Quantifying the uncertainty introduced by internal climate variability in projections of Canadian crop production

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Abstract

Internal climate variability (ICV) is one of the major sources of uncertainty in climate projections, yet it is seldom quantified for projections of crop production. Our study focuses on quantifying the uncertainty due to ICV in projections of crop productions in Canada. We utilize climate scenarios from two large ensembles (LEs, CanESM2-LE and CanRCM4-LE with 25 members each) as inputs to the crop models in the Decision Support System for Agrotechnology Transfer. We simulate crop yields for canola, maize and spring wheat under the future climates of four global warming levels. The coefficient of variation (CV) of the projected crop production across the LE members is used to quantify the uncertainty related to ICV and this is compared with the CVs generated using the 20 GCMs in the Coupled Model Intercomparison Project Phase 5 (CMIP5). Crop production in Canada could increase with global warming, e.g. spring wheat production could increase by up to 21% at the warming level of 3.0 \(\degree\)C. The projections often produce larger uncertainty associated with the GCMs than from ICV at all warming levels above 2.0 \(\degree\)C. The results from an asymptotic test for the equality of CVs show a significant difference in CVs of projections of canola production between CanESM2-LE/CanRCM4-LE and CMIP5 for the warming level of 3.0 \(\degree\)C. However, the test results do not indicate a significant difference among the ensembles at all four warming levels for maize and spring wheat. The uncertainty due to ICV is often comparable to that associated with GCMs at the warming level of 1.5 \(\degree\)C, e.g. a CV of 6.0 and 6.4% for CanESM2-LE and CanRCM4-LE and 6.6% for CMIP5 in the projections of spring wheat production. We conclude there is a need to account for uncertainty related to ICV in projections of Canadian crop production, especially at lower warming levels.

1. Introduction

The potential negative impact of climate change on global crop production combined with the food demands and rapid increase in the global population has raised great concern for future food security (Wheeler and von Braun 2013). Projecting crop yields and production under future climate scenarios is essential for assessing food security. Modelling is a key tool to explore agricultural impacts of and adaptations to climate change (Rötter et al 2018). (Porter et al 2019) found that climate change impacts on agriculture and food security in the Intergovernmental Panel on Climate Change (IPCC) Assessment Reports (ARs) relied strongly on projections from computer crop simulation models. Crop growth models have been widely used to assess climate change impacts on crop yields and production around the world (e.g. Rosenzweig et al 2014, Asseng et al 2017, Wang et al 2017, Chen et al 2018, Faye et al 2018, Qian et al 2019). There are however large uncertainties attributed to crop yields and production under future climate scenarios that are associated with the structure and parameterization of these models and the future climate scenarios used to drive them (Asseng et al 2013, Tao et al 2018, Zhang et al 2019).

Quantification of the uncertainty in crop yield projections is typically ascertained using multiple crop models, and using an ensemble of climate scenarios from multiple global climate models (GCMs),
under different forcing scenarios. Quantifying this uncertainty has been one target of the global research efforts in the Agricultural Model Intercomparison and Improvement Project (AgMIP) (Rosenzweig et al 2013). Some modelling studies (e.g. Bregaglio et al 2017, Giuliani et al 2019) describe possible sources of uncertainties in crop yield projections which are associated with crop models, climate projections (GCMs) and the methods employed for simulating changes in agricultural management and adaptation strategies. While studies have found that a greater portion of the uncertainty in climate change impact projections was due to variations among the crop models than to the variations amongst the downscaled GCMs (Asseng et al 2013), a recent study (Zhang et al 2019) claims that the uncertainty in the maize-yield simulations might mostly be from the GCM models, followed by the crop models and RCPs. (Tao et al 2018) found that the contribution of crop model structure to the total variance of ensemble output was larger than that from downscaled climate projections and crop model parameters. However, they also noted that the contribution of downscaled climate projections was, on average, larger than that of crop model parameters. Nevertheless, future climate scenarios are significantly contributing to the uncertainty in projections of crop yields and production at different scales from local, regional to global.

Internal climate variability (ICV) or natural climate variability, which is typically referred to as the variations resulting from the chaotic nature of the climate system without external forcings, together with climate model response and forcing scenarios are the three major sources of uncertainty in climate projections (Tebaldi and Knutti 2007, Hawkins and Sutton 2009, Deser et al 2012a). As climate models improve, uncertainty associated with model response can be reduced. Internal climate variability, however, has inherent limits to climate predictability and the related uncertainty is difficult to reduce. Deser et al (2012b, 2014) demonstrated the important role of ICV in the projections of future North American climate based on a 40-member ensemble of climate change simulations conducted with the National Center for Atmospheric Research Community Climate System Model version 3 (CCSM3). Furthermore, characterization of climate uncertainty at regional scales over near-term planning horizons (0–30 years) is crucial to ensure that appropriate climate adaptations are enacted while ICV dominates climate uncertainty over decadal prediction horizons at regional to local scales (Kumar and Ganguly 2018).

