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Data assimilation of in situ soil moisture measurements in hydrological models

- Third annual doctoral progress report, work plan and achievements -

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List of abbreviations

θ_s	saturated water content
θ_r	residual water content
Ce	Nash–Sutcliffe coefficient of model efficiency
CTRS	central total sensitivity analysis
CV	coefficient of variation
DOE	depths of explorations
ECa	apparent soil electrical conductivity
ECw	soil water (fully saturated soil or soil solution)
EMI	electromagnetic induction
ET	evapotranspiration
ETo	reference evapotranspiration
FF	formation factor
GWL	ground water level
K(h)	unsaturated hydraulic conductivity
Ks	saturated hydraulic conductivity
MVG	van Genuchten-Mualem
OC	organic carbon
PTF	pedotransfer functions
R^2	coefficient of determination R –square
RMSE	root-mean-square deviation
Se	degree of saturation
SA	sensitivity analysis
θ(h)	soil water retention curve
ρ_b	bulk density

Management summary

Efficient water utilization and optimal water supply/distribution to increase food and fodder productivity are of utmost importance in confronting worldwide water scarcity, climate change, growing populations and increasing water demands. In this respect, irrigation efficiency, which is influenced by the type of irrigation and irrigation scheduling, is an essential issue for achieving higher productivity. To improve irrigation strategies in precision agriculture, soil water status can be more accurately described using a combination of advanced monitoring and modeling. Our study focuses on the combination of high resolution hydrological data with hydrological models that predict water flow and solute (pollutants and salts) transport and water redistribution in agricultural soils under irrigation. Field plots of a potato farmer in a sandy region in Belgium were instrumented to continuously monitor soil moisture and water potential before, during and after irrigation in dry summer periods. The aim is to optimize the irrigation process by combining online sensor field data with process based models. This research is part of Activity 305 'Precision agriculture and remote sensing' of the VITO GWO.

Over the past 3 years, we applied a combination of in-situ monitoring and numerical modeling -Hydrus 1D- to estimate water content fluctuations in a heterogeneous sandy grassland soil under irrigation with water table fluctuating between 80 and 155 cm. Over the last year, more sampling and analyses were carried out to further characterize the hydraulic properties over the entire field. Modeling results for the field demonstrated clearly the profound effect of the position of the GWL, and to a lesser extent, the effect of spatially variable soil hydraulic properties (*Ks*, *n* and α) on the estimated water content in the sandy two-layered soil under grass. Our results show that currently applied uniform water distribution using sprinkler irrigation seems not to be efficient since at locations with shallow groundwater, the amount of water applied will be excessive as compared to the plant requirements while in locations with a deeper GWL, requirements will not be met.

To derive the optimal parameter set best describing the measured soil moisture content, 37 optimization scenarios were conducted with two to six parameters using various parameter combinations for the two soil layers. The best performing parameter optimization scenario was a 2-parameter scenario with *Ks* optimized for each layer. The results showed a better identifiability of the parameters (less correlations among parameters) with equal performance as compared to three, four or six parameter optimization. Model predictions using the calibrated model (with data from 2012) for an independent data set of soil moisture data in the validation period (2013) showed satisfactory performance of the model in view of irrigation management purposes. Comparing the degree of water stress for different optimization scenarios of groundwater depth, showed that grass was exposed to water stress in summer in 2013 but not for such a long period as compared to the 2012 growing season. The degree of water stress simulated with Hydrus 1D suggested to increase the irrigation amount in 2012 and 2013 and at least one or two times in the summer (June and July) and further distributing the amount of irrigation during the growing season, instead of using a huge amount of irrigation later in the season, as is common practice by the farmer.

A second part of the study focused on finding a relation between measured soil hydraulic properties and apparent electrical conductivity ECa. Our measurements of hydraulic properties of the field clearly confirm that there is considerable spatial variability in the field and that this has an impact on the simulation of soil moisture content. Therefore this should be taken into account when upscaling soil hydraulic properties to the field scale in order to in understand and model flow, solute and energy fluxes in the field and develop strategies for efficient irrigation. Upscaling soil hydraulic properties to the field scale can be done by linking them to apparent electrical conductivity (ECa), which can be measured efficiently and inexpensively so a spatially dense dataset for describing within-field spatial soil variability can be generated. In this study relations between the spatial variation of soil hydraulic properties and apparent soil electrical conductivity ECa measured with DUALEM-21S sensors at two depths of explorations (DOE) 0-50 and 0-100 cm were investigated. A predictive modelling approach, i.e. a simple regression was developed and it was compared how it was able to explain the observed values of hydraulic parameters.

Results demonstrated the spatial variability and heterogeneity of ECa and soil hydraulic conductivity K_s. We derived a regression relationship ($r^2 \geq 0.70$) between *log Ks* and ECa measured with the DUALEM sensor. The predicted results were tested vs measured data and confirmed that the performance of the $DUALEM_{p,100}$-*Ks* model is relatively better than direct interpolation (RMSE = 0.74 cmh^{-1}, R^2 = 0.67). This site-specific relation between ln *Ks* and ECa was used to predict saturated hydraulic conductivity over 0-50 cm depth for the whole field. The relationship was then used to produce a detailed map of saturated hydraulic conductivity, *Ks* for the whole field allowing to predict spatially distributed water content with a soil hydrological model for precision irrigation applications.

In the third year, quasi 3D-modelling of water flow at the field scale was set-up and the hydrological model was combined with the crop based model LINGRA-N. This combination gives a direct simulation of the impact of irrigation strategies on crop yield at the field scale. In this modeling set-up, the field is modeled as a collection of 1D-columns representing the different field conditions (combination of soil properties, GWL, root zone depth). Also a second study site has been set up in a nearby field where potatoes are grown. It has been instrumented with soil moisture sensors, tensiometers, groundwater level loggers at two spots (low and high land) and a weather station in spring (11 Apr 2014). In the harvest time (22-24 Sep 2014) one profile was dug out at each sensor location and field hydraulic conductivity was measured using tension disc infiltrometer experiments at 4 depths in 2 replications. At the same depth 3 samples were taken to measure lab hydraulic conductivity (constant head) and soil water retention data. Soil hydraulic properties were also estimated inversely from the infiltration data using the DISC software package. The two methods were compared and results showed that the inverse estimation using field tension disc infiltrometer data is very useful and allows fast parametrization of hydraulic properties of the potato farm. The dataset will be applied in hydrological model to optimize irrigation management.
In the fourth year, the quasi 3D-modelling of water flow will be finalized. A third study site has been equipped with groundwater level loggers in combination with soil solution extractors at three depths (25, 50 and 75 cm) and at four spots (low to high land) to evaluate nitrate leaching using the calibrated model.

Keywords: soil, Hydrus, modeling, water flow and solute transport, tensiometers, water content profile probes, sensitivity analysis, Ks, ECa, upscaling, model calibration, validation and optimization

Chapter 1 Introduction

1.1 Scientific background

Efficient water use and optimal water supply to increase food and fodder productivity are of great importance when confronted with worldwide water scarcity, climate change, growing populations and increasing water demands (FAO, 2011). In this respect, irrigation efficiency which is influenced by the type of irrigation and irrigation scheduling is essential for achieving higher water productivity. In particular, precision irrigation is adopting new methods of accurate irrigation scheduling (Jones, 2004). Various irrigation scheduling approaches such as soil-based, weather-based, crop-based, and canopy temperature-based methods have been presented (Jones, 2004; Evett *et al.*, 2008; Pardossi *et al.*, 2009; Mohanty *et al.*, 2013).

