

1 **Global implications of regional grain production through virtual water trade**

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## 11 **Abstract**

12 Crop yields (Y) and virtual water content (VWC) of agricultural production are affected by climate  
13 variability and change, and are highly dependent on geographical location, crop type, specific  
14 planting and harvesting practice, soil property and moisture, hydro-geologic and climate  
15 conditions. This paper assesses and analyzes historical (1985-2009) and future (2040-2064) Y and  
16 VWC of three cereal crops (i.e., wheat, barley, and canola) with high spatial resolution in the  
17 highly intensive agricultural region of Alberta, Canada, using the Soil and Water Assessment Tool  
18 (SWAT). A calibrated and validated SWAT hydrological model is used to supplement agricultural  
19 (rainfed and irrigation) models to simulate Y and crop evapotranspiration (ET) at the sub-basin  
20 scales. The downscaled climate projections from nine General Climate Models (GCMs) for RCP  
21 2.6 and RCP 8.5 emission scenarios are fed into the calibrated SWAT model. Results from an  
22 ensemble average of GCMs show that Y and VWC are projected to change drastically under both  
23 RCPs. The trade (export-import) of wheat grain from Alberta to more than a hundred countries  
24 around the globe led to the annual saving of ~5 billion m<sup>3</sup> of virtual water (VW) during 1996-  
25 2005. Based on the weighted average of VWC for both rainfed and irrigated conditions, future  
26 population and consumption, our projections reveal an annual average export potential of ~138  
27 billion m<sup>3</sup> of VW through the flow of these cereal crops in the form of both grain and other  
28 processed foods. This amount is expected to outweigh the total historical provincial water yield of  
29 66 billion m<sup>3</sup> and counts for 47% of total historical precipitation and 61% of total historical actual  
30 ET. The research outcome highlights the importance of local high-resolution inputs in regional  
31 modeling and understanding the local to global water-food trade policy for sustainable agriculture.

32 **Keywords:** crop modeling, climate change, virtual water content, virtual water flow, Canada

## 33 **1. Introduction**

34 Both land and water resources are limited and already under heavy pressure from population  
35 growth, economic development, and varying diets, therefore, future agricultural production needs  
36 to be highly productive and also sustainable (van der Esch et al., 2017; Porkka et al., 2017).  
37 However, climate change is expected to influence the spatial and temporal heterogeneity of water  
38 resources worldwide (Schewe et al., 2014). Currently, many regions across the globe are unveiling  
39 significant depletion of freshwater resources due to withdrawal for agriculture, which uses 70% of  
40 total water withdrawal of global freshwater (Falkenmark, 2013; Wada et al., 2014; Tuninetti et al.,  
41 2015; Kaune et al., 2017; Ren et al., 2018). In the 21<sup>st</sup> century, meeting the increasing water  
42 demand of ecosystems and societies is one of the major environmental challenges. Hence, the  
43 water-food nexus has drawn much attention in order to understand the effects of global  
44 environmental change and provide sustainable development for the ever-increasing global  
45 population (Konar et al., 2011).

46 Many countries could compensate for the limited and uneven distribution of freshwater  
47 resources and associated food production by importing virtual water through international trade of  
48 agricultural products (Dalin et al., 2017). International trade transfers large amounts of virtual  
49 water from one region of production to other regions of consumption, so-called ‘Globalization of  
50 Water’ (Hoekstra and Chapagain, 2008). Virtual water content (VWC) refers to the water that is  
51 embedded in the production process of particular goods and services, and virtual water trade  
52 (VWT) refers to the amount of water traded through the flow of commodities between and within  
53 countries (Allan, 1993). The concept has been evolved over recent decades, and VWT is  
54 considered as an alternative solution for water and food security in overpopulated regions with  
55 limited water resources and/or regions with a scarcity of fertile lands. The VWT strategy

56 potentially promotes regional and global food security, water savings, and water use efficiency  
57 (WUE) (Faramarzi et al., 2010; Carr et al., 2013). There will be a net water saving if the trade  
58 direction is from countries with low VWC to countries with high VWC. Countries can benefit  
59 from trade if they specialize in the production of goods and services for which they have a  
60 comparative advantage while importing goods and services for which they have a relative  
61 disadvantage (Chapagain et al., 2006). International trade in staple foods has been estimated to  
62 save approximately 238 billion m<sup>3</sup> of water annually, equivalent to 6-7% of global water use in  
63 agriculture (Dalin et al., 2012).