To our knowledge, the uncertainty due to ICV in the projections of crop yields and production is seldom quantified. Very few studies (Sultan et al 2019, Dale et al 2017, Lobell and Tebaldi 2014) included the effects of ICV in their assessment on climate change impacts. This gap might be related to the availability of large ensembles of climate simulations by climate models designated for the study of ICV.

In a previous study, we quantified the climate change impacts on Canadian crop yields and production using three crop simulation models across 20 GCMs (Qian et al 2019). The objectives of our current study are (i) to quantify the uncertainty introduced by ICV in projected crop production for three major crops—canola, spring wheat and maize in Canada, and (ii) to compare this estimate with the uncertainty associated with simulating crop production across an ensemble of multiple GCMs. The uncertainty due to ICV is quantified using the crop growth models in the Decision Support System for Agrotechnology Transfer (DSSAT v4.6, Hoogenboom et al 2015) driven by climate scenarios from 25 members of each large ensemble performed with CanESM2 and CanRCM4, a global climate model and a regional climate model developed in Canada (Kirchmeier-Young et al 2017a, Scinocca et al 2016). This study allowed us to compare the contribution of ICV with the uncertainty previously estimated from the multi-GCM ensemble in the projection of three major crops in Canada under future climate change. Understanding the magnitudes of the associated uncertainties with projections of crop production is especially valuable to decision-makers for near-term policy planning.

2. Materials and methods

2.1. Crop production in Canada

To be consistent with methodologies in (Qian et al 2019), this study is based on regions that represent areas of similar agricultural production in the Canadian Regional Agricultural Model (CRAM, Horner et al 1992). Crop production data for the CRAM regions are most readily available for the 10 years from 2006 to 2015 which we use as the baseline period. Until recent years spring wheat had been the dominant Canadian crop but it has been replaced by canola. Canola is grown mostly (99%) on the Canadian Prairies and approximately one half of the cultivated area is in Saskatchewan. A majority (98%) of spring wheat is cultivated on the Canadian Prairies with a contribution of 51% in Saskatchewan, 35% in Alberta and 14% in Manitoba. Only spring wheat is investigated in this study, therefore, we define ‘wheat’ hereafter as to represent spring wheat. Maize is a prominent crop but its production is restricted to southern Ontario, Quebec and Manitoba due to its climate requirements. Maize is currently cultivated mostly in Ontario (61%), Quebec (30%) and a small portion in Manitoba (8%). The distribution of these three crops across the agricultural regions in Canada is detailed in figure 1. Projections of crop yields and production are based on the current cultivation areas of these crops. Water stress is currently a critical factor limiting canola and wheat yields on the Canadian Prairies while heat units with a short growing season have
limited maize production in Canada. It should be noted that the cultivation areas may change under future climates and are dependent on the global commodity market, but these aspects are outside the scope of this study.

2.2. Climate scenarios
Climate scenarios developed from the climate change simulations under RCP8.5 by 20 GCMs included in the Coupled Model Intercomparison Project Phase 5 (CMIP5, Taylor et al 2012) were used in (Qian et al 2019). CanESM2 (Arora et al 2011), a coupled Earth system model developed at the Canadian Centre for Climate Modelling and Analysis (CCCma), was one of these 20 GCMs. The CMIP5 submission included five ensemble members for each GCM although only one member for each GCM was used in (Qian et al 2019). The Canadian Sea Ice and Snow Evolution Network and the Climate Change and Atmospheric Research Network proposed a large-ensemble project to expand the initial five-member ensemble of CanESM2 by branching each of the original five members into ten ensemble members (CanESM2-LE, Kirchmeier-Young et al 2017a). A large ensemble by the Canadian Regional Climate Model (Scinocca et al 2016) (CanRCM4-LE) was an extension of CanESM2-LE. Each ensemble member of CanRCM4-LE was driven by a member of CanESM2-LE. Each member of CanESM2-LE was based on very small perturbations to cloud overlap parameters in 1950. The result was a 50-member initial condition ensemble in which all members shared the same radiative forcings, i.e. ICV was the only thing that made them different.

