Monitoring Agricultural Risk in Canada Using L-Band Passive Microwave Soil Moisture from SMOS

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ABSTRACT

Soil moisture from Soil Moisture Ocean Salinity (SMOS) passive microwave satellite data was assessed as an information source for identifying regions experiencing climate-related agricultural risk for a period from 2010 to 2013. Both absolute soil moisture and soil moisture anomalies compared to a 4-yr SMOS satellite baseline were used in the assessment. The 4-yr operational period of SMOS was wetter than the 30-yr climate normal in many locations, particularly in the late summer for most regions and in the spring for the province of Manitoba. This leads to a somewhat unrepresentative baseline that skews anomaly measures at different parts of the growing season. SMOS soil moisture does, however, show a clear trend where extremes are present, with drier-than-average conditions during periods that drought and dry soil risks were identified and wetter-than-average conditions when flooding and excess moisture were present. Areas where extreme weather events caused crop losses were identifiable using SMOS soil moisture, both at the provincial and regional scales. The variability in soil moisture between at-risk areas and normal areas is very small but consistent, both geographically and over time, making SMOS a good real-time indicator for risk assessment.

1. Introduction

Agricultural risk assessment is a key tool for determining potential and actual losses in food production that result from climatic extremes such as deficits and excesses of moisture in the soil and at the surface. Soil moisture is a key determinant of crop production, impacting field accessibility for seeding, harvest, and field management; sustaining productive crop growth; and often determining vulnerability of crops to disease and pests. Characterizing soil moisture and soil moisture extremes has been done through in situ monitoring networks (Keyantash and Dracup 2004; Nandintsetseg and Shinoda 2013; Sridhar et al. 2008; Vicente-Serrano 2006) and land surface models (Sheffield and Wood 2007). Progress in the development of satellite technology and retrieval algorithms for quantifying soil moisture from active and passive microwave satellite platforms has provided a new suite of tools to the risk assessment community that are now able to provide near-real-time measurements of soil moisture conditions at the surface.

The Soil Moisture Ocean Salinity (SMOS) mission was launched in November 2009 with goals that included the direct measurement of soil moisture at the earth’s surface and the integration of these measurements into land surface models to estimate root zone soil moisture conditions (Kerr et al. 2001). Beginning with the 2010 growing season and continuing to the end of the 2013 growing season, Agriculture and Agri-Food Canada (AAFC) piloted the use of SMOS observations to produce soil moisture maps in near–real time to help assess climatic risk to Canada’s agricultural sector (www.agr.gc.ca/drought). In this relatively short period of time, these maps have captured instances of drought and flood, sometimes occurring in the same regions in the same year.

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AAFC uses these surface soil moisture condition maps primarily as a visual tool rather than a quantitative one, for use in conjunction with other visualized datasets, such as meteorological data, modeled soil moisture, and drought indicators as well as agricultural impact reports from government agencies, journalists, citizen scientists, and farmers to determine spatial distribution of production risk. Using data that are objective and perceptive, as well as quantitative and nonquantitative, allows the risk assessment community to provide a more complete picture of risk and impacts to help determine action outcomes where crop damage and failure occur. SMOS soil moisture, along with future soil moisture satellite missions such as the Soil Moisture Active Passive (SMAP) mission datasets, can form an integral tool in the assessment of climatic risk, particularly in regions where other data sources (such as climate stations) are spatially sparse.

Soil moisture data from SMOS have been evaluated in numerous global studies to quantify errors in the retrieval (Al Bitar et al. 2012; Dall’Amico et al. 2012; Jackson et al. 2012; Lacava et al. 2012; Sanchez et al. 2012; Srivastava et al. 2013). In general, results have shown that SMOS shows a good agreement with general trends from in-situ measured soil moisture, but that there is an overall dry bias in the moisture retrievals. This dry bias has been attributed to factors such as an overestimation of surface brightness temperature by SMOS compared to airborne measurements and to errors in estimating ancillary information in the SMOS retrieval algorithm, such as vegetation water content and the choice of the soil moisture mixing algorithm to convert soil dielectric to soil moisture (Bircher et al. 2012; Jackson et al. 2012; Rowlandson et al. 2012). While the soil moisture measured by SMOS contains errors, the use of soil moisture information from SMOS for risk assessment depends less on the absolute accuracy of the soil moisture and more on how it captures relative trends to determine if conditions are outside the climatic norms.