64 Earlier studies discussed the importance of VWT strategy in water resource management  
65 (e.g., Hoekstra, 2003; Wichelns, 2005), and subsequent studies emphasized the role of VWT in  
66 the globalization of water, world food demand, network of VWT, water savings evolution and  
67 regional water systems (Faramarzi et al., 2010; Seekell et al., 2011; Dalin et al., 2012; Carr et al.,  
68 2013; Goswami and Nishad, 2015; Oki et al., 2017; Qu et al., 2018). Contemporary to the  
69 conceptual evolution of the approach, the methodological advancements of calculating VWC  
70 helped reduce uncertainty in VWT analysis (Fader et al., 2011; Hanasaki et al., 2010; Liu et al.,  
71 2018; Lovarelli et al., 2016; Qu et al., 2018; Wichelns, 2015; Zhang et al., 2018). However, the  
72 majority of the earlier studies conducted at a global scale, only concerning international food trade  
73 between countries. Few recent studies considered regional effects of natural and management  
74 factors in quantifying VWC (Goswami and Nishad, 2015; Ma and Ma, 2017; Marano and Filippi,  
75 2015; Shtull-Trauring and Bernstein, 2018). Such global scale studies lack reliability in the results  
76 since local processes and site-specific data were not considered in the simulation of crop yield and  
77 crop water requirements. The VWC of a given commodity in a given geographic location and time  
78 depends on location-specific agricultural practices, soil properties, hydro-geologic and climate

79 conditions (Mekonnen and Hoekstra, 2011). For instance, a more significant amount of water is  
80 generally required to produce one ton of a cereal crop in the arid region than that in the humid  
81 region (Yang and Zehnder, 2007; Goswami and Nishad, 2015). In addition, comparison of the  
82 local water renewals was not considered in VWT studies, and the studies of the VWT concept as  
83 a policy option for water management were only based on water consumptions (Hoekstra, 2011).

84 Physical and process-based models have been typically utilized to account for spatial and  
85 temporal heterogeneity in large-scale VWT analysis. However, various assumptions in large-scale  
86 modeling framework such as hydro-climatic inputs, soil water balance, and crop growth  
87 simulations often limit the quality of predictions and lack representation of regional or local level  
88 processes (Folberth et al., 2016; Xinchun et al., 2018). Liu et al. (2013) and Flach et al. (2016)  
89 highlighted the critical importance of using spatially explicit data such as crop-specific fertilizer  
90 application rates, crop specific planting and harvesting data, and high-resolution geospatial and  
91 hydro-climate input in modeling to capture local variation and avoid significant errors in the  
92 estimation of crop yield (Y) and VWC. While large-scale models are efficient tools helping to  
93 understand processes and factors affecting VWC, the local scale inputs to the models are inevitable  
94 to provide reliable estimates of VWC and related parameters (Goswami and Nishad, 2015;  
95 Lovarelli et al., 2016). Reliable estimates of VWC and VWT can provide significant insights into  
96 the local/regional dynamics of water resources and the policy implications for global water savings  
97 (Tamea et al., 2016; Shtull-Trauring and Bernstein, 2018).

98 Increased attention has been paid to the consequences of climate change for water and food  
99 security through exploring VWT (Konar et al., 2013; Orłowsky et al., 2014). Changing patterns of  
100 precipitation and evapotranspiration (ET), and rising CO<sub>2</sub> will impact the relative advantage of  
101 countries concerning agricultural production and trade (IPCC, 2013; Konar et al., 2013; Deryng et

102 al., 2016; Zhao et al., 2017). For instance, spring barley Y is projected to decrease by 7-25% in  
103 France, while it is expected to increase by 30-70% in the UK during the 21<sup>st</sup> century (Yawson et  
104 al., 2016; Gammans et al., 2017). This will likely induce the shifting of agricultural production in  
105 some countries, which will, in turn, change the regional and international patterns of food trade.  
106 Importantly, the redistribution of international food trade has been proposed as a potential  
107 adaptation measure to a changing climate (Nelson et al., 2009). Thus, it is essential to understand  
108 how world food trade system will be impacted by a region-specific climate change, as VWC is  
109 highly dependent on the local climate conditions.