In our current study, we utilize climate scenarios from 25 members, respectively in CanESM2-LE with a resolution approximately at 2.8° latitude × 2.8° longitude and CanRCM4-LE with a resolution of 0.44° × 0.44°. We use daily solar radiation (Rad), daily maximum temperature (T_{\text{max}}), daily minimum temperature (T_{\text{min}}) and daily precipitation (P), from the CanESM2-LE output which was downscaled and bias-corrected based on a multivariate form of quantile mapping (Kirchmeier-Young et al 2017b, Cannon 2018). A previous study (Oettli et al 2011) found large variations in estimated sorghum yields when using ten RCMs in a climate/crop modelling system, but promising results were obtained after applying a bias-correction technique to the RCM outputs. Thus the bias-correction procedure based on the multivariate form of quantile mapping (Cannon 2018) was applied to the CanRCM4-LE output. In our study, the bias-correction is based on the 1971–2000 historical observations at a representative station located in the agricultural areas in each CRAM region. The timing
when the global mean temperature would reach the warming levels for all members in CanESM2-LE and CanRCM4-LE is deemed the same, i.e. 2014, 2028, 2039 and 2050, respectively, for the levels of 1.5 °C, 2.0 °C, 2.5 °C and 3.0 °C.

2.3. Crop simulation

Crop simulation models, CSM-CROPGRID-Canola, CSM-CERES-Wheat and CSM-CERES-Maize in DSSAT v4.6, were previously used to simulate crop growth and yields for canola, spring wheat and maize across CRAMs where these crops are currently grown (Qian et al. 2019). A synthetic description of these crop models can be found in the supplementary material (available online at stacks.iop.org/ERL/15/074032/mmedia). These crop models have been widely used in climate change impact studies worldwide, and they have been calibrated and evaluated with field experimental data in Canada (Jing et al. 2016a, 2016b, 2017), and further used to assess climate change impacts (Qian et al. 2016, 2018, 2019). In our current study, we only use one crop model for each crop to easily distinguish the uncertainty related to climate scenarios rather than that associated with crop models. However, it should be noted that the range of variation in the projected crop yields and production might be different if other crop models are used.

Climate and soil data, crop parameters and crop management data are required as inputs to the crop simulation models and these inputs determine the simulated crop yields in the models. In this study DSSAT simulations are performed to estimate crop growth and yield for the 25 members of CanESM2-LE and CanRCM4-LE and we also compare to the DSSAT simulations with the 20 GCMs of CMIP5 carried out in (Qian et al. 2019). To be comparable with the previous results, we use the same settings in crop simulations as used in (Qian et al. 2019) except the climate scenarios are from CanESM2-LE and CanRCM4-LE. The models are run across three soil textures (sandy loam, loam, and clay loam) for each CRAM region. Direct effects of atmospheric CO$_2$ concentration on crop yields are simulated by using the historical and projected values of the atmospheric CO$_2$ concentration based on (Meinshausen et al. 2011). All simulations are also conducted using atmospheric CO$_2$ concentrations at the current level (~380 ppm) to investigate the effects of atmospheric CO$_2$ concentration on projected crop yields. The atmospheric CO$_2$ concentration levels can be different among the CMIP5 ensemble members due to the difference in the timing of the global warming levels in a GCM.

To focus on the climate impacts, we simulated the potential yield ($Y_p$) for seeds/grains and the water-limited yield ($Y_w$) of the crops grown without N stress. The crop models in DSSAT have simulation options to turn off both water stress and N stress for simulating $Y_p$ or turn off only N stress for $Y_w$.

Simulated yields across the three soil textures are averaged for each CRAM by using the areal fractions of the three types in the CRAM region as weighting. Crop production for each CRAM region is estimated by multiplying the yield with the average acreage of the crop during 2006–2015 in the region, and then the Canadian production is derived by summing up the production from each CRAM region where the crop is grown.

We adopt a drought stress index (DSI) of (Semenov and Shewry 2011) to investigate the impact of water stress on uncertainty in projected crop yields and production. It is important to account for water stress as the uncertainty in projections of precipitation is often considered large and crop production in Canada is 99% under rainfed conditions. DSI is defined as a percentage of the yield loss due to water stress, thus

$$DSI = \frac{(Y_p - Y_w)}{Y_p} \times 100.$$  

(1)

Medians of DSI (DSI$_{med}$) are calculated from the annual production based on the simulated $Y_p$ and $Y_w$ for the baseline climate and the 30-yr periods for each climate scenario at the four global warming levels.