The purpose of this study is to examine the use of SMOS for agricultural risk assessment in Canada and, more specifically, to examine if SMOS soil moisture accurately quantifies known risk events that have occurred during this period. To accomplish this, SMOS soil moisture and soil moisture anomalies (i.e., deviations from baseline conditions) were compared against both quantitative and qualitative risk assessment tools to determine how well SMOS is capturing adverse conditions impacting the agricultural sector. An assessment against historical climate events was used to provide guidelines on how SMOS soil moisture can be used as a simple, near-real-time risk assessment tool.

2. Methodology

The area examined in this study covers the agricultural extent of Canada (defined as the area where climate, soils, and land cover permit crop production). This covers a very diverse geographical region, with maritime agriculture in the eastern provinces; temperate agriculture in the mountain-valley regions of British Columbia; cold-region prairie agriculture in Manitoba, Saskatchewan, and Alberta; and diverse agriculture in the mountain-valley regions of British Columbia (BC). The specific agricultural areas chosen for analysis were identified using AAFC’s Circa 2000 Agricultural Land Cover Map (Fisette et al. 2005). Only areas where the majority of grid cells were classified as agricultural land use were retained for analysis (Fig. 1, bottom). The resulting study area covers 10 Canadian provinces, although the majority of the agricultural land is located in the three “Prairie provinces” (Alberta, Saskatchewan, and Manitoba) and the temperate regions of Ontario and Quebec (Fig. 1).

Soil moisture estimates from SMOS observations were compiled over the Canadian agricultural growing season (from 1 April to 31 October) for the 4-yr period 2010–13. This annual time period was chosen to be consistent with other national agroclimate monitoring periods, and it largely reflects the period when the agricultural regions of Canada are primarily snow-free and the ground is unfrozen and suitable for cultivation. It is important to avoid periods when the ground may be frozen, because SMOS soil moisture retrievals cannot be reliably obtained under such surface conditions.

SMOS is an L-band passive microwave satellite that measures brightness temperatures using an interferometric (multiangular) approach. Microwave emissions from the earth’s surface at L bands are attenuated by dielectric materials. These attenuation patterns can be used to estimate soil moisture due to the high contrast in dielectric properties between dry and wet soils. The estimation of soil moisture is complicated by other factors that impact the signal strength and attenuation, such as vegetation water content, surface temperature, surface roughness, and the presence of natural surface water bodies. At L bands, microwaves are less impacted by vegetation and surface roughness characteristics compared to other microwave frequencies available from satellite platforms, making this the most suitable electromagnetic information for estimating soil moisture from currently available satellites. The signal measured by microwave satellites is related primarily to the surface soil moisture conditions. While the SMOS sensing depth varies with soil moisture conditions, it is generally less than 5 cm from the surface (Escorihuela et al. 2010).
Level 2 SMOS soil moisture observations were acquired from the European Space Agency (ESA) and processed using version 5.51 of the soil moisture processor. The level 2 soil moisture processor estimates soil moisture and other geophysical parameters for a set of fixed earth grid points using available brightness temperature information at each grid point (Kerr et al. 2012). Grid points are distributed over the earth’s surface on a $15\text{ km} \times 15\text{ km}$ matrix. The retrieval model estimates brightness temperature by iteratively adjusting soil dielectric values to minimize a cost function between modeled and measured brightness temperatures. Vegetation water content is first estimated using an empirical relationship between vegetation leaf area index (LAI) and vegetation water content, with LAI values initiated using values based initially on ECOCLIMAP, and then is estimated through SMOS observations from past inversions (Kerr et al. 2012). The models are parameterized differently based on the land cover type, with aggregate land cover classes assigned to each node and a decision tree model used to select a model for soil moisture retrieval based on the dominant land cover type. Since most regions consist of relatively low biomass cropland, such as cereal crops and oilseeds like corn and soybean, the land is largely modeled using the “nominal” model for bare soils and low biomass vegetation. Retrieved dielectric constants are then converted to volumetric soil moisture using the Mironov dielectric mixing model (Kerr et al. 2012; Mironov et al. 2004).