110 In this study, we aimed to address the knowledge gap in understanding global and regional  
111 effects of local processes in VWT analysis and food security by utilizing locally adapted high-  
112 resolution models and data. We introduced a novel approach in the analysis of future VWF  
113 potentials by comparing water consumptions with local water resource renewals. We analyzed  
114 future water use of the three water-intensive and major cereal crops, namely wheat, barley, and  
115 canola by developing high-resolution (sub-basin scale; used a threshold drainage area of ~200  
116 km<sup>2</sup>) agro-hydrological models under both rainfed and irrigated conditions at a provincial scale.  
117 We also used a high-resolution, locally adapted hydrology model to account for spatiotemporal  
118 variation of water balance components. A primary objective of this study was to use a process-  
119 based, transient, biophysical model, Soil and Water Assessment Tool (SWAT) (Arnold et al.,  
120 1998), to simulate hydrology and soil-plant-water interactions at a daily time step, considering  
121 local climate and agricultural management operations using Alberta, Canada as a case study.  
122 Canada is known as one of the topmost export-oriented countries, and Alberta is one of the largest  
123 provincial exporters (Alberta Agriculture and Forestry, 2017). This study also provides a  
124 framework for projecting VWF under various climate change scenarios, which improve our

125 understanding of global implications of VWF to other countries. The methods developed in this  
126 paper consists of a step-wise and detailed procedure involving spatially explicit simulation of Y,  
127 crop ET, VWC, and VWT of spring wheat (hereafter called as wheat), barley and canola, and  
128 calculation of crop demand and supply based on local population and consumption data.

## 129 **2. Methods**

### 130 **2.1 Study area**

131 Alberta, with an area of about 66 million hectares (Mha), has a highly variable climate with warm  
132 summers and cold winters (Fig. 1). Historically, the mean temperatures range from 10 to 20 °C,  
133 and the mean precipitation varies from 160 to 400 mm during the crop growing season (May-  
134 August) (Masud et al., 2018). The western side of the province receives higher precipitation, while  
135 the south-eastern side is drought-prone as it receives less precipitation with higher temperature  
136 (Masud et al., 2017a). The province has 17 river basins, where most of the southern river basins  
137 are snowmelt dominated in their upstream highland areas, and glacier melt plays a major role in  
138 supplying downstream water needs in late summer.

139 Alberta extensively uses irrigation in the southern part (Fig. 1), accounting for 75% of the  
140 licensed water allocation (Islam and Gan, 2015), and has one of the world's most productive  
141 agricultural economies, contributing 23% of total Canadian farm revenue. Total agricultural land  
142 in Alberta is over 21 Mha and represents 31.2% of the Canadian total of 68 Mha. Wheat, barley,  
143 and canola are the three topmost farm cash crops. Exporting to over a hundred countries, Alberta's  
144 international exports of primary and processed agri-food totaled > \$10 billion in 2016. About 74%  
145 of the total wheat, barley, and canola produced in 2016 were shipped to the USA, China, Japan,  
146 Mexico, and South Korea (Alberta Agriculture and Forestry, 2017).

## 147 **2.2 Data**

148 Historical climate data including daily precipitation, temperature, solar radiation, humidity, and  
149 wind speed were obtained from Faramarzi et al. (2015), who used a suite of four climate time  
150 series from local meteorological records, gridded products, and satellite data at a provincial  
151 coverage to reproduce historical streamflow records by using a calibrated SWAT hydrologic  
152 model. Other hydrological data include vegetation cover, soil characteristics, potholes, daily  
153 operation of large reservoirs and dams, and glacial maps in order to better represent natural and  
154 human-induced hydrological processes at sub-basin levels (Faramarzi et al., 2017). Agricultural  
155 management data such as the date of planting and harvesting, volume, and rate of fertilizer and  
156 irrigation application were obtained to develop the SWAT crop models. The crop-specific fertilizer  
157 application rate (N:P:K ratio), the maximum amount of annual fertilizer application (kg/ha/year),  
158 and the potential heat units required for crops were additionally obtained from the Government of  
159 Alberta (Table A1). Yearly Y statistics for irrigated and rainfed crops were taken from Alberta  
160 Financial Service Corporation (AFSC) and Alberta Agriculture and Rural Development (AARD)  
161 over the period 1980–2009 for model calibration and validation. Here, Y data for irrigated and  
162 rainfed crops were collected at the county level from AFSC (Fig. 1b) and at the Census  
163 Agricultural Region (CAR) level from AARD (Fig. 1a), respectively. For calibration and  
164 validation purposes, simulated data at sub-basin level and measured irrigated data at the county  
165 level were aggregated to CAR level to follow the same spatial resolution as the measured rainfed  
166 data, i.e., CAR level (see Table A1).