Numerical models are increasingly adopted in water resources planning and management. They contain numerical solutions of the Richards equation (Richards, 1931) for water flow and root water uptake (Vrugt *et al.*, 2001; Skaggs *et al.*, 2006). Hydrological models require determination of hydraulic properties, upper boundary conditions related to atmospheric forcing (evapotranspiration and precipitation) and groundwater dynamics at the lower boundary of the soil profile. The numerical model Hydrus-1D (Šimůnek *et al.*, 2013) has been used in a wide range of irrigation management applications. The tool has been combined with crop-based models to calculate degree of soil-water stress for irrigation management and for predicting the crop productivity by coupling Hydrus-1D with a crop-growth model (WOFOST) for maize (Li *et al.*, 2012) and wheat (Zhou *et al.*, 2012).

Model calibration is a common way to identify the parameters of a hydrological model. Sensitivity analysis has been used to better estimate values, to better understand and reduce uncertainty (Rocha *et al.*, 2006), and to investigate the effects of various parameters or processes on water flow and transport (van Genuchten *et al.*, 2012). To reduce the number of parameters that need to be optimized, local sensitivity analyses are often performed that evaluate model output for each parameter perturbation using a one-at-a-time approach.

Due to the highly parameterized framework of numerical hydrological models, direct measurement of its parameters may be inaccurate, insufficient or inefficient for predictions at the field scale (Verbist *et al.*, 2012). As an alternative, parameters can be determined by inverse modeling. A single-objective inverse parameter estimation using the Levenberg–Marquardt optimization procedures has been used in different studies (Abbasi *et al.*, 2004; Jacques *et al.*, 2012; Šimůnek et al., 2013). Soil scientists are often confronted with non-uniqueness in the optimization process, leading to parameter identifiability problems (Hopmans *et al.*, 2002). Non-uniqueness can be reduced by decreasing the number of parameters to be estimated based on a sensitivity analysis.

Agricultural management requires detailed data at relevant management scales such as the field or the landscape scale. Digital soil property mapping methods and characterizing hydraulic properties at the field scale (Brosten et al., 2011; Chaplot et al., 2011; Sudduth et al., 2013) are increasingly being used. Such obtained data in combination with hydraulic properties measured at multiple locations in the field are vital to predict and understand flow, solute and energy fluxes in soil (Vereecken et al., 2007) and needed in various applications.

An example is precision irrigation, where accurate information about the spatial variation of field-scale soil hydraulic properties is required (Carroll and Oliver, 2005; Slater, 2007). Direct measurements of these properties (in the field or laboratory) are not only time-consuming, labor-intensive and expensive, but they also perturb the system. Moreover, a high sampling density (in size and space) is generally required (Jury and Horton, 2004) to obtain an acceptable spatial resolution.

Linking hydraulic properties to apparent electrical conductivity (ECa) measured with electromagnetic induction (EMI) may be a way forward to estimate the spatial distribution of these hydraulic parameters across a field. Such ECa measurements are extensive, less expensive, non-destructive, efficient, reliable and timely (Corwin and Lesch, 2005; Segal et al., 2008; Sudduth et al., 2005). In addition, in precision agriculture, EMI measured ECa (Hedley et al., 2013) allows to complement the limited density of direct soil samples (Saey et al., 2009b) and assess soil hydraulic properties at higher resolution. Soil ECa is a function of a variety of soil properties including soil-water content, porosity, texture and structure (bulk soil properties), salinity (soil solution properties), cation exchange capacity (CEC), organic matter content, particle shape, size and distribution (solid particle properties), and soil layer thickness and topology (Corwin and Lesch, 2005; Friedman, 2005; Saey et al., 2008; Sudduth et al., 2013). Parameters affecting ECa are similar to those that affect soil physical and hydraulic properties, especially hydraulic conductivity, *K* (Doussan and Ruy, 2009; Pulido Moncada et al., 2014; Sudduth et al., 2005). Therefore, ECa can be considered an indirect indicator of hydraulic properties.

Over the past two decades, a large volume of research has focused on predicting hydraulic properties from basic soil properties to map Ks distribution (Friedman, 2005; Slater, 2007; Weynants et al., 2009; Wosten et al., 1999). On the other hand, empirical and semi-empirical relationships were established between ECa and soil properties. Researchers have applied Archie's semi-empirical law (Archie, 1942) to link K and ECa (Huntley, 1986). Both positive and negative significant linear regressions between log ECa and log K were reported (Brosten et al., 2011; Chaplot et al., 2011; Doussan and Ruy, 2009; Morin et al., 2010; Mualem and Friedman, 1991; Purvance and Andricevic, 2000a).

1.2 Aim of the research and research strategy

The objective of the PhD is to develop and test methods for optimizing irrigation efficiency using a combination of sensors and process based soil hydrological models. Sensors that has been used are soil moisture sensors and online tensiometers that measure water content and water potential in a fully automated field setup for quantitatively identifying flow processes in an agriculture soil. The monitoring data are continuously used to improve the model predictions of water status in the plant root zone and therefore the steering of the irrigation.

We will develop and test methods for irrigation management purposes, which are extremely relevant for arid and semi-arid conditions, such as Iran, but also for the management of intensively used agricultural fields in West- and Southern Europe suffering from summer droughts related to climate change.

The specific objectives are to:

1) Simulate the root water uptake in vadose zone and status of water in rhizosphere (including concentrations of solutes and nutrients or pollutants) using the Hydrus-1D model in combination with other state of the art crop based models like Lingra-N for grass and AquaCrop for potato

2) Upscale and determine soil hydraulic properties based on soft data and transfer methods

3) Investigate the tempo-spatial variability of soil hydraulic properties

4) Improve irrigation management using sensors and models for water flow and redistribution in soils.

1.3 Summary of the research of the past years

The original study site was further investigated and the modelling exercise refined. In 2011, soil samples had already been taken at eight locations and two depths 25 and 75 cm (traditional sampling strategy) to determine soil hydraulic and some other basic soil properties. Then in 2013, at 21 locations within the field, duplicate undisturbed (100 cm^3 Kopecky rings) soil samples to determine the soil hydraulic properties, and one disturbed sample to measure soil properties such as texture, dry bulk density and organic matter, were taken from the of the Ap horizon. The selection of sampling locations was done by combining a design-based and model-based sampling strategy to account for the maximum variation in soil properties based on a geophysical survey with an DUALEM-21S proximal sensor.

Also the modeling of water flow for this field was further refined. Simulation of water flow and root water uptake of the field for two growing seasons (from 1 Mar. until 25 Nov. 2012-2013) was carried out by using Hydrus 1D version 4.16. The model was calibrated based on sensitivity analysis. The effect of changing bottom boundary conditions on model performance was evaluated in a first step. Then, a systematic local sensitivity analysis was used to identify dominant hydraulic model parameters. Afterwards, automated model calibration was performed using inverse modeling with field data to estimate the hydraulic properties. Finally, the degree of soil water stress was calculated with different parameterization scenarios to show to what extent parameter choice and boundary conditions may affect estimations of irrigation requirements. The sensitivity to model boundary conditions was assessed by applying incremental constant head and free drainage lower boundary conditions. The results indicate that the position of the groundwater is dominant in soil water content prediction. The results show that, even for a sandy soil with groundwater depths below 120 cm, a constant head boundary condition yields a much better agreement with the soil water content observations in the upper 50 cm as compared to a free drainage condition. To reduce the number of parameters of optimization and finalize the calibration process, local SA was conducted by calculating the central total parameter relative sensitivity “CTRS”. According to the results α, n and Ks are most sensitive (in decreasing order) and the sensitivity changed over time with the seasonal changes in water status in both soil layers.