Soil moisture was extracted from level 2 SMOS half-orbit data and gridded to daily averages on a flat $0.25^\circ$ grid. This grid resolution represents an undersampling of the native SMOS data, which have a nominal resolution of approximately $42\text{ km}$ but are distributed on
a 15-km discrete global grid. The impact of this on the SMOS brightness temperature data has been found to be minimal (Dumedah et al. 2013), and spatial averaging used in the final analysis further minimizes this impact. Daily files were used to compute biweekly and monthly averages [referenced to International Organization for Standardization (ISO) standard week numbers]. The volumetric soil moisture from spatially and temporally gridded products was then used to calculate baseline soil moisture for each grid cell using the 4-yr satellite record.

The 4-yr SMOS baseline was used to compute biweekly and monthly variations of current soil moisture conditions from the long-term average. Several approaches to calculating anomalies were tried: 1) the current soil moisture expressed as a percentage of the SMOS baseline, 2) the absolute difference of current soil moisture from the SMOS baseline, and 3) the percentile of soil moisture compared to the SMOS baseline (Fig. 2). These three ways of expressing anomalies were found to be highly correlated, so the absolute soil moisture difference from the SMOS baseline was used primarily for the analysis. For the analysis, absolute soil moisture and soil moisture anomalies (using soil moisture absolute difference from baseline) from SMOS pixels were compared over two geographic summary regions, with spatial summary statistics calculated for each Canadian province and each Census of Agriculture Region (CAR).

Volumetric soil moisture and soil moisture anomalies were compared to several datasets used in the risk assessment process. Precipitation data from 225 meteorological stations located in agricultural regions were used to assess the average wetness conditions over the study area. Meteorological stations with minimal data gaps from 1 January 1970 to 31 October 2013 were selected for analysis. Data from stations with short periods of missing observations were gap filled using measurements from nearby stations. For each station, the 30-yr normal precipitation was calculated for both the 1971–2000 and 1981–2010 periods. Normals were calculated according to the World Meteorological Organization (WMO) standard using total precipitation on a monthly basis over each 30-yr record. To relate these to weekly and biweekly periods, monthly normals were distributed for each day and then summed to create weekly and biweekly equivalents. The two normal periods were compared and were found to be strongly correlated, with the exception of some regions and time periods when the 1981–2010 baseline was found to be wetter than the 1971–2000 baseline, particularly in areas of southern Manitoba (Fig. 3). In addition, these normals were compared to the precipitation over the SMOS baseline from 2010 to 2013 (Fig. 4).

Maps indicating areas of extreme wetness and drought were collected for the study period. Drought maps were taken from the Canadian portion of the North American Drought Monitor (NADM). This dataset is a categorical representation of drought conditions based on expert interpretation of many drought indicator datasets, including meteorological drought indicators, modeled soil moisture, satellite vegetation condition, runoff, and streamflow maps and surface temperature maps (Lawrimore et al. 2002; Svoboda et al. 2002). These maps quantify drought severity on a scale that represents severity and the percentile chance of occurrence in the area, with ratings of D0 (abnormally dry or 30th percentile), D1 (moderate drought or 20th percentile), D2 (severe drought or 10th percentile), D3 (extreme drought or 5th percentile), and D4...
For each analysis region (CAR and province), the area classified as each drought category was extracted. While these maps are spatial generalizations, they represent the best expert consensus based on observed datasets where risk is occurring.