126° W 122° W 118° W 114° W 110° W

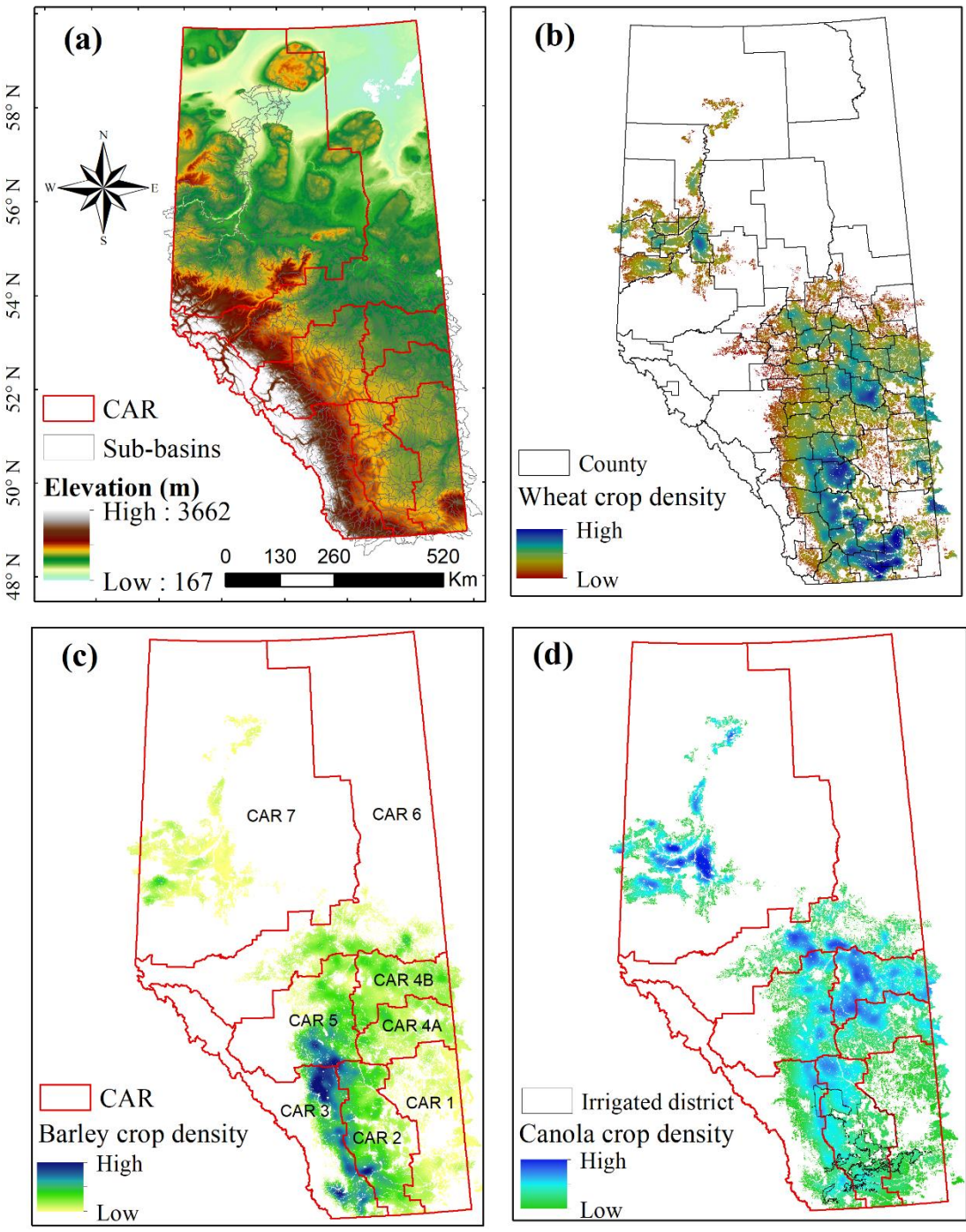


Fig. 1. Study area (a) and crop density maps for different cereal crops wheat (b) barley (c) and canola (d). Here, CAR is Census Agricultural Region.

168 Table 1. List of General Circulation Models (GCMs) used in this study.

Model	Institution	Center
CanESM2	Canadian Centre for Climate Modeling and Analysis	CCCma
CCSM4	National Center for Atmospheric Research	NCAR
CNRM-CM5	Centre National de Recherches Meteorologiques/Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique	CNRM-CERFACS
CSIRO-MK5	Commonwealth Scientific and Industrial Research Organization in collaboration with the Queensland Climate Change Centre of Excellence	CSIRO-QCCCE
GFDL-ESM2G	Geophysical Fluid Dynamics Laboratory	NOAA/GFDL
HADGEM2-ES	Met Office Hadley Centre (additional HadGEM2-ES runs by Instituto Nacional de Pesquisas Espaciais)	MOHC (INPE)
MIROC5	Meteorological Research Institute	MIROC
MPI-ESM-LR	Max Planck Institute for Meteorology	MPI-M
MRI-CGCM3	Meteorological Research Institute	MRI