In the calibration step, to avoid non-uniqueness of the parameter sets (Šimůnek and Hopmans, 2002), 37 parameter optimization scenarios were selected and analyzed for correlations among optimized parameters, i.e., optimizing six parameters (1 scenario purposed by SA), four parameters (9 scenarios), three parameters (18 scenarios) and two parameters (9 scenarios). Finally, the best performing parameter set was selected for validation using independent data from 2013 (from 1 Mar. until 12 Sep. 2013). Irrigation water amount as calculated from crop water requirement for grass was insufficient to satisfy the water requirement over the optimization period. Water stress calculations suggested to increase the irrigation amount (up to 40 mm) for at least two times in summer (June and July) and further distributing of irrigation during the growing season.

More work was done on developing relationships between soil hydraulic properties and ECa in order to be able to upscale measured soil hydraulic properties to the field scale. It was shown before (Mertens et al., 2005; Verbist et al., 2012) that field water content predictions using a hydrological model are very sensitive to saturated hydraulic conductivity, *Ks*. Therefore, a better characterization of the field scale heterogeneity of *Ks* by using ECa data is very beneficial for precision management purposes. We investigated empirical relationships of field ECa data and *Ks* to predict *Ks* more effectively and precisely at the field scale. In a first step, we performed a statistical analysis of the soil properties (*Ks*, ECa, bulk density, texture and organic carbon). We established statistical relationships between co-located soil saturated hydraulic conductivity, some selected soil physical properties and EMI-ECa. These relationships were then evaluated using an independent dataset of saturated hydraulic conductivity. In a nutshell, results demonstrated the large spatial variability of all studied properties with *Ks* being the most variable one (CV = 86.21%). A significant negative correlation was found between ln-transformed *Ks* and ECa (r = 0.83; P≤0.01) at two depths of exploration (0-50 and 0-100 cm). This site-specific relation between ln *Ks* and ECa was used to predict saturated hydraulic conductivity over 0-50 cm depth for the whole field. The empirical relation was validated using an independent dataset of measured *Ks*. The statistical results demonstrate the robustness of this empirical relation with mean estimation error MEE=0.46 (cm h^{-1}), root-mean-square estimation errors RMSEE = 0.74 (cm h^{-1}), coefficient of determination r^2 = 0.67 and coefficient of model efficiency Ce = 0.64. The relationship was then used to produce a detailed map of saturated hydraulic conductivity, *Ks* for the whole field allowing to predict spatially distributed water content with a soil hydrological model for precision irrigation applications.

A second study site has been selected and monitoring equipments were installed in the field at two locations (high and low topography). At this potato field, also a combination of field monitoring and modeling (hydrological and crop based models) is applied to estimate hydraulic properties and predict water content distribution, water flow, crop yield and root water uptake at the field scale for irrigation management. At the locations, a 130 cm profile was dug to observe and measure soil properties. A tension disc infiltrometer was used to conduct field infiltration experiments from soil surface (topsoil) to subsoil (0, 25, 45, 80 cm) in two replications, to obtain estimates of the soil hydraulic properties. Four successive tensions of 12, 6, 3, and 0.1 cm were used for all infiltrometer experiments. The disc infiltrometer had a diameter of 20 cm and consisted of a nylon mesh. Soil hydraulic properties were estimated inversely from the infiltration data using the DISC software package. Four MVG soil hydraulic parameters (i.e., the saturated water content, θs, the shape factors α and n, and the saturated hydraulic conductivity, Ks) were estimated.

Three replications of undisturbed soil samples were collected additionally at depths of 0–10 cm at various measurement locations (max 5 cm distance) using a 100 cm^3 Kopecky rings. In these samples, *Ks* was determined using a constant head laboratory permeameter (M1-0902e, Eijkelkamp Agrisearch Equipment, Giesbeek, the Netherlands). The soil water retention curve, (SWRC, *θ(h)*), was determined using the sandbox method (Eijkelkamp Agrisearch Equipment, Giesbeek, the Netherlands) up to a matric head of -100 cm and the standard pressure plate apparatus (Soil moisture Equipment, Santa Barbara CA, USA) for matric heads equal to or below -200 cm, following the procedure outlined in (Cornelis et al., 2005). The bulk density was obtained by drying volumetric soil samples (100 cm^3) at 105 °C. Soil texture was determined using the pipette method for clay and silt fractions and sieving method for sand particles (Gee and Bauder, 1986). The organic matter content was determined by the Walkley and Black method (Walkley and Black, 1934). Soil hydraulic properties were determined according to the van Genuchten (1980) and Mualem (1976) conductivity model (MVG model) using the RETC program for Windows, version 6.02 (van Genuchten, et al., 1991). The results of field and lab methods as different parameter sets were used in Hydrus to evaluate the effects of initial values on model performance. Results showed the inverse solution of tension disc infiltrometer data is very useful for a fast parametrization of hydraulic properties of the potato farm.

Chapter 2 Report of the past period

2.1 Achieved Results

2.1.1 Further characterisation of study site 1

The study site is located in a sandy agricultural area at the border between Belgium and the Netherlands (central coordinates 51°19′ 05″ N, 05°10′ 40″ E) characterized by a temperate maritime climate with mild winters and cool summers. The site is almost flat (less than 1%) and runoff is not considered to be important. The depth of the ground water table was between 80 and 150 cm below the ground surface at various locations across the field depending on the topography, sloping up from NW to SE and SW. The field site is around 10.5 ha and is partly artificially drained by parallel pipes connected to a ditch in the North-West border of the field (Fig. 1) which are placed in 10 to 20 m intervals at around 90 cm below the soil surface (as measured in the ditch). The field was planted with grass during the study period 2011-2013.