Areas of excessive wetness were identified in part using agricultural land use classifications from 2010 and 2011 that were created using a combination of optical [Landsat and Advanced Wide Field Sensor (AWiFS)] and active radar (RADARSAT-2) satellite imagery (Fiset et al. 2013). This land use classification is based on high-resolution optical and radar satellite data, as well as extensive ground truth information obtained from crop insurance records and direct observation. Because of extensive spring flooding in the Prairies for these growing seasons, large areas were classified as “too wet to seed,” indicating that wetness conditions prevented farmers from seeding their fields late into the spring, leaving these areas uncultivated for the entire growing season. For 2010, only data from Saskatchewan and Alberta were available and for 2011, data from all Prairie provinces were used (Alberta, Saskatchewan, and Manitoba). For these, the area classified as too wet to seed was extracted for each CAR and was used to identify areas where impacts were greatest.

Finally, risk assessment conditions were assessed for 2012 and 2013 using government reports from the Agriculture Canada National Climate Related Production Risks Committee (CRPRC) reports. These reports are produced biweekly during the vegetation growth season (April–September) and monthly during the late winter/early spring (February/March) and fall (October/November). Climate analysts review numerous datasets, including meteorological data, seasonal weather forecasts, yield predictions, media reports, and producer-reported climate impacts collected through the Agroclimate Impact Reporter (AIR; www.agr.gc.ca/air). Reports consist of a textual description describing risk conditions in each region and the evidence base for these conclusions, as well as a “dashboard” that simplifies the risk assessment by classifying risk conditions for each province using a spectrum of risk from “no significant climate risk” to “one or more significant climate risks, large or urgent disaster impacts.” These dashboard assessments and CRPRC reports were used to compare stated risks in each region to soil moisture conditions as conveyed by the satellite record to determine if soil moisture trends are consistent with observed risk.

3. Results

Over the time period that SMOS has been operating, there have been a number of agricultural disasters related to both wet and dry extremes in Canada. The spring (April–June) period in the Prairies for both 2010 and 2011 saw periods of high rainfall combined with flooding on waterways to produce fields that were in many cases too wet to seed. In 2012, dryness evolved into drought in many areas of Ontario, Quebec, and the Maritimes. Data were assessed at both the monthly provincial scale and the CAR biweekly scale to determine how general trends as well as these specific risk events were captured by the SMOS soil moisture.

a. SMOS baseline as a surrogate for climate normals for risk assessment

Given the known errors in the absolute accuracy of SMOS soil moisture data, the use of anomalies (rescaling
of data around a long-term average) provides a means of interpreting data that show a lower absolute accuracy but may provide a good relative measurement. One of the limitations of satellite data records, especially the SMOS data record considered here, is that they cover a relatively short period of time and, therefore, are less representative of the statistical normals needed to detect relevant trends (Champagne et al. 2011). While this problem can be remedied by using a lengthier multi-satellite or modeled data record that is intercalibrated to a common soil moisture climatology, this can introduce other errors related to variable accuracy levels of the intercalibrated datasets (Albergel et al. 2013). The use of a 4-yr baseline was examined by comparing the average monthly precipitation using meteorological data from only the period when SMOS was operating (2010–13) to a more statistically robust 30-yr baseline from 1981 to 2010, derived according to WMO standard methods (Fig. 4). The 4-yr SMOS period shows some variability both geographically and temporally compared to the 30-yr normal, with April precipitation in Manitoba 12% higher than the 30-yr normal and May precipitation in the same province 11% lower than the 30-yr normal, representing the highest differences found. In general, monthly conditions for most provinces were near the 30-yr normal in April, below the 30-yr normal in May, wetter than the 30-yr normal for July–September, and drier than the 30-yr normal conditions in October. For most provinces and time periods, the SMOS period was drier than the 30-yr normal, but where the conditions were found to be wetter, the differences from the 30-yr normal were higher than the dry differences.