169  
 170 The climate projections of nine General Circulation Models (GCMs) over the period 2040–  
 171 2064 were obtained under two contrasting emission scenarios of RCP 2.6 and 8.5 (Representative  
 172 Concentration Pathways) from the Pacific Climate Impacts Consortium ( PCIC; Cannon, 2015) at  
 173 a resolution of 5 arcmin (~10 km) (Table 1). The change factor approach (Chen et al., 2011) was  
 174 used to downscale the data based on the local climate conditions of Alberta. Overall, an ensemble  
 175 of eighteen climate projections (9 climate models by 2 scenarios) was downscaled and used in the  
 176 calibrated SWAT model. We set the CO<sub>2</sub> concentration as 350, 450, and 750 ppm for the historical,  
 177 RCP 2.6, and RCP 8.5, respectively. For each GCM and RCP combination, a total of 1000 SWAT  
 178 simulations were performed on a daily basis using the calibrated parameter ranges (see section  
 179 2.3). Although the model simulation was performed under each climate model-scenario  
 180 combination, here we describe the results based on the ensemble average.

181 Changes in population size are important in determining the future demands for goods and  
 182 services, particularly for food (Ercin and Hoekstra, 2014). We used the Government of Alberta  
 183 population projection data for the historic (1985-2009) and future periods (2040-2064). Future

184 population growth is based on historical trends of fertility, mortality, and migration, accounting  
185 for possible future patterns of change (Table A1). Per capita food consumption data were taken  
186 from FAOSTAT (FAOSTAT, 2018). The best available crop import and export data were collected  
187 for the 1996-2005 period from the Statistics and Data Development Section of Alberta Agriculture  
188 and Forestry (Alberta Agriculture and Forestry, 2018a). All input data are listed in the  
189 supplementary Table A1.

### 190 **2.3 Model set-up and performance indicators**

191 In this study, a calibrated hydrological model of the province (Faramarzi et al., 2017, 2015) was  
192 utilized to develop a crop growth model using the ArcSWAT 2012 (Rev. 632). The SWAT crop  
193 growth model was built to simulate Y and crop ET for both historical (1980-2009) and future  
194 (2040-2064) periods. In the hydrological model, a threshold drainage area of 200 km<sup>2</sup> was used to  
195 delineate the study area into a total of 2255 sub-basins, based on a 10 m Digital Elevation Model  
196 (DEM). The sub-basins were characterized based on soil, land use, slope, and associated physical  
197 parameters available from local sources, and further processed to meet the model requirements  
198 (Faramarzi et al., 2017). To simulate crop growth in this study, we developed and calibrated two  
199 separate models for each crop simulations (wheat, barley, and canola) to represent rainfed and  
200 irrigated conditions, respectively. In general, setting up a crop growth model based on a calibrated  
201 hydrological model has been recommended to improve soil-water dynamics in crop growth  
202 simulations (Faramarzi et al., 2010; Vaghefi et al., 2014). Heat unit requirements were optimized  
203 in the model through our calibration procedure to represent different varieties of crops that differ  
204 in growing degree-days across the province. Auto fertilizer and auto irrigation options of the  
205 SWAT model were used to represent the management calendar and were controlled by nutrient  
206 stress factor and plant-water-stress threshold, respectively. Planting and harvesting dates were

207 obtained from available sources and communication with local experts. Since the cropping  
208 calendar did not fully cover the study domain, the suggested dates by local experts were further  
209 tuned through our calibration scheme over our study area.

210 For the model sensitivity, calibration, validation and uncertainty analysis, the Sequential  
211 Uncertainty Fitting (SUFI-2) program of the SWAT-CUP software was used (Abbaspour, 2015).  
212 The SUFI-2 was used to calibrate the model for the 1995–2009 and to validate it for the 1983–  
213 1994 period. A three-year window was considered as a spin-up period for both calibration and  
214 validation to mitigate the effect of initial conditions in the model. The inverse time periods were  
215 used for calibration and validation since better data were available in the later period. Based on an  
216 extensive literature review and author's judgment, a total of 14 to 30 physical and phenological  
217 parameters sensitive to water balance and crop growth was selected for each CAR under rainfed  
218 and irrigated conditions (Table A2). A global sensitivity analysis (GSA) was applied through the  
219 SWAT-CUP tool to screen the most sensitive parameters. The parameters were then sampled  
220 within a physically meaningful range using a Latin Hypercube Sampling (LHS) approach (Mckay  
221 et al., 1979) for 1000 model runs of each model simulation (under the historical period and 18  
222 climate model-scenario combinations). The mean square error (MSE) was used as an objective  
223 function to compare simulated versus observed Y on a yearly basis for each CAR and parameter  
224 tuning for the next calibration iteration. In SUFI-2, the 95% prediction uncertainty (95PPU) of the  
225 output variables was considered to evaluate the model performance. The 95PPU has been  
226 calculated at 2.5% and 97.5% levels of the cumulative distribution functions of an output variable  
227 that was generated through the propagation of the parameter uncertainties using LHS. Simulation  
228 results for Y and VWC are shown as of median of 1000 runs and indicated as M95PPU hereafter.