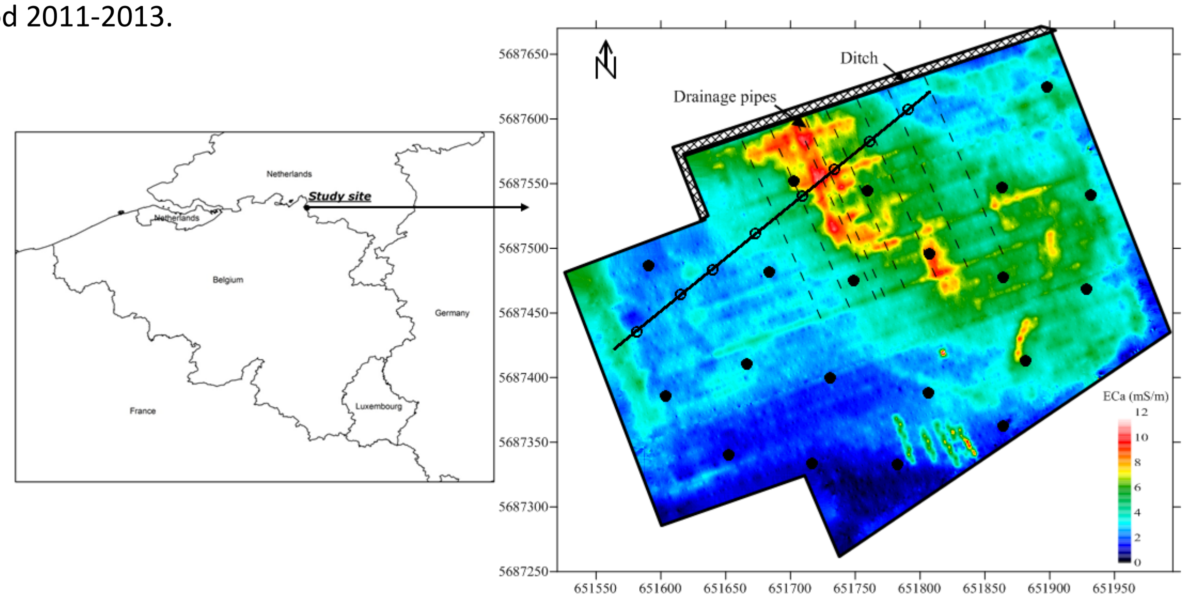


Fig. 1. Location of the study field and the classified map of 0-100 cm soil ECa with location of the 20 soil sampling locations (black bullets) from the ESAP software (calibration) and the eight additional points along the transect (validation). The 20 locations are well distributed over the FuzzyMe-derived ECa classes, with 7 locations belonging to class A (0.02 < ECa 2.949 mS m^{-1}), 6 locations to class B (2.95 < ECa 4.629 mS m^{-1}), and 7 locations to class C (4.63 < ECa 11.96 mS m^{-1}).

2.1.2: Predicting and upscaling Ks in a sandy grassland using ECa

2.1.2.1: Spatial variation of selected soil properties

The summary statistics of selected soil physical properties, *Ks* and ECa of the field site are given in Table 1. The mean values of ECa measured with DUALEM-21S increase with increasing the depth of exploration (DOE). Increasing DOE increases the ECa standard deviation (SD) due to the higher differences in absolute values and due to larger soil-water content and clay content variations (Table 1). Indeed, at greater depths (DOE = 0-100 cm), ECa could be affected by fluctuations in groundwater level. ECa gradually increased down-slope, reaching the highest level in the middle of the field (Fig. 1). The hydraulic parameter *Ks* exhibited a lognormal distribution ($p<0.05$). *Ks* values ranged from 0.6 to 9.61 cm h^{-1}, with a geometric mean 3.70 cm.h^{-1}. The saturated hydraulic conductivity shows a standard deviation of 3.19

cm^2/h^2 corresponding to a coefficient of variation CV of 86%. Soil bulk density, ρ_b, varied between 1.43 and 1.69 g cm^{-3} with an average of 1.61 g cm^{-3}. The average sand, silt and clay content were 91.0±1.3%, 7.3±1.1% and 1.7±0.5%,respectively. Soil organic carbon ranged between 1.06 and 4.46%. The largest CVs were observed for soil clay content (31%) and organic carbon (27%), whereas those for ρ_b, sand and silt content are rather low (<16%) (Table 1).

Table 1. Summary statistics of selected soil properties. ρ_b is soil bulk density, OC is organic carbon content, Sand, Silt, Clay are sand, silt and clay content, respectively. *Ks* is laboratory saturated hydraulic conductivity. ECa is apparent electrical conductivity (at 25 °C), with subscripts p,50 and p,100 denoting ECa of DUALEM-21S 0-50 cm and 0-100 cm perpendicular, respectively.

Variable	No. of samples	Min	Max	Mean	SD	CV (%)
ρ_b (g cm^{-3})	28	1.43	1.69	1.61	0.06	3.72
OC (%)	28	1.06	4.46	2.20	0.59	26.86
Sand (%)	28	88.1	93.5	90.99	1.31	1.43
Silt (%)	28	4.30	9.30	7.27	1.14	15.68
Clay (%)	28	1.10	3.60	1.72	0.54	31.39
***Ks* (cm h^{-1})**	28	0.61	9.61	3.23	2.30	71.21
$ECa_{p,50}$ (mS m^{-1})	98216	0.06	9.99	2.84	1.59	55.98
$ECa_{p,100}$ (mS m^{-1})	98442	0.02	10.91	3.44	1.85	53.77

2.1.2.2: Relation between selected soil properties, Ks and soil ECa

Pearson correlation coefficients between selected physical properties, *Ks* and ECa are shown in Table 2. In general, the highest significant negative correlations with ECa are obtained between ln *Ks* and ECa from both soil volumes (r = -0.83 in both cases). ln *Ks* is negatively correlated with silt (r = -0.46, P <0.05) and clay (r = -0.38, P <0.05), while a positive significant correlation between ln*Ks* and sand (r = 0.55, P <0.01) was found. On the contrary, ECa was negatively and positively correlated with sand (r = -0.54, P <0.05; for $ECa_{p,50}$ and r = -0.49, P <0.05; for $ECa_{p,100}$ and) and silt (r = 0.55, P <0.05; for $ECa_{p,50}$ and r = 0.50, P <0.05; for $ECa_{p,100}$) respectively. No significant correlation could be detected between ρ_b, OC, and the ECa values measured from different soil volumes or *Ks* (Table 2).

Table 2. Pearson correlation coefficient between the selected soil physical properties, Ks and ECa.

	ρ_b	OC	Sand	Silt	Clay	ln*Ks*	$ECa_{p,50}$	$ECa_{p,100}$
ρ_b	1							
OC	0.17	1						
Sand	-0.23	-0.41*	1					
Silt	0.26	0.46*	-0.91**	1				
Clay	0.02	0.04	-0.52**	0.12	1			
ln*Ks*	-0.35	-0.03	0.55**	-0.46*	-0.38*	1		
$ECa_{p,50}$	0.17	0.27	-0.54*	0.55*	0.16	-0.83**	1	
$ECa_{p,100}$	0.18	0.12	-0.49*	0.50	0.15	-0.83**	0.94**	1

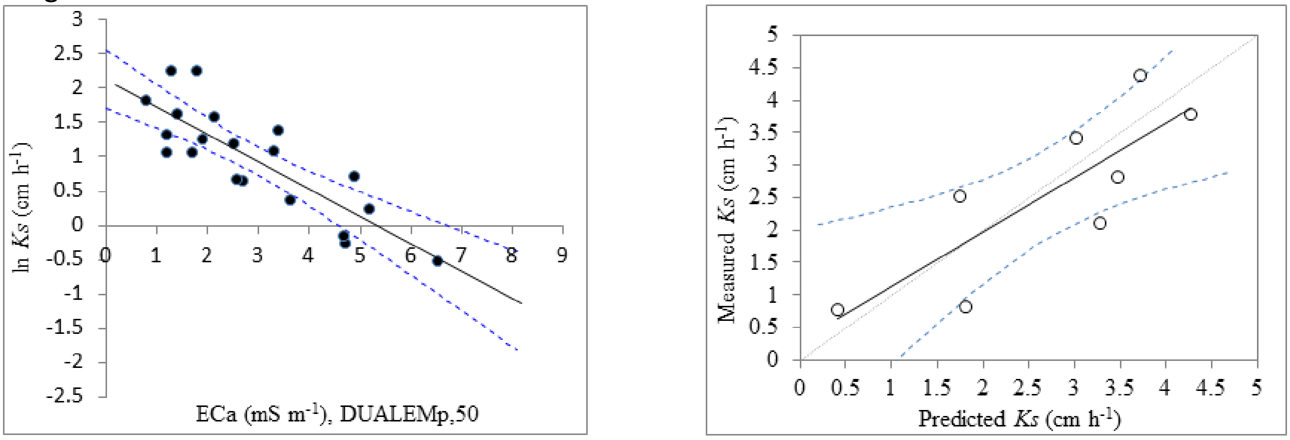
**and * marked correlation significant at P ≤0.01 and P ≤0.05 level respectively.