Precipitation and soil moisture are generally highly correlated, with precipitation events triggering a rapid soil wetting up, most dramatically at the surface, and then evapotranspiration and drainage processes leading to a slower dry-down period. At a very general level, precipitation and soil moisture should show a reasonable correlation. Figure 5 shows the relationship between average monthly SMOS soil moisture for the SMOS baseline and average monthly precipitation from meteorological stations for the same period. Overall, there is a Pearson correlation coefficient $R$ of 0.6 between these two datasets, showing that while there is some skill in using precipitation to determine SMOS soil moisture, there is a high degree of variability in the SMOS data that is not explained by the precipitation data. This likely reflects both errors in the SMOS data and the physical relationship between soil moisture and precipitation, because the soil moisture state is impacted by precipitation as well as temperature, soil type, and land management decisions.

b. Evaluation of SMOS soil moisture against agricultural risk events

1) Satellite soil moisture thresholds for risk events

Both the SMOS soil moisture difference from baseline and the SMOS soil moisture percentile were examined for their skill in capturing risk-related extremes at the monthly provincial scale. These indices were highly correlated, although in a nonlinear manner (Fig. 6). Soil moisture percentile values below 80% show a highly linear relationship, with each percentile representing approximately a 1%
difference from the SMOS soil moisture baseline, with values above the 80th percentile representing a larger than 1% change for each percentile.

The SMOS soil moisture and soil moisture anomaly data were summarized for each risk category related to moisture state outlined in the 2012/13 CRPRC reports (Fig. 7). The reports identified areas where conditions of flooding, excess wetness, dryness, drought, and heat conditions were detected. SMOS soil moisture was, in general, higher for areas experiencing wet extremes and lower for areas experiencing dry extremes. The SMOS soil moisture difference from the 2010–13 baseline shows moisture levels approximately 1% below the baseline for drought, dry, and heat-risk areas, while excess moisture and flood-risk areas are shown as 0.9% and 3% above the baseline, respectively. Differences between wet and dry extremes, and extremes and normal conditions, were found to be statistically significant for at least the $t = 0.10$ significance level using a paired $t$ test, with differences between wet and dry and wet and normal showing the highest level of statistical significance ($t = 0.005$ and $t = 0.05$, respectively). This shows that, at a very general level, SMOS is capturing critical moisture differences for risk assessment, and that the soil moisture anomalies, in spite of the short baseline period, are capturing trends related to agricultural risk. The 1% difference from the SMOS baseline for drought areas corresponds to the 37th percentile for soil moisture, which is somewhat higher than the 20% soil moisture percentile used to classify drought conditions in studies using modeled soil moisture data with a longer baseline (Sheffield et al. 2012).

This relatively small difference between drought and normal conditions seen in the SMOS data may reflect both the gross spatial scale of the data (drought may be occurring in part of the province, but not all of it, but the province is still identified as being under a drought risk), as well as related to the short baseline period. When the more geographically specific NADM data are examined, the threshold for drought is somewhat lower (less than $-1.9\%$ below the baseline for drought categories D0, D1, and D3, corresponding to 30th percentile or less; Table 1). Areas classified as D2 showed a higher soil moisture and soil moisture percentile, with less difference from the 4-yr baseline, which may be related to the

<table>
<thead>
<tr>
<th>SMOS volumetric soil moisture (%)</th>
<th>SMOS soil moisture difference from baseline (%)</th>
<th>SMOS soil moisture percentile (% of baseline)</th>
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<tr>
<td>Normal</td>
<td>18.2</td>
<td>0.3</td>
</tr>
<tr>
<td>D0</td>
<td>15.6</td>
<td>$-1.9$</td>
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<tr>
<td>D1</td>
<td>15.7</td>
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</tr>
<tr>
<td>D2</td>
<td>13.8</td>
<td>$-1.2$</td>
</tr>
<tr>
<td>D3</td>
<td>16.6</td>
<td>$-3.4$</td>
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FIG. 8. Time series of SMOS soil moisture difference from (left) baseline and (right) precipitation anomalies from geographically coincident meteorological stations for each growing season and each province.
small number of D2 areas and that many of these areas were localized drought, so the regional average reflects both drought and nondrought areas. This may also be related to the time scales of the NADM versus the satellite data; while the SMOS data in this case are showing monthly average soil moisture conditions, the NADM tends to reflect a mix of both short- and longer-term conditions.