229           The p-factor and r-factor have been used to quantify the calibration performance of the  
230 model (Abbaspour et al., 2015; Faramarzi et al., 2017). The p-factor is the percentage of observed  
231 data covered by the 95PPU, and the r-factor is the thickness of the 95PPU, which is calculated as  
232 the ratio of the average width of the 95PPU to the standard deviation of the measured variable. A  
233 p-factor value of 1 (100%) and a r-factor value of zero is ideal. However, due to inherent  
234 uncertainties in input data, physical parameters, and model conceptualization in large-scale  
235 studies, the p-factor of above 0.5 (50%) and r-factor of around 1-2 and 3-5 is considered  
236 satisfactory in hydrologic and crop Y simulations, respectively (Abbaspour et al., 2015).  
237 Importantly, our calibration approach does not search for an optimal parameter set as a single  
238 solution to replicate historical data, rather an envelope of best solutions represented by the 95PPU.  
239 In other words, observed data for a specific year should fall within the 95PPU band.

240           The crop ET is simulated based on crop biomass development, soil water dynamics in  
241 different soil layers, and potential crop ET on a daily basis. The Penman-Monteith approach is  
242 generally considered reliable and was used to estimate potential ET. Y and ET were simulated on  
243 a daily basis and aggregated for the growing season (planting to harvesting period; May to August).  
244 These output variables were simulated at sub-basin scale and then aggregated to CAR scale for  
245 calibration and validation purposes.

#### 246 **2.4 Virtual water content (VWC) accounting**

247           The VWC (m<sup>3</sup>/tonne) is the volume of water required to produce a unit of mass production and is  
248 defined as the ratio of crop water consumption (ET; mm) during a crop growing period to the crop  
249 yield (Y; tonne/ha).

$$VWC = \frac{ET}{Y} \times 10 \tag{1}$$

250 where, 10 is the factor used to convert ET (mm) into m<sup>3</sup>/ha. A larger value of VWC indicates a  
 251 higher amount of water used for a unit mass production and a lower WUE. We used M95PPU of  
 252 simulated Y and ET to compute the VWC of wheat, barley, and canola for the historical (1985-  
 253 2009) and future (2040-2064) periods for each sub-basin.

254 The sub-basins with simulated crop-specific VWC were then aggregated to a provincial  
 255 level as follow:

$$VWC_p = \frac{\sum_s(VWC \times Y \times A)}{\sum_s(Y \times A)} \quad (2)$$

256 where  $VWC_p$  is the virtual water content at the provincial level (m<sup>3</sup>/tonne),  $s$  is the sub-basin  
 257 number within the province and  $A$  is the area under cultivation (ha). However, sub-basins located  
 258 in the southern Alberta consist of both rainfed and irrigated production. In this case, the VWC of  
 259 a specific sub-basin is calculated as:

$$VWC_s = \frac{\sum_s((VWC_R \times Y_R \times A_R) + (VWC_I \times Y_I \times A_I))}{\sum_s((Y_R \times A_R) + (Y_I \times A_I))} \quad (3)$$

260 Where,  $R$  denotes rainfed and  $I$  denotes irrigated crop production. This provincial level calculation  
 261 of VWC is helping us to analyze the VWT of a specific crop and corresponding water saving (see  
 262 section 2.5).

## 263 **2.5 Virtual water trade (VWT)**

264 Although Alberta is considered as a net exporting province, small amounts of wheat, barley, and  
 265 canola are also imported (Figure 2). In order to account for water savings in this province, the trade  
 266 was analyzed based on the actual import and export data that are available only for the 1996-2005  
 267 period. Therefore, the net virtual water export associated with the production of a given crop is  
 268 calculated as:

$$NVWE_p = (EXP_p \times VWC_p) - (IMP_p \times VWC_{sc}) \quad (4)$$

269 where, *EXP* and *IMP* denote for export and import of a crop in tonne/year, respectively. For  
 270 import, the  $VWC_{sc}$  is considered from the respective source country based on the study of Hoekstra  
 271 and Chapagain, (2006) and Mekonnen and Hoekstra (2011).