2.1.2.3: Estimation of Ks from ECa measurements and upscaling

A regression analysis between the field ECa data derived for the top 50 cm ($ECa_{p,50;}$ collected in 2011) and the 20 ln *Ks* values taken at similar depth, i.e., 5-15 cm (sampled in 2013), resulted in the following equation:

$$\ln Ks = -0.398\, ECa_{p.50} + 2.13 \qquad r^2 = 0.694, \qquad SD = 0.439 \qquad (1)$$

where *Ks* and SD (standard error of estimation), in cm h^{-1} and ECa in mS m^{-1}.
The relatively low standard error and large coefficient of determination confirm a strong estimation capacity of *Ks* from ECa as a proxy. The cross plot of co-located ln *Ks* for the 20 observation points versus ECa with the 95% confidence limits on the prediction is presented in Figure 2a.



(a) **(b)**

Fig. 2. The scatter plot of co-located ln *Ks* for the 20 observation points versus $ECa_{p,50}$ (a); Scatterplot of measured vs. predicted *Ks* (Eq. 1),(b), for eight validation points. The dashed lines shows the 95% confidence limits on the prediction. *Ks* is laboratory saturated hydraulic conductivity and $ECa_{p,50}$ is apparent electrical conductivity (at 25 °C) measured with a DUALEM-2S EMI sensor over 0-50 cm.

Linking the developed relation between *Ks* and ECa with the ECa map (Fig. 3a) resulted in a high resolution *Ks* map for the whole field (Fig. 3b). This *Ks* map illustrates three distinct zones corresponding to the FuzzMe ECa classes (Fig. 1). The *Ks* values measured at eight additional locations versus those predicted from Eq. 1 (obtained from the map) are presented in Figure 2b. The statistical performance indicators of the relation and its map showed a high r^2 between predicted and measured *Ks* (0.67), coefficient of model efficiency (Ce = 0.64), and a relatively low RMSE (0.74 cm h^{-1}). This indicates a high accuracy of the developed regression model. However the model slightly over (at high values) and under-estimated (at low values) *Ks* with a bias of 0.46 cm h^{-1} indicated by the MEE.

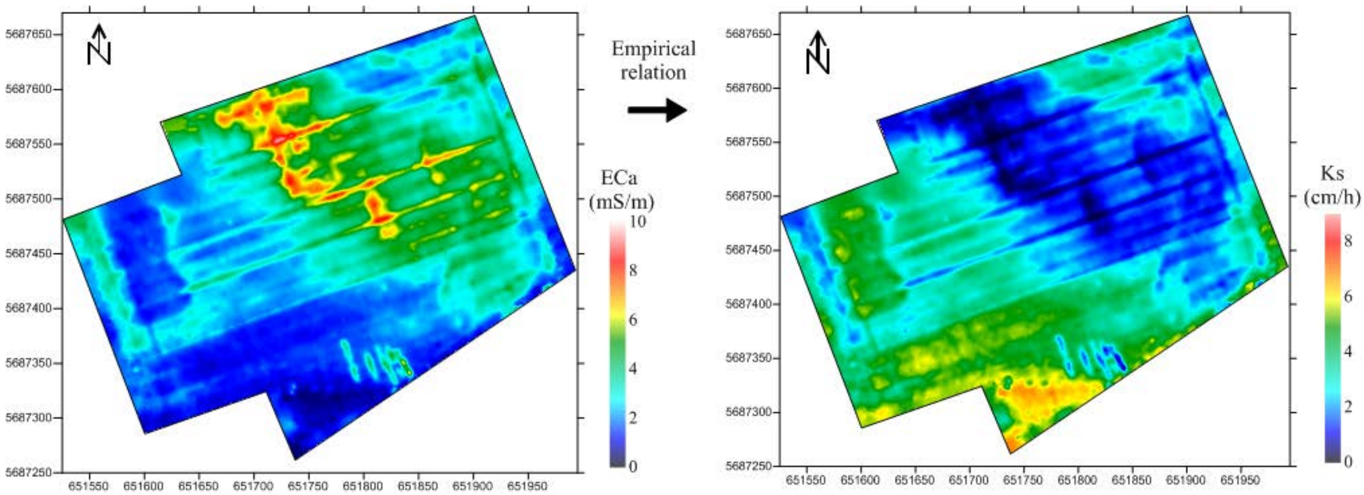


Fig. 3. Kriged $ECa_{p,50}$ map and estimated*Ks* from the site-specific empirical (geophysical) relation (Eq. 1). *Ks* is laboratory saturated hydraulic conductivity, $ECa_{p,50}$ is apparent electrical conductivity (at 25 °C) measured with a DUALEM-2S EMI sensor over 0-50 cm.

2.1.2.4: Conclusion of predicting and upscaling Ks from ECa

We found a good correlation of soil saturated hydraulic conductivity, and some selected physical properties to the ECa data derived by DUALEM-21S sensor measuring over 0-50 cm and 0-100 cm. A simple linear regression approach using high tempo-spatial resolution EMI-ECa data, was applied to predict and upscale *Ks* over the entire field. In this study, the semi-log empirical relation was established and validated to estimate the spatial distribution of *Ks* using ECa, as a proxy data. A detailed map of *Ks* was produced with satisfactory accuracy for hydrological modeling. The utilization of the semi-log empirical relation to produce the detailed map of *Ks* is an efficient way to predict spatial distribution of water content or water fluxes by hydrological models and to perform crop yield modeling for precision irrigation management purposes.

2.1.3: Soil hydrological model for a 2-layered sandy soil for irrigation management

2.1.3.1 Summary of the 1D soil hydrological modelling of grass field

The results of modelling study demonstrated clearly the profound effect of the position of the groundwater table on the estimated soil water content in a sandy two-layered soil under grass in a temperate maritime climate (refer to annual progress report 2014). Indeed, field scale variations in soil water content can be very large, due to topography and variable depth of the groundwater. Furthermore, the model performance is affected by the spatial variability of hydraulic parameters such as K_s. Results show that the uniform distribution of water using gun sprinkler irrigation seems not to be the efficient approach since at locations with shallow groundwater, the amount of water applied will be excessive as compared to the crop requirements, while in locations with a deeper groundwater table, the crop irrigation requirements will not be met.

The results showed that the effect of groundwater level is dominant in soil water content prediction, at least under conditions similar to those in our study. This reflects the need for accurate determination of the bottom boundary condition, both in space and time. In a subsequent field experiment in an adjacent field (second field), the temporal fluctuation of the groundwater table was measured based on diver measurements in boreholes (next paragraphs). The temporal changes are smaller than the expected variation due to topography which may well range over half a meter even for relatively flat areas. This has important consequences for precision irrigation management and variable water application at sub-field scale. The use of detailed (cm scale) digital elevation models recorded by unmanned airborne vehicles (UAVs), geophysical measurement techniques such as electromagnetic induction or ground penetrating radar as proxies for hydraulic parameters will serve as valuable data sources for hydrological models to calculate variable irrigation requirements within agricultural fields. The parameterization scenarios in the calibration and validation stage of model development should be kept simple in view of the information they generate. We showed that it is sufficient to estimate a limited amount of key parameters and that optimization strategies involving multiple parameters do not perform better in view of the optimization of irrigation management. The combination of accurate and spatially distributed field data with appropriate numerical models will allow to accurately determine the field scale irrigation requirement, taking into account the variations in boundary conditions across the field and spatial variations of model parameters. One of the limitations of hydrological models is that they do not consider crop yield. Therefore, it is recommended to combine the hydrological model with a crop model and to run the tool at different locations when using it for in irrigation studies. The information gained in this study with respect to dominant parameters and effect of the boundary condition at the plot scale (1D) will be scaled up in a quasi 3D approach to the field scale using detailed spatial information on groundwater depth and hydraulic conductivity K_s.