A comparison between precipitation anomalies and SMOS soil moisture anomalies was conducted (Fig. 8). Soil moisture and precipitation anomalies followed a somewhat similar pattern in 2012 and 2013 for most regions, with the largest divergence for the BC and Maritimes regions. This may be due to high errors in the SMOS soil moisture for these regions because of complex mountainous topography in BC and the impact of saline water in the coastal Maritimes. Both regions also have a relatively small agricultural area, so the small sample size may also be an issue. The most pronounced differences are in 2010, where the SMOS soil moisture shows a normal to dry spring (April–June) for most areas, whereas the precipitation anomalies show a relatively wet spring in western Canada (BC, Alberta, Saskatchewan, and Manitoba) for the same period. This may be due to the skewed nature of the SMOS baseline, particularly in Manitoba, where the spring precipitation during the 2010–13 period was quite different from the 30-yr normal (Fig. 4). This failure to capture soil wetness may also be related to a lingering drought in the region: the NADM ratings for this period show large areas of BC, Alberta, Saskatchewan, and Manitoba as under drought conditions, and the large rainfall events that spring may have not sufficiently wetted an already dry soil surface (Fig. 9). It should also be noted in Fig. 8 that very dry events in September and October 2011 are not very obvious in the SMOS soil moisture anomalies, as are the precipitation anomalies in August and September 2012. This corresponds to the earlier observation that wet events may be captured more robustly than dry events in the SMOS data record.

2) DETAILED (CAR LEVEL) TRENDS

To determine if these general trends established using monthly data averaged at the provincial level hold up when more detailed temporal and spatial data are used, three CARs were examined from each of the impacted areas from 2010, 2011 floods, and 2012 drought (Fig. 10). For CAR 4751 (Wadena, Saskatchewan, which is located south of Yorkton), approximately 37% of the land area was left unseeded in 2010 as a result of high spring precipitation and flooding. Similarly, the region covered by CAR 4710 (near Estevan, Saskatchewan) experienced excessive moisture primarily in 2011, where 67% of the land area was shown as being unseeded by satellite crop maps. SMOS soil moisture shows that soil moisture was predominantly above the baseline, with soil moisture 6% higher than the baseline for the first two weeks of June 2010 in Wadena and 5% above baseline for Estevan for late May and early June 2011. These thresholds are more pronounced than is seen in the monthly provincial data. In April 2013, abnormally
low soil moisture was obtained from SMOS in the Wadena area, which is likely erroneous and represents frozen soils that were not captured by the temperature screening by the SMOS soil moisture retrieval algorithm. Figure 10 (top left) shows the very small dynamic range of soil moisture detected in this region by SMOS, which could make anomaly measurements very sensitive to small errors in soil moisture retrieval. The dry anomalies observed in eastern Ontario in 2011 and 2012 are more pronounced than can be seen in the more general monthly provincial data, with differences of up to 8% below normal seen during these dry periods (Fig. 10, bottom). This suggests that the thresholds for wet and dry extremes may be better delineated using more geographically detailed datasets.
3) SATELLITE SOIL MOISTURE AS A GEOSPATIAL INDICATOR OF EXTREME CONDITIONS

In 2010 and 2011, large areas of Saskatchewan and Manitoba were too wet for fields to be seeded, and these were captured geographically by annually produced national crop inventory maps. A visual comparison between the areas classified as too wet to seed and the difference from SMOS baseline soil moisture for the period from 31 May to 13 June 2010 shows a good visual correspondence (Fig. 11, top). Areas where soil moisture was found to be 2% above normal or higher correspond well to areas where the most extensive land area was left unseeded. The area northwest of Yorkton, Saskatchewan, was where the damage was most extensive, and for the most part, these areas show soil moisture
5% higher than normal. The area to the south that is shown as dry by the SMOS data in 2010 but that was also left unseeded may be erroneous because of the high soil moisture conditions in this area in 2011, which may have skewed the baseline.