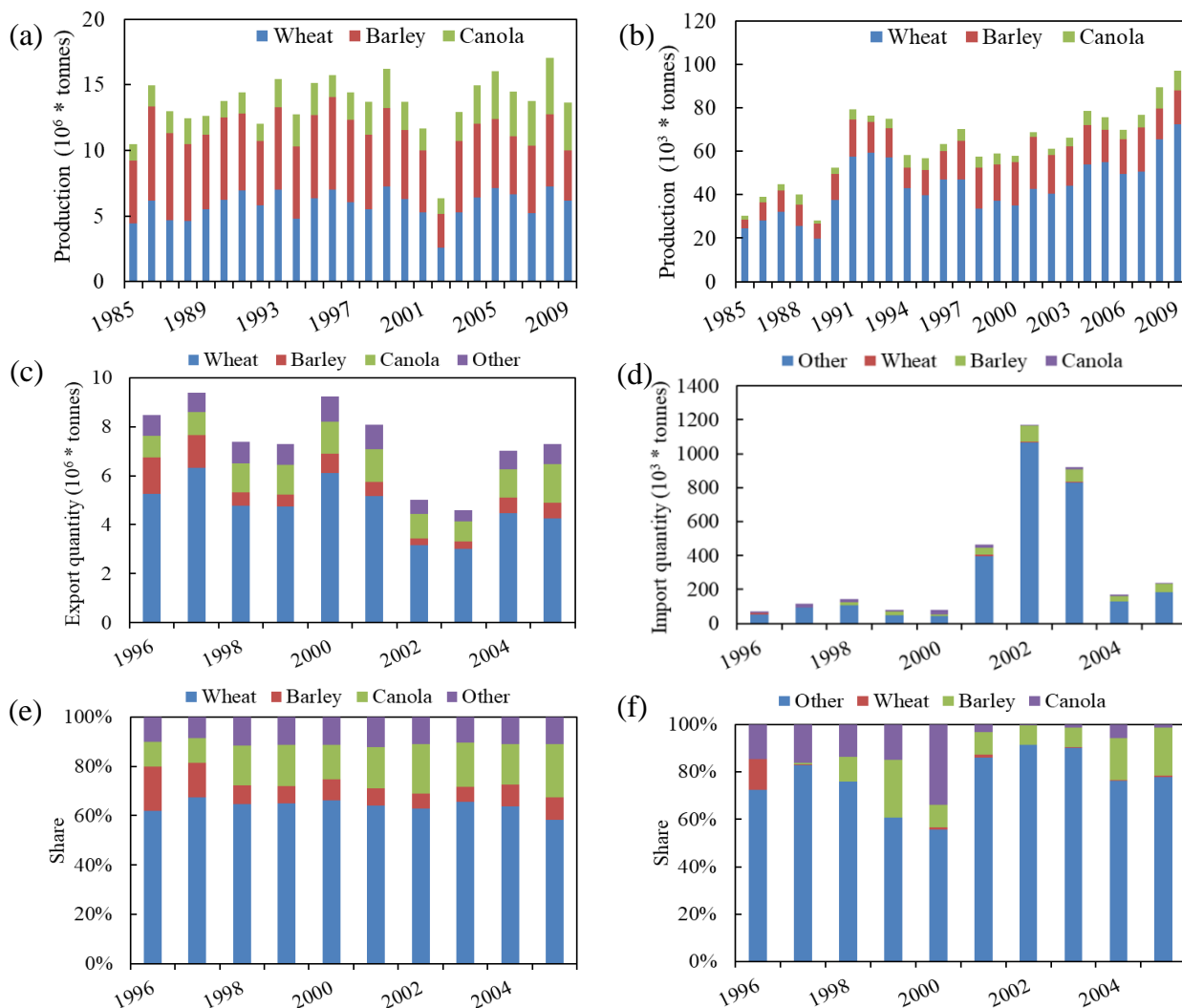


Fig. 2. Rainfed (a) and irrigated (b) cereal production during the historical period. Annual crop import (c), export (d), and their corresponding shares (%) in (e) and (f), respectively in the province.

272 Based on the per capita consumption and total population, the required production  
 273 ( $P_r$  in tonne) of a crop in Alberta in a year is defined as (Ercin and Hoekstra, 2014; Karandish et  
 274 al., 2015):

$$P_r = 1.2 \times \text{per capita crop consumption} \times \text{Total population} \quad (5)$$

275 where, the crop consumption is in kg/capita/day. The actual crop production ( $P_a$  in tonne) is  
 276 computed as:

$$P_a = \sum_s ((Y_R \times A_R) + (Y_I \times A_I)) \quad (6)$$

277 In this study, we estimated the  $P_r$  and  $P_a$  for each year but averaged the results for the entire period.  
 278 We assumed the area under cultivation ( $A$ ) in the future period is the same as that of the historic  
 279 period. There is no measured data available for the area under cultivation at the sub-basin scale.  
 280 We used the crop density raster maps (Fig. 1b,c,d), with a spatial resolution of  $230 \text{ m} \times 230 \text{ m}$ , to  
 281 estimate the area under cultivation for each sub-basin. As higher crop density values represent  
 282 higher likelihood for crop production, we calculated  $P_a$  by omitting low crop density cells. Here,  
 283 we developed a hypothetical scenario by considering cells with  $>10\%$  crop density values (Fig.  
 284 A1) for cropping areas.