2.1.3.2: Quasi 3D modeling and coupling the crop based and hydrological models

To run the model for thousands of point of the field, Lingra-N was calibrated for each 21 locations, (Fig. 1) and grass yield was computed for each point for 2012 and 2013. Also leaf area index, LAI, has been used as an upper boundary condition in hydrological model (Fig. 4). We run the model for different scenarios e.i. optimum condition, current irrigation and water stress condition. The results of the yield are shown in Figure 5.

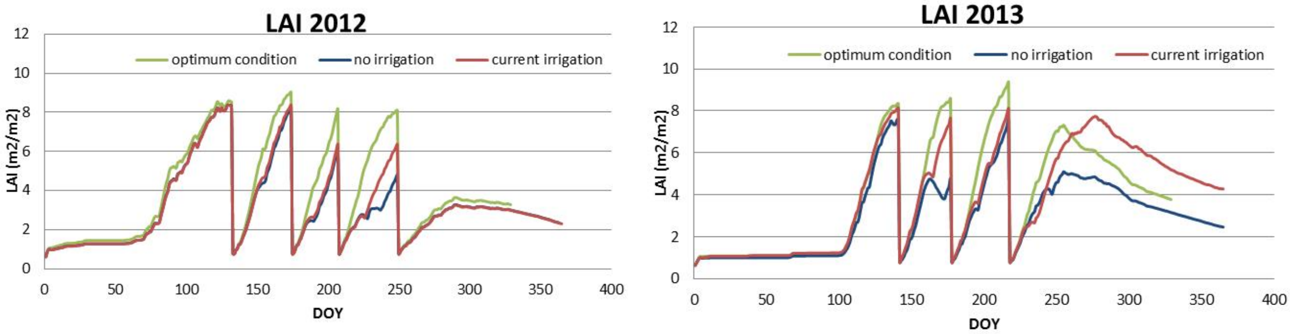


Fig. 4. LAI from Lingra-N as an input in Hydrus.

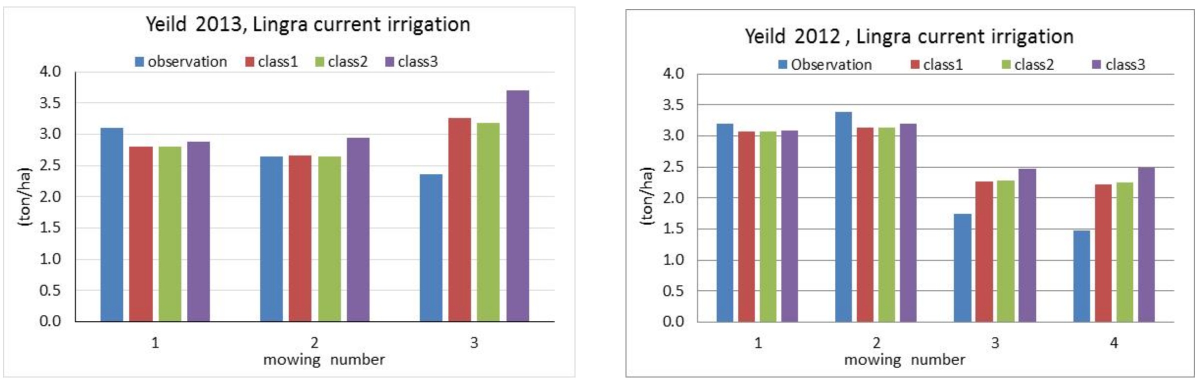


Fig. 5. Yield prediction from Lingra-N for grass field.

The hydrus model was run for each location (21 locations, Fig. 1) with location-specific measured groundwater levels, depths of the profile layers and hydraulic parameters K_s, α, *n*, θ_r. and θ_s and LAI simulated with Lingra-N. Soil water stress for all location was computed (Table. 3). The comprehensive quasi 3D modeling is under study and results will be achieved soon.

Table. 3. Soil water stress calculated from coupled models for 2012 and 2013.

Harvesting time (DOY)	Water stress (2012)			
	Class 1	class2	Class 3	Whole field
135	0.936	0.960	0.998	0.96
176	0.926	0.941	0.973	0.95
209	0.934	0.959	0.987	0.96
251	0.895	0.918	0.954	0.92
	Water stress (2013)			
141	0.792	0.805	0.906	0.834
177	0.888	0.914	0.945	0.914
217	0.898	0.914	0.930	0.913

2.1.4: Characterisation of study site 2- potato field: field measurements and experimental results

Figure 6 shows the soil profile of the site 2 and the field infiltrometry experiment. A uniform dark brown layer of sand (A horizon) with higher organic matter content was situated from the surface to a depth of about -45 cm, followed by a brownish to yellow sand including stones and gravels (-50 to -70 cm, B2 horizon). The deeper profile from -70 to -135 cm was light gray sand (C horizon) including more stones and gravels (max 20%) with the similar hydraulic properties of B2 horizon. The interface between A and B1 horizon is a compacted black layer with around 5 cm deep.

Fig. 6. Three-layered typical soil profile of the field at the location of the sensors (left), and the disc infiltration measurement (right).

The groundwater table based on diver measurements in boreholes shown in Fig. 7 indicate that groundwater depth fluctuated between 75- 130 cm. The differences of GWL for high and low land was about 10 cm, while the difference in two points elevation is around 2 meter. The sum of irrigation and precipitation over the measuring period (11 Apr. to 22 Sep. 2014) was 556 mm (96 mm irrigation and 460 mm precipitation). The calculated potential-reference evapotranspiration (ETo) values for the same period was 422 mm.