In 2011, areas of the provinces of Saskatchewan and Manitoba were once again too wet to seed, with the area of extensive flooding shifted south of flooded areas in 2010 (Fig. 11, bottom). These areas are largely classified 2% above baseline soil moisture for this time period. There are large areas east of Brandon, Manitoba, where the SMOS data show very wet conditions but that do not show up as too wet to seed in the classified map for 2011. This may be because of land management decisions made by farmers, who in some cases were able to seed fields prior to the flooding and some crops were able to rebound and thrive as the growing season progressed. The latter is corroborated in CRPRC reports.

The 2012 growing season was a dry extreme for many areas, with areas in Ontario, Quebec, and the Maritimes experiencing dry extremes that formed part of an extensive drought that impacted many parts of North America as part of a La Niña (NOAA/NCDC 2013). Areas in southern and eastern Ontario were most severely impacted, with the NADM showing moderate to severe drought over much of the area in July and August (Fig. 12). SMOS soil moisture for the region at a monthly time scale shows drier-than-normal conditions for most of the impacted region in July, with areas near Ottawa, Ontario, showing the driest conditions. This is somewhat
consistent with the NADM ratings. The conditions for August (Fig. 12, bottom) show an improvement in conditions for most regions using both the NADM and the SMOS soil moisture anomalies. The area southeast of Toronto, Ontario, is still under severe drought in August, but this area shows only somewhat drier than baseline conditions. This may be due to precipitation events that led to an overall increase in surface soil moisture, but these precipitation events were not sufficient to alleviate the drought conditions in that region. Overall, drought conditions as categorized by the NADM show a gradation of soil moisture from normal to level D3, with the most severe drought areas showing SMOS soil moisture 3% below baseline conditions (Table 1).

4. Discussion and conclusions

At a very general level, the SMOS data from 2010 to 2013 is able to capture relevant trends related to agricultural climatic risk. The differences between extreme conditions and normal conditions are often quite small, leaving large room for errors in identifying these trends. Areas where the SMOS baseline period is either much wetter or much drier than the 30-yr normal are most problematic. Areas where moisture is extreme enough to cause flooding are identifiable at both the provincial and regional scale (showing differences from the 4-yr baseline of 5% or higher). Areas where dryness or drought are occurring are up to 3% lower than the baseline, but the more subtle dry areas are only 1%-2% drier than the SMOS baseline, which may reflect the limitations of the short SMOS baseline; errors in the SMOS soil moisture itself; and the limitation of satellite soil moisture remote sensing, which is limited to surface conditions only. Errors that are particularly relevant for northern regions, such as frozen or partially frozen soil conditions in the spring that are not adequately flagged, can lead to erroneous dielectric measurements that appear as dry soils where the soils are instead partially frozen.

In spite of these limitations, the SMOS soil moisture dataset does provide a good general picture of risk-related soil moisture trends, and the thresholds become more evident when smaller regions and shorter time scales are used. Large-scale events such as the 2010 and 2011 Prairie flooding and excess moisture were captured well by the SMOS data, and drought conditions were apparent for 2012. The provincial and regional trends showed variable errors at specific time periods, primarily during periods of excess dryness. The limitations of the short SMOS baseline could be minimized by increasing the baseline period either through time or using a modeled/measured surrogate baseline (Liu et al. 2012). Overall, these results suggest that SMOS soil moisture data can be a very robust tool for identifying risk conditions, particularly in areas where meteorological data are sparse. SMOS provides a near-instantaneous assessment of risk when data are examined in near–real time, which can be particularly useful for determining the areal extent of excess wetness, and can be used over a longer time span to assess slowly emerging risks such as drought and dry spells. Future work will examine the robustness of using multisensor or modeled soil moisture baselines, as well as looking at modeled root zone soil moisture derived from satellite-data-assimilated land surface models.

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