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Integrated sensing of soil moisture at the field-scale: Measuring, modeling and sharing for improved agricultural decision support

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ABSTRACT

Determining the best way to efficiently use limited water resources, for food and energy-dedicated crops, has become crucial due to the rise in extreme events (floods/droughts) and higher variability in rainfall attributed to global climate change. Changing climate conditions will require new crops to be adapted to a changing agricultural environment. Reliable information on seasonal trends in crop growth and evapotranspiration with associated uncertainty/confidence ranges is crucial to guide the development of new crops and management strategies to cope with future climate. Given that crop growth is strongly coupled to soil moisture, developing reliable growth curves requires a detailed understanding of soil moisture at the field-scale. Typically, it is impractical to collect soil samples to adequately assess soil moisture that represents both spatial distribution at the field-scale and temporal dynamics on the scale of a growing season (e.g. 110 days for cereals). A novel way to address soil moisture monitoring challenges is through an integrated, agro-ecosystems-level approach using an integrated sensing system that can link data from multiple platforms (wireless sensors, satellites, airborne imagery, near real-time climate stations). Assimilated data can, then, be fed into predictive models to generate reference crop growth curves and predict regionally-specific yield potentials. However, integrated sensing requires interagency cooperation, common data processing standards and long-term, timely access to data. Large databases need to be reusable by various organizations and accessible, in the future, with comprehensive metadata. During the 2012 growing season a feasibility study was conducted which involved measuring field-scale soil moisture with sensor network technology. The experiment utilized radially-distributed sensors for tracking in-season soil moisture. OpenGIS-compliant services and standards were utilized to provide long-term access to sensor data and construct corresponding metadata. Sensor Model Language, an inter-operable metadata format, was used to create documentation for the sensor system and sensing components. Two different third party implementations of the Sensor Observation Service were tested for providing long-term access to the data. This work discusses a set of key recommendations for monitoring field-scale soil moisture dynamics for integration with remote sensing and models, including: (1) Improved in situ sensing technology that would allow for less restrictive soil moisture measurements. (2) Integration of field-scale in situ networks with regional remote sensing monitoring. (3) The development of software and web services to integrate data from multiple sources with models for decision support.

1. Introduction

Increasing pressures from climate change have led to substantial uncertainty in the most efficient use of scare resources, especially in more arid regions (IPCC, 2007). Increased vulnerability and risks for rain-fed crop systems from extreme weather events and the need to adapt to longer-term climate change variability is anticipated. Substantial changes in land use and crop rotations are expected, accompanying changes in the availability of water for agricultural production of food and energy-dedicated crops. Crop adaptation

Abbreviations: ET_c, crop evapotranspiration; ET_0, reference evapotranspiration; K_c, crop coefficient; K_s, water stress coefficient; APSIM, Agricultural Production Systems Simulator; SWE, sensor web enablement; OGC, open geospatial consortium; XML, Extensible Markup Language; SOS, Sensor Observation Service; SensorML, Sensor Model Language; WFV, Water fraction volume; AAFC, Agriculture and Agri-Food Canada; RTU, radio telemetry unit; GeoCENS, geospatial cyberinfrastructure for environmental sensing; SMOS, soil moisture ocean salinity; SVAT, soil–vegetation–atmosphere.

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will be increasingly important in order to maintain productivity, especially in regions where local food supply and its regional distribution is insecure and most vulnerable (Lobell et al., 2008). For a given region, certain crops may no longer be suitable while others will become more viable alternatives. New crop alternatives, for an example forage *Brassicas*, Ethiopian mustard (*Brassica carinata*) and Camelina (*Camelina sativa*) (Blackshaw et al., 2011), could potentially enable farmers to improve water-use efficiency, expand management options, reduce farm inputs, and enhance cropping system resilience. In this way, such crops could be introduced within existing rotations, thereby reducing pressures on land for growing food and supplying bioenergy. Crop adaptation, potentially, allows farmers to make better use of scarce and variable water resources (i.e., changes in precipitation amounts and variability). Better utilization of water in rain-fed crop systems could potentially enhance the stability of agricultural production, improve system resilience or maintain the flow of ecological goods and services in the face of climatic change.