2.4. Quantifying the uncertainty in projections

Uncertainty in projections of crop yields and production is often measured by the range of variations in such projections. The coefficient of variation (CV) was used to quantify the uncertainty in (Asseng et al. 2013) from simulated wheat yields using 26 crop models and 16 downscaled climate scenarios. The CV is also known as a relative standard deviation and often expressed as a percentage. In this study, the CVs are calculated from 30-year means of all members in an ensemble for each global warming level. We also use the CV to quantify the uncertainty in projections of growing season precipitation but use standard deviation (SD) to quantify the uncertainty in projections of growing season mean temperature ($^\circ$C). The CV and SD are calculated across the 25 members of CanESM-LE and CanRCM4-LE, as well as the 20 GCMs of CMIP5, for the global warming levels at 1.5, 2.0, 2.5 and 3.0 °C respectively.

An asymptotic test for the equality of coefficients of variation (Feliz and Miller 1996) is applied to test if there is a significant difference in the CVs of projections between the ensembles as well as between the global warming levels. In the asymptotic test, the test statistic $D’AD$ in the equation (2) follows a central $\chi^2$ distribution with $k - 1$ degree of freedom. The hypothesis of equality is rejected if the $p$-value for the statistic exceeding the estimated value is smaller than the significance level.

$$D’AD = \tau^{-2} \left(0.5 + \tau^2\right)^{-1} \sum_{i=1}^{k} \frac{m_i \left(\frac{s_i}{M}\right)^2 - \tau^2}{M}.$$  

(2)
Table 1. Ensemble means of crop production (Mt) for the baseline (B, 2006–2015) and projected changes (%) for the time periods under the global warming levels at 1.5, 2.0, 2.5 and 3.0 °C using climate scenarios from CMIP5, CanESM2-LE and CanRCM4-LE with/without the direct effects of CO2.

| Climate scenarios (°C) | Warming level | Crop          |                |                |                |
|------------------------|---------------|---------------|----------------|----------------|----------------|
|                        |               | Canola        | Maize          | Wheat          |
|                        |               | CO2           | Without CO2    | CO2            | Without CO2    |
| CMIP5                  | B             | 15.50 (Mt)    | 15.14 (Mt)     | 11.52 (Mt)     | 11.47 (Mt)     | 23.84 (Mt)     | 23.39 (Mt)     | 4.7 | 0.6 |
|                        | 1.5           | 1.8           | -5.0           | 2.1            | 0.3            | 4.7            | 0.6            | 10.4 | 1.1 |
|                        | 2.0           | 5.4           | -8.6           | 0.3            | -3.3           | 10.4           | 1.1            | 15.6 | 0.9 |
|                        | 2.5           | 3.6           | -15.1          | -1.0           | -6.4           | 15.6           | 0.9            | 20.9 | 0.2 |
|                        | 3.0           | 0.4           | -22.1          | -5.6           | -12.6          | 20.9           | 0.2            |
| CanESM2-LE             | B             | 13.20 (Mt)    | 12.93 (Mt)     | 11.17 (Mt)     | 11.12 (Mt)     | 24.06 (Mt)     | 23.97 (Mt)     | 4.6 | -0.2 |
|                        | 1.5           | 0.9           | -0.4           | 0.4            | 0.0            | 1.4            | 0.2            |
|                        | 2.0           | -0.8          | -7.5           | 1.2            | -0.8           | 4.6            | -0.7           |
|                        | 2.5           | -7.2          | -17.0          | -1.4           | -4.9           | 7.3            | -2.2           |
|                        | 3.0           | -17.4         | -28.5          | -6.0           | -10.8          | 12.1           | -2.7           |
| CanRCM4-LE             | B             | 14.11 (Mt)    | 13.8 (Mt)      | 11.57 (Mt)     | 11.52 (Mt)     | 24.65 (Mt)     | 24.42 (Mt)     | 12.1 | 2.7 |
|                        | 1.5           | -1.5          | -3.0           | 0.3            | -0.1           | 0.9            | -0.04          |
|                        | 2.0           | 0.4           | -7.5           | 1.6            | -0.5           | 5.9            | 1.0            |
|                        | 2.5           | -3.2          | -14.9          | 2.1            | -1.4           | 9.8            | 0.8            |
|                        | 3.0           | -8.4          | -23.1          | 0.1            | -4.9           | 16.0           | 1.6            |

*All numbers aligned with warming levels are the projected changes (%) in crop production relative to the baseline means.

\[ m_i = n_i - 1 \] (3)

\[ M = \sum_{i=1}^{k} m_i \] (4)

\[ \tau = \left( \frac{\sum_{i=1}^{k} m_i s_i^2}{M} \right) \] (5)

where \( n_i \) is the number of members in the \( i \)th ensemble, i.e. 20 for CMIP5 and 25 for CanESM2-LE and CanRCM4-LE, respectively; \( \bar{x}_i \) and \( s_i \) are the ensemble mean and standard deviation for the projections in the \( i \)th ensemble; and \( k \) is 2 when the test is performed for two ensembles. We considered that the equality of coefficients of variation between the two ensembles should be rejected if the \( p \)-value is smaller than 0.05.

