpolated map (kriging) of the simulated water flux below the root zone using *"site-specific"* K_c-values for 1999. A negative flux indicates a downward movement.

In Figure 5 a kriged map of the simulated net-flux below the root zone simulated with the standard Feddes K_c –factors is presented. Spatial variability here is caused by spatial variable soil physical characteristics such as retentivity and conductivity curve. The net fluxes in Figure 5vary between 319 and 416-mm yr^{-1}. Using spatial variable K_c –factors in combination with spatial variable soil physical characteristics, to calculate the net flux from the root zone, increased the variability significantly; net fluxes varied between 273 and 624 mm yr^{-1} as can be seen in Figure 6. For making risk assessments in terms of leaching potential of *e.g.* nitrogen or pesticides these differences can be considered as relevant. For example to not exceed the 50 g m^{-3} nitrate-N level in the ground water a net flux of 624 mm yr^{-1} allows a nitrate load of approximately 70 kg N ha^{-1} where as a net flux of 273 mm yr^{-1} only allows a nitrate load of approximately 30 kg N ha^{-1}.

CONCLUSIONS

This study shows that relative simple remote sensing techniques such as a digital camera equipped with different optical filters operated from a CESSNA plane can already provide adequate remote sensing information to be used within decision support systems for precision farming. Such a low budget system is necessary to make application economical feasible. This technical low-level approach also allows high flexibility with respect to timing of the flight and preparation time and costs.

With respect to the objective of this study the following conclusions can be made:

- The proposed *a-priori* integration of remote sensing information in simulation modeling had a clear synergetic effect. Spatial patterns of crop transpiration were more realistically compared to model scenarios that used homogeneous K_c – factors. The synergy between the sensing-based and model-based approach is therefor evident.
- The reliability of simulation models in decision support systems for precision farming is better accounted for, due to more reliable and spatially better defined K_c– values. Thus allow more accurate prediction of leaching of agro-chemicals and nutrient supply to the crop.

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