$$ET_c = K_s K_c ET_0 \tag{1}$$

Water and nutrient requirements must be integrated with seasonal crop growth to reliably guide decisions about crop selection, adaptation and development. Crop growth curves (termed ‘crop curves’) with associated uncertainty/confidence ranges provide a method to describe seasonal crop production under varying conditions. Typically, crop curves are computed by considering the crop specific consumptive use of water, such as evapotranspiration. The crop evapotranspiration (ET_c) can be predicted using a suitable reference evapotranspiration (ET_0) observed from analysis of weather conditions at a set of distributed climate/weather stations (Eq. (1)). ET_0 is then multiplied by a crop coefficient that varies through the season depending on the growth stage of the crop. The Penman–Monteith method (Allen et al., 1998), Eq. (1), has been the recommended standard method for the definition and computation of the ET_0 with ET_c from crop surfaces under standard conditions determined by specific crop coefficients (K_c). Standard conditions refer to regions that are disease-free, have well-fertilized crops, grown in large fields, under optimum soil water conditions, and achieve full production under the prescribed climatic conditions. Clearly, such conditions are idealized and most crop production would be expected to occur under a mix of sub-optimal conditions. However, crop surfaces under non-standard conditions require specification of additional factors/adjustments related to environmental variables driving stress on growth. For example, if considering just water, this would be accomplished by introducing a water stress coefficient (K_s) and/or by modifying the crop coefficient under expert opinion.

Complex process-based models could be used to represent and integrate stress factors for computing regional and crop-specific reference growth curves. Typically, sufficient data for complex process-based models may not be available and the broader assumptions may be too strict and idealized. Statistical models that enable a flexible mix of expert knowledge with available data, likely provide a better solution to producing crop curves that can be refined and further evaluated using more complex process-based agro-ecosystem models. Such enhanced crop curves could provide reference on soil productivity and crop yield (production) across crop phenological development stages. Enhanced crop curves may provide reference crop water consumption and be used to comprehensively identify alternative crops better suited to specific climates, projected extreme variability, and soil quality.

Given that crop growth is strongly coupled to soil moisture, reliable crop curves require a detailed understanding of soil moisture at the field-scale, within the growing season (May–August in southern Alberta). Currently, the scarcity of field-scale soil moisture and crop growth monitoring, is attributable to technical and financial constraints (i.e. it is technically demanding and expensive). Soil moisture variability has been shown to increase with observation scale (field to regional) (Famiglietti et al., 2008). Regional climate changes could potentially affect profound responses in soil moisture (McGinn and Shepherd, 2003; Porter and Semenov, 2005). In semi-arid agro-ecosystems, soil moisture has two separate flow patterns related to the wetness of the soil. A vertically dominated pattern when the soil is closer to dry and horizontally dominated pattern when the soil is nearer to saturation (during and immediately after precipitation events) (Grayson et al., 1997). Monitoring of soil moisture could be very difficult due to these uncertainties induced by sampling and changing environmental conditions. Soil moisture is especially difficult to sample in order to obtain the best field-scale representation of its spatial distribution and how this changes over the growing season. The use of distribution-based/probabilistic models has the potential to provide crucial insights to better sample, integrate across data platforms, and identify best management practices and generate in-season forecasts of crop yield (Challinor et al., 2009). In irrigated crop systems, soil moisture data may be used to inform irrigation scheduling. In rain-fed crops, however, soil moisture data could provide crucial information on the intensity, duration and timing of moisture stress under rival cropping systems and management practices. Crops may be identified that might be more tolerant of moisture stress or escape detrimental moisture stress with earlier seeding. Better timing of fertilizer nitrogen applications with adequate available soil water, potentially improving water use efficiency. In rain-fed systems the value soil moisture and crop monitoring might be less as means to adapt management in real-time, as in the case of irrigation scheduling. Instead, as rainfall may become even more difficult to predict, soil moisture and crop monitoring may be a means to better understand a crop system. Confidence intervals of soil moisture for future years possibly allow better manage scarce and variable moisture supplies in subsequent growing seasons.

Sensor based precision agriculture generally utilizes one of two soil sensing methods: reactive (real-time) sensing and predictive (map-based sensing) sensing. A decision support system using reactive sensing would provide management recommendations based on local conditions at that time. A predictive system would generate soil information only after off-site processing and interpretation of the data (Adamchuk et al., 2011; Mahmood et al., 2012). For rain-fed cropping systems the predictive method could be utilized to predict future in-field soil moisture dynamics. Better estimates of future growing season water scarcity may lead to more appropriate crop selection and planting dates. The prediction of soil moisture across time and space also requires analytical methods/model development using long-term monitoring data. The best way to address such challenges and uncertainty could be through an integrated, agro-ecosystems-level approach. This involves developing an integrated sensing system that can link data from multiple platforms (wireless sensors, satellites, airborne imagery, near real-time climate stations) and integrate it into predictive models for evapotranspiration, crop growth curves and potential yields. Integrated sensing has the potential to provide enhanced field-scale decision support on crop water use and its variability over time and space. Integrated sensing has been defined as the fusion of remote sensing observations and in situ measurements for use in models to generate biogeophysical information (Teillet et al., 2002). Interagency cooperation, common data processing standards and long-term timely access to data are also critical to support and enhance integrated sensing and remote data delivery (Teillet et al., 2002).

Integration of data from multiple different sensors (both in situ and remote) could potentially improve predictive modeling of soil crucial variables by providing complementary data that varies in