3. Results and discussion

3.1. Ensemble mean of projected changes in crop production

A comparison of the ensemble means of projected changes (%) in crop production is shown in table 1 for three ensembles, CanESM2-LE, CanRCM4-LE and CMIP5, together with ensemble means of the production for the baseline period. Since crop production in Canada is mostly under rainfed conditions, we consider the simulated crop production under rainfed to be an attainable measure of future production whereas the simulations of potential yield are mainly used for understanding the mechanisms of climate impacts.

We find that the baseline climate simulated by CanESM2-LE and CanRCM4-LE is slightly unfavourable for canola production in comparison to CMIP5 but is similar for maize and slightly favourable for spring wheat. Furthermore, the projected future changes in canola production are slightly positive for CMIP5 although the increase peaks at the warming level of 2.0 °C and then declines from 5.4% to 0.4% at the warming level of 3.0 °C. In contrast, canola production is projected to more likely decrease for CanESM2-LE and CanRCM4-LE, especially CanESM2-LE with a decrease starting at 2.0 °C but a slight positive change (0.4%) at 2.0 °C for CanRCM4-LE. These results help to explain the differences reported between previous studies, (Qian et al 2019) versus (Qian et al 2018). Future climate scenarios used in (Qian et al 2018) which were developed from one member of CanRCM4-LE, driven by CanESM2, were unfavourable for canola growth and yield. A relatively large increase in canola yields by 6.1%, 11.1%, 10.8% and 7.7% at the global warming levels of 1.5 °C, 2.0 °C, 2.5 °C and 3.0 °C, respectively, was simulated with CMIP5 in (Qian et al 2019).

Simulations indicate that the future climate of CanRCM4-LE is more favourable for maize production than CMIP5 and CanESM2-LE. We project a decrease in maize production by approximately 1% at 2.5 °C and 6% at 3.0 °C for CMIP5 and CanESM2-LE, respectively, but there is a slight simulated increase for CanRCM4-LE. These differences may be related to the fact that the growing season mean T max is lower in CanRCM4-LE with slightly more precipitation than the other two ensembles (figure 2). Since maize production is concentrated in a smaller region, mainly in southern Ontario, climate in such a small region
Figure 2. Growing season (May 1st–September 30th) mean $T_{\text{max}}$ and precipitation total averaged across the maize production regions in Canada simulated by three climate ensembles, CMIP5, CanESM2-LE and CanRCM4-LE, for the baseline (2006–2015) and the time periods of the projected global warming levels at 1.5, 2.0, 2.5 and 3.0 $^\circ$C. The boxplots show the 10th, 25th, 50th, 75th, and 90th percentiles of simulated values across the 20 GCMs in CMIP5 and 25 members of CanESM2-LE and CanRCM4-LE. One member of CanESM2 included in CMIP5 is marked with a circle.

simulated by the regional model can be largely different from that simulated by its driving GCM. In other words, the approaches used for downscaling GCM outputs could have remarkable effects on the projections of crop production at the regional scale.

We project wheat production to continuously increase under all global warming levels and the three ensembles in this study. Larger increases in wheat production for CMIP5 can be partially attributed to higher realized CO$_2$ levels. This is because the time for many CMIP5 models to reach the same global warming level is later than for CanESM2. Again, the scenarios with CanESM2-LE appear to be less favourable for wheat production than CanRCM4-LE, as determined for the other two crops (table 1).

Overall, the projections of crop production for canola, spring wheat, and maize in Canada are in line with our multi-model assessment (Qian et al 2019). As a northern country, crop production could be benefited from global warming, especially from elevated atmospheric CO$_2$ concentration, providing adaptation measures related to agronomic management practices are implemented. Comparing the large differences in the projected changes of canola production between CanESM2-LE and CMIP5, we reassert the necessity of using climate scenarios from multiple
GCMs in the assessment of climate change impacts on crop production as the assessment could be very much biased otherwise.