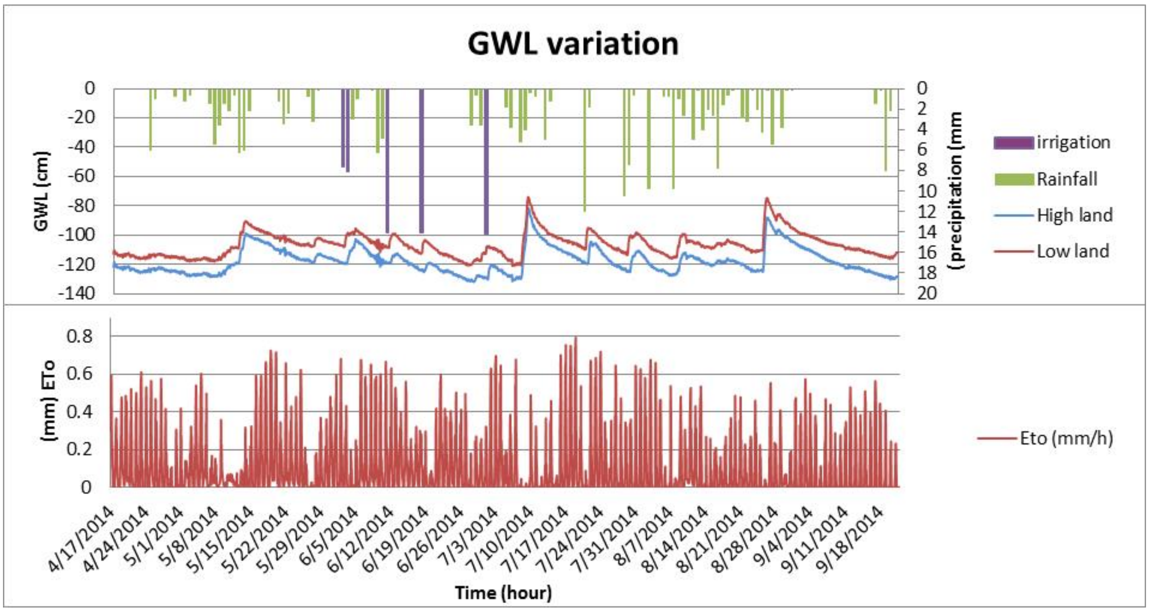


Fig. 7. Groundwater level, precipitation and ETo of the field at the sensor locations.

For disc infiltration methods, a set of calculation techniques can be applied. We used steady-state methods (wooding approach) and transient methods (numerical solution using Disc software). The results in Table 4 indicate that the saturated hydraulic conductivities (Ks) of the lab measurements were approximately two to fifty times higher than field measurements for both calculation methods. Few differences were observed among the field methods.

Table 4. saturated hydraulic conductivity for two soil profile at different depths using various measurement/calculation methods.

Location	Depth (cm)	*Ks* (cm/h)		
		Steady state	Numerical solution	laboratory
Low land	0-20	0.56	0.24	0.88
	20-45	0.55	0.71	10.0
	45-50	0.10	0.06	2.84
	50-70	1.19	1.19	34.04
	70-90	1.68	1.33	60.42
High land	0-20	0.71	0.63	1.48
	20-45	0.84	0.61	3.36
	45-50	0.13	0.20	0.76
	50-70	0.90	1.17	5.75

In addition, there were few differences between MVG parameters n and α for laboratory (RETC software) and field infiltration (Disc software). The differences are more obvious for deeper soil profile. Results show that using field infiltration measurements and optimizing MVG parameters using Disc or Hydrus 2/3D software are a useful and fast method to derive initial hydraulic parameters for hydrological studies. Results showed hydraulic properties from disc infiltrometry and laboratory are significantly correlated (Ks: 0.74, n: 0.77 and α: 0.71 at 0.05 level).These initial sets were evaluated with the hydrological model and results indicated simulations using field experiment parameters were more in agreement with observed soil water potential (Fig. 9).

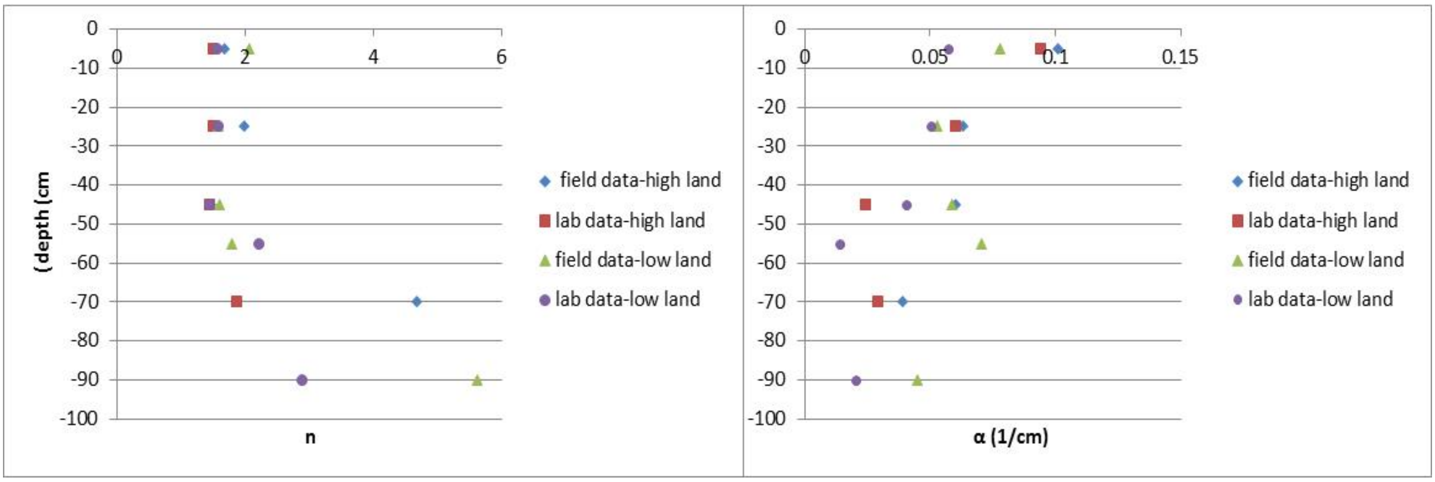


Fig. 8. Comparison MVG soil hydraulic parameters n and α for two profiles using field and lab measurement methods.

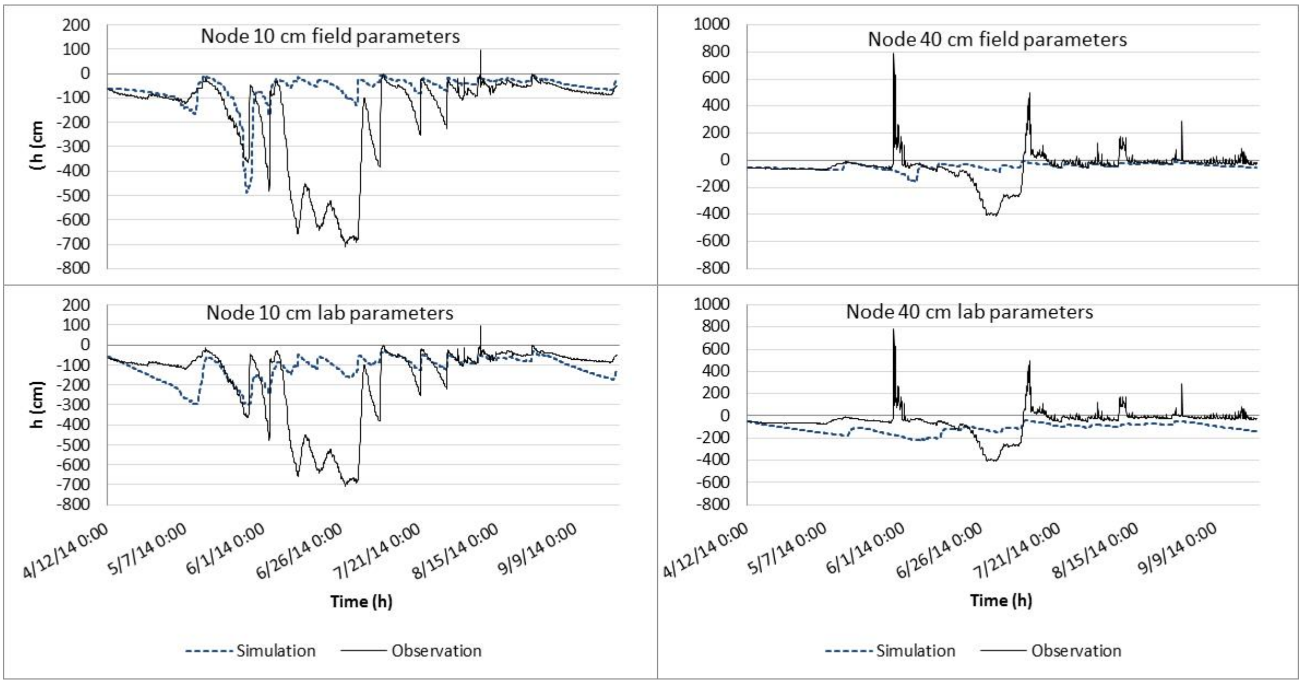


Fig. 9: Water potential estimations at 10 and 40 cm depths using the uncalibrated model for field and lab parameter sets at the soil moisture sensor location- low land.