3.2. Uncertainty in the projections
We presented the boxplots of simulated crop production for canola, maize and wheat under the global warming levels at 1.5, 2.0, 2.5 and 3.0 °C, based on climate scenarios from CMIP5, CanESM2-LE and CanRCM4-LE in figure 3. The ranges of projected crop production based on CMIP5 are often larger than those based on CanESM2-LE and CanRCM4-LE, for all three crops. For CMIP5, these ranges increase with rising global warming

Figure 3. Crop production (million tonne) of canola, maize and wheat in Canada for the projected global warming levels at 1.5, 2.0, 2.5 and 3.0 °C, based on the simulated rainfed yields with climate scenarios from three climate ensembles, CMIP5, CanESM2-LE and CanRCM4-LE. The boxplots show the 10th, 25th, 50th, 75th, and 90th percentiles of simulated values across the 20 GCMs in CMIP5 and 25 members of CanESM2-LE and CanRCM4-LE. One member of CanESM2 included in CMIP5 is marked with a circle.
Table 2. Ensemble means of crop production (Mt) and coefficient of variation (CV, %) across the ensemble members for the time periods under the global warming levels at 1.5, 2.0, 2.5 and 3.0 °C simulated with climate scenarios from CMIP5, CanESM2-LE and CanRCM4-LE with/without (in brackets) the direct effects of CO₂.

| Climate scenarios | Warming level (°C) | Canola Mean (Mt) | Canola CV (%) | Maize Mean (Mt) | Maize CV (%) | Wheat Mean (Mt) | Wheat CV (%) |
|------------------|-------------------|-----------------|---------------|----------------|--------------|----------------|--------------|
| CMIP5            | 1.5               | 15.78 (14.38)   | 15.0 (13.2)   | 11.76 (11.51)  | 7.7 (7.5)    | 24.95 (23.54)  | 6.6 (5.9)    |
|                  | 2.0               | 16.34 (13.84)   | 21.7 (17.1)   | 11.56 (11.09)  | 8.4 (8.0)    | 26.31 (23.69)  | 8.2 (5.2)    |
|                  | 2.5               | 16.06 (12.86)   | 27.7 (21.5)   | 11.41 (10.74)  | 9.9 (9.7)    | 27.55 (23.60)  | 9.2 (6.4)    |
|                  | 3.0               | 15.56 (11.88)   | 32.3 (25.3)   | 10.87 (10.02)  | 13.3 (13.4)  | 28.82 (23.44)  | 10.3 (7.3)   |
| CanESM2-LE       | 1.5               | 13.32 (12.88)   | 12.3 (12.0)   | 11.21 (11.12)  | 5.5 (5.5)    | 24.39 (24.01)  | 6.0 (6.2)    |
|                  | 2.0               | 13.09 (11.96)   | 11.0 (10.5)   | 11.30 (11.03)  | 6.7 (6.8)    | 25.17 (23.81)  | 5.4 (5.5)    |
|                  | 2.5               | 12.25 (10.73)   | 14.4 (12.8)   | 11.01 (10.58)  | 5.5 (5.6)    | 25.81 (23.45)  | 5.1 (5.2)    |
|                  | 3.0               | 10.90 (9.24)    | 17.5 (15.1)   | 10.50 (9.92)   | 6.8 (6.9)    | 26.98 (23.32)  | 5.6 (5.8)    |
| CanRCM4-LE       | 1.5               | 13.90 (13.39)   | 15.1 (14.7)   | 11.61 (11.51)  | 5.5 (5.5)    | 24.88 (24.41)  | 6.4 (6.5)    |
|                  | 2.0               | 14.17 (12.77)   | 14.5 (13.6)   | 11.75 (11.46)  | 6.1 (6.2)    | 26.10 (24.67)  | 5.2 (5.3)    |
|                  | 2.5               | 13.66 (11.74)   | 15.2 (13.6)   | 11.81 (11.36)  | 4.5 (4.6)    | 27.06 (24.62)  | 4.9 (5.0)    |
|                  | 3.0               | 12.92 (10.61)   | 19.9 (17.3)   | 11.58 (10.96)  | 5.8 (5.9)    | 28.60 (24.80)  | 5.9 (6.1)    |

Table 3. Results (p-value*) from an asymptotic test for the equality of coefficients of variation in projections of canola production.

| Climate scenarios | Warming levels (°C) | 1.5 | 2.0 | 2.5 | 3.0 |
|------------------|-------------------|-----|-----|-----|-----|
| CMIP5            |                   |     |     |     |     |
| 1.5              |                   |     |     |     |     |
| 2.0              |                   | 0.1156 |     |     |     |
| 2.5              |                   | 0.0631 | 0.0407 |     |     |
| 3.0              |                   | 0.0374 | 0.0251 | 0.0158 |     |
| CanESM2-LE       |                   |     |     |     |     |
| 1.5              |                   |     |     |     |     |
| 2.0              |                   | 0.2169 | 0.1225 | 0.0655 | 0.0380 |
| 2.5              |                   | 0.2385 | 0.1330 | 0.0704 | 0.0406 |
| 3.0              |                   | 0.1830 | 0.1055 | 0.0574 | 0.0337 |
| CanRCM4-LE       |                   |     |     |     |     |
| 1.5              |                   |     |     |     |     |
| 2.0              |                   | 0.1722 | 0.0999 | 0.0547 | 0.0323 |
| 2.5              |                   | 0.1814 | 0.1047 | 0.0570 | 0.0335 |
| 3.0              |                   | 0.1074 | 0.0653 | 0.0372 | 0.0227 |

*p-values smaller than 0.10 are in italic and 0.05 in bold.

level while they remain more consistent for CanESM2-LE and CanRCM4-LE. These results imply that uncertainty in projected crop production in Canada increases with the global warming level in the multi-GCM ensemble but the uncertainty related to ICV in CanESM2-LE and CanRCM4-LE remains more stable. However, the ranges of the projections based on either CMIP5 or the large ensembles for ICV are comparable for the near-term, i.e. the period up to the global warming level of 1.5 °C.

Ensemble means and the corresponding CVs in projections of crop production for canola, maize and wheat based on climate scenarios from the three ensembles are shown in table 2, for simulations with/without the direct effects of elevated CO₂ concentration. As aforementioned, climate simulated by CanESM2-LE appears to be unfavourable for canola production, thus the ensemble means are often lower than those by CMIP5. These observations are also applicable to wheat. Ensemble means of canola production decreased after the warming level of 2.0 °C with increasing CVs for all three ensembles; however, the CVs for CMIP5 are much larger than those for CanESM2-LE and CanRCM4-LE. The CVs for CMIP5 are still larger when the direct effects of elevated CO₂ concentration are not accounted for in simulations. This implies that the larger uncertainty in CMIP5 is associated more to climate differences in multiple GCMs rather than to the differences in CO₂ related to the timing differences in the GCMs for the selected global warming levels. Larger and increasing CVs are also seen for maize and wheat for CMIP5 than for the other two ensembles. As expected, the effects of CO₂ on maize production are much smaller than for canola and wheat because there is no effective CO₂ response to C assimilation in C₄ crops (such as maize) in comparison to C₃ crops (wheat, canola, etc) (Leakey et al. 2006). When the direct effects of elevated atmospheric CO₂ concentration is not simulated, canola and maize productions are projected to decrease with rising global warming levels for all three ensembles mainly due to the rising growing season temperature (table 4). Higher temperatures may reduce crop productivity by shortening the
crop life cycle of current cultivars (Qian et al. 2018), in addition to resulting in heat stress that is less favourable for photosynthesis. While the growing season precipitation is not projected to have large changes (table 5), higher temperatures may increase evapotranspiration resulting in water stress that can further reduce crop productivity. In contrast, the projected wheat production does not always decrease with rising warming levels when the direct CO2 effect is not simulated. This could be related to the temperature thresholds in the CSM-CERES-Wheat model, which did not include the impacts of heat stress during anthesis and other related phenological periods (Qian et al. 2019). These results show that the uncertainty associated with climate models is often larger than the uncertainty related to ICV in projections of crop production in Canada, especially for canola.

However, results from an asymptotic test for the equality of coefficients of variation in projections of crop production for three crops did not indicate a significant difference in CVs of projected crop production for maize and spring wheat either between the ensembles or between the warming levels, at the significance level of 0.05 (not shown). The test results for canola are shown in table 3, indicating a significant difference between CMIP5 and CanESM2-LE/CanRCM4-LE at the global warming level of 3.0 °C. A significant difference is also observed in projections with CMIP5 between the global warming level of 3.0 °C and lower warming levels, which is seen in projections neither with CanESM2-LE/CanRCM4-LE nor between CanESM2-LE and CanRCM4-LE. Therefore, the CVs for CanESM2-LE and CanRCM4-LE were often comparable to those for CMIP5 in projections of crop production, especially at the warming levels of 1.5 °C and 2.0 °C, demonstrating the importance of accounting for the uncertainty resulting from ICV in projections for crop production in Canada.
Figure 4. Median values of drought stress index (DSI) for crop production of canola, maize and wheat in Canada for the projected global warming levels at 1.5, 2.0, 2.5 and 3.0 °C, based on the simulated crop yields with climate scenarios from three climate ensembles, CMIP5, CanESM2-LE and CanRCM4-LE. The boxplots show the 10th, 25th, 50th, 75th, and 90th percentiles of simulated values across the 20 GCMs in CMIP5 and 25 members of CanESM2-LE and CanRCM4-LE. One member of CanESM2 included in CMIP5 is marked with a circle.