2.2: Scientific in *and output*

Courses and workshops

- Aquacrop workshop from Monday 16th to Friday 20th July 2012 at KU Leuven University, by Dirk Raes.
- ENVITAM course on HP1 (HYDRUS + PHREEQC). From 25th to 28th March 2013 at Gent University (Faculty of Bioscience Engineering), by Diederik Jacques.
- Contaminant transport in soil, second semester 2012-2013, Gent University, by Prof. Piet Seuntjens.
- Soil physics, first semester 2012-2013, Gent University (Faculty of Bioscience Engineering), by Prof. Wim Cornelis.
- Land information system, second semester 2012-2013, Gent University (Faculty of Bioscience Engineering), by Prof. Ann Verdoodt.
- Intermediate academic English course, first semester 2012-2013, Gent University, by university language center (UTC).
- Advanced Academic English: Conference Skills - Presentation Skills in English, first semester 2013-2014 Gent University, by university language center (UTC).
- Let's talk science, summer school, 2-4 July 2014, Brussel/Gent/Antwerp/Hassalt universities.

Publications

Journals:

Rezaei, M., P. Seuntjens., I. Joris, W. Boënne, S. Van hoey., W. Cornelis. 2014. Sensitivity analysis of a soil hydrological model for estimating soil water content in a two-layered sandy soil for irrigation management purposes. submitted

Rezaei, M., P. Seuntjens., I. Joris, W. Boënne., W. Cornelis. 2014. Upscaling and predicting hydraulic properties using apparent electrical conductivity in a sandy grassland for precision agriculture. submitted.

Conference proceeding:

Rezaei, M., P. Seuntjens., I. Joris, W. Boënne, S. Van hoey., W. Cornelis. 2013. Optimizing Hydrus 1D for irrigation management purposes in sandy grassland. In proceeding of: The 2nd European Symposium of Water Technology & Management, At Leuven, Belgium. pp 122-126. Poster.

Rezaei, M., P. Seuntjens., I. Joris, R. Shahidi., W. Boënne, J. De Pue., W. Cornelis. 2014. Effects of spatial variability of soil hydraulic properties on hydrological model for irrigation management purposes. In the 9th International Soil Science Congress on "The Soul of Soil and Civilization" in Side, Antalya, Turkey on October 14-17, 2014. Abstract.

Rezaei, M., P. Seuntjens., I. Joris, W. Boënne, W. Cornelis. 2014. An alternative tool to predict and upscale soil saturated hydraulic conductivity: apparent soil electrical conductivity. In the 9th International Soil Science Congress on "The Soul of Soil and Civilization" in Side, Antalya, Turkey on October 14-17, 2014. Abstract.

Rezaei, M., P. Seuntjens., I. Joris, W. Boënne, W. Cornelis. 2014. Estimation of the spatial distribution of soil hydraulic characteristics using apparent soil electrical conductivity as proxy data. TERENO International Conference 2014, 29 Sep-2 Oct. 2014 Bonne Germany. *oral.*

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Chapter 3: Future perspectives

3.1 Evaluation of the results and currently missing elements

The dataset now consists of data for two growing seasons for grassland. In the coming period a quasi 3D model will be set up for this data set with a combination of Hydrus 1D and the Lingra-N crop based model (Wolf, 2012). At the second field, again a combination of field monitoring and modeling will be used to calibrate the model and estimate hydraulic properties and predict water content distribution, water flow and root water uptake at the field scale in a three layered sandy soil for irrigation management and possibly for N or pesticide leaching purposes. In the coming months the results of these two field will be finalized and published. Also a third field has been selected to measure soil water content (5 depths), nitrate (3 depths) and GWL at four locations. In the different management zones a monitoring well was installed with 2 x 2 Rhizons sensors for soil water sampling. For each management zone a monitoring well was installed with a (ground) cutting filter. The groundwater level will be continuously monitored by divers. The Rhizons at each management zone are installed at three different depths (25, 50 and 75 cm).

The objectives of the study at the third field are to:
a) Carry out the previous systematic methodology in modeling approach to predict water content distribution, water flow and root water uptake of potato with Hydrus 1D and crop yield with AquaCrop model (crop based model);
b) Investigate and simulate the fate of applied fertilizer (N) in soils (leaching).

In the field, monitoring equipment has been installed in Spring (29 Apr. 2015). A short description of the installation is given below:

Sensors locations: based on EMI survey, GWL and field condition and management four locations were determined where the sensors were installed.

Setup field monitoring system at each point:
- A diver to measure the ground water fluctuations at location.
- Three Rhizon sensors at 25, 50 and 75 depths.
- ➢ *At one point:*
- One soil water content profile probe (type Dacom, The Netherlands), to measure soil-water content at 10, 20, 30, 40, 50 and 60 cm depths.

3.2 Planning

Reporting is done to Ghent University, Vito and the Ministry of science, research and technology of Iran. Below is an updated work schedule for the four year period (Table 5) and the status for May 2015.

Table 5: Overview of working schedule

<Meisam Rezaei>		Actualised working schedule on <8.5.2015>															
Started on <15.02.2012>																	
Tasks and parts of tasks		Year 1				Year 2				Year 3				Year 4			
Task 1	**Literature Review, existing data analysis and work plan**																
	literature review: models, processes, inverse modeling, data assimilation methods, ECa, Penetrometer																
	data analysis existing data field site at Vandenborne site 1 and 2																
	GIS analysis field data and point-to-field extrapolation of hydraulic properties (in collaboration with UGhent)																
	Finding relationship between soil properties and available data (correlation and regression)																
	completing proposal writing work plan																
Task 2	**Parameter estimation and model calibration**																
	manual calibration of historical data set																
	inverse optimisation using Hydrus																
Task 3	**Modelling**																
	setup 1D hydrological models for individual soil columns																
	root distribution, plant uptake and ET- Crop based modeling																
	setup quasi 3D hydrological model (parallel columns) for the field site at Vandenborne																
	Application of methods to include weather forecast and sensor data in predictions on water flow																
Task 4	**Field work and additional collection of data**																
	Installation of new sensor																
	Checking the data set and equipments twice to four times a month																
	Soil description and delineation of groundwater depth- soil sampling																
	Laboratory analysis																
Task 5	**Reporting**																
	Draft paper on the modelling																
	Draft a paper ECa data set																
	take a note and writing a draft of thesis																
	Journal and conference paper																
Task 6	**Doctoral education**																
	Speciall courses and summer school courses																
	English language and writing course																

Legend: (The vertical green line indicates the end of the present quarter)

Planning starting doctorate ■ Finished Not planned, additional quarters Planned but not realised

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