An earlier study (Dale et al 2017) demonstrated that internal variability was a major source of uncertainty in both within-model and between-model ensembles and explained the majority of the spatial distribution of uncertainty in yield projections. They used the ‘delta’ method by applying the simple change factors from GCMs to historical climate data to create the climate scenarios to drive the AquaCrop model. A possible shortcoming of using the ‘delta’ method is that it does not incorporate changes in climate variability, and furthermore it does not account for potential changes in precipitation occurrences that can be critical to crop growth and yields, especially in dry regions. We used climate scenarios from both GCM and RCM with bias correction using a multivariate form of quantile mapping that preserves...
inter-site and inter-variable dependence structure. This approach may better incorporate the differences in climate variability that are important for simulating crop growth and yields in relation to the simple ‘delta’ method.

3.3. Connections between uncertainties in projections of climate and crop production

Since we only use one crop model for each crop to project crop production in Canada, the uncertainty in projections can be attributed to the climate scenarios although the magnitudes of the uncertainties in crop production might differ if other crop models were used. Projected temperatures may impact simulated crop potential and rainfall yields while precipitation would only affect rainfall yields. DSI reflects the effects of water stress on crop yields/production under climate change resulting from low precipitation inputs and/or higher evapotranspiration rates due to increased temperatures. Figure 4 shows boxplots of DSI_{med} for canola, maize and wheat calculated from simulated rainfall and potential crop production with climate scenarios from CMIP5, CanESM2-LE and CanRCM4-LE, for periods of projected global warming levels at 1.5, 2.0, 2.5, and 3.0 °C. It is clear that the range of DSI_{med} for all three crops with CMIP5 is often larger than for CanESM2-LE and CanRCM4-LE. Furthermore, the range increases with rising global warming levels for CMIP5 while it remains relatively unchanged for CanESM2-LE and CanRCM4-LE. Nevertheless, the ranges are comparable among the three ensembles at 1.5 °C for three crops, and also at 2.0 °C for maize and wheat. These results are consistent with the assessments of yield uncertainty in figure 3 and thus indicate that water stress is a dominant driver behind the yield projection while increasing temperatures can limit crop yield potentials.

Larger ranges of DSI_{med} and their increasing trends with CMIP5, are related to larger uncertainties in projected temperatures and precipitation. It is worthwhile to note that the simulated canola yields are more sensitive to water stress than the other two crops. Such differences may be related to crop model structures as the CSM-CROPGRO-Canola model in DSSAT differs significantly from CSM-CERES-Wheat and -Maize models. Ensemble means and their corresponding CVs and SDs are shown in tables 4 and 5, for the growing season mean T_{max} and precipitation, respectively, for CMIP5, CanESM2-LE and CanRCM4-LE. Noticeable differences in the projected growing season climate conditions, especially precipitation, can be observed among the ensembles. For example, the growing season precipitation in CanESM2-LE is slightly smaller than for the other two ensembles. While these differences are associated with large uncertainties in climate projections by the climate models, downscaling methods (CanESM2-LE vs. CanRCM4-LE) may also have a role. It is clear that the SDs for T_{max} increase with the global warming level in CMIP5 while they remain almost constant in CanESM2-LE and CanRCM4-LE. They are often larger in CMIP5 than in the other two ensembles, especially at higher global warming levels. The SDs at the warming level of 1.5 °C are similar for CMIP5 and CanRCM4-LE but the SDs are always smaller for CanESM2-LE than the other two ensembles. It is also notable that the CVs of growing season precipitation in CMIP5 increase with the rising global warming levels but there is little change for CanESM2-LE and CanRCM4-LE. Similar CVs are found at the warming level of 1.5 °C for all three ensembles, indicating the unneglectable role of ICV in climate projections for the near term. Furthermore, a recent study (Libardoni et al 2019) suggested that using a single model to approximate the internal climate variability produced distributions that are too narrow due to differences in model structure. Large ensembles of more climate models are required to better quantify the uncertainty associated with ICV.

4. Conclusions

In this study, the uncertainty of internal climate variability on projected crop production in Canada is investigated using crop growth models in DSSAT coupled with climate scenarios based on CMIP5, CanESM2-LE and CanRCM4-LE. The uncertainty in projections is often smaller but not significantly different from the uncertainty resulting from multiple climate models, especially at global warming levels under 2.5 °C. The uncertainty using CMIP5 is often found to significantly increase with rising warming levels while little change is found for CanESM2-LE and CanRCM4-LE. Therefore, the uncertainty related to internal climate variability needs to be accounted for in projections of crop production, especially for the near future. We also noticed that the uncertainty associated with internal climate variability in the regional climate model CanRCM4 is often larger than in the global climate model CanESM2. Such characteristics in projections of crop production in Canada can be traced back to projections of temperatures and precipitation in these ensembles.

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Data availability

The data that support the findings of this study are openly available at https://open.canada.ca/data/en/dataset?keywords=large+ensembles.
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