285 Next, we calculated the “potential” net virtual water export (NVWE) for future period as  
 286 follows:

$$NVWE = (P_a - P_r) \times VWC_p \quad (7)$$

287 With the above formulation, any crop production that is not directly consumed by local  
 288 population was considered as crop surplus and potential for export to outside. It is noteworthy that  
 289 a large share of crop surplus is ‘indirectly’ exported through production and export of meat (e.g.,  
 290 beef), live animals (e.g., cattle, calve), dairy products and beverage under status quo situation in  
 291 Alberta (Alberta Agriculture and Forestry, 2017). In this study, we did not explicitly calculate  
 292 VWC and VWF of these commodities, but assumed all crop surplus could be exported directly in  
 293 the form of grain (i.e., no processed production). Thus, our estimates are the first order estimates  
 294 of VWC and VWF of agricultural production in Alberta.



## 295 **3. Results**

### 296 **3.1 Model set-up and performance statistics**

297 Calibration and validation were performed for 67 counties (barley) and 8 CAR (wheat and canola).  
298 For brevity, we only present the results of our analysis at the provincial level for both irrigated and  
299 rainfed crops in Table 2. For details on the calibration and validation of the crop models, we refer  
300 to the supplementary information (Tables A3-A6). The model performed well for all rainfed crops  
301 over the calibration period. The average p-factor of the calibrated rainfed crop model is mostly  
302 >90% (88-99%), which indicated the percentage of observed Y data bracketed well by simulated  
303 95PPU, with an average r-factor of 2.69, 4.48 and 3.46 for wheat, barley and canola, respectively  
304 (Table 2). The average MSE values for all rainfed crop models were less than 1 at the provincial  
305 scale. Similar statistical performance was obtained for the validation period. For all rainfed crops,  
306 the minimum and maximum statistics of all counties and CARs indicated an overall satisfactory  
307 performance. In general, irrigated crop models statistically performed slightly better than those of  
308 rainfed crops for the calibration period, since irrigated crops are grown under controlled  
309 conditions, and rainfall variability is attenuated by irrigation. Relatively poor model performance  
310 of irrigated crop models for validation period is due to the limited availability of historical or  
311 transient management data over time such as cropping, harvesting, and fertilizer at the county and  
312 CAR levels. It is important to note that the performance of p-factor improved at the expense of a  
313 larger r-factor and higher MSE in some areas. Therefore, a right balance needs to be reached  
314 between the p-factor and r-factor through a calibration procedure. A larger uncertainty (greater r-  
315 factor) in some areas was obtained for some of the crops, e.g., rainfed barley and canola, and  
316 irrigated canola during both calibration and validation. This inherent uncertainty is not uncommon  
317 in large-scale models due to errors in the model input data, process simplification and variation in

318 historical management practices. Overall, model performance was satisfactory for most of the  
 319 regions and times in the study area.

320 Table 2. The minimum and maximum statistics for the county and CAR-based calibration and  
 321 validation. The provincial average statistics are also provided.

	Calibration			Validation			Calibration			Validation		
	p-factor	r-factor	MSE	p-factor	r-factor	MSE	p-factor	r-factor	MSE	p-factor	r-factor	MSE
	<u>Rainfed Wheat</u>						<u>Irrigated Wheat</u>					
Minimum	0.93	1.5	0.03	0.6	1.4	0.03	0.87	2.08	0.05	0.2	2.58	0.59
Maximum	1	4.17	0.15	1	5.67	0.23	1	2.71	0.66	0.43	2.69	0.71
Average	0.99	2.69	0.07	0.83	3.88	0.1	0.96	2.45	0.26	0.32	2.64	0.65
	<u>Rainfed Barley</u>						<u>Irrigated Barley</u>					
Minimum	0.53	1.91	0	0.55	1.65	0.11	0.8	1.21	0.01	0.5	0.61	0.17
Maximum	1	8.04	2.1	1	8.93	2.3	1	3.22	0.61	0.93	3.66	1.9
Average	0.88	4.48	0.6	0.85	5.35	0.59	0.92	2.13	0.23	0.82	2.34	0.68
	<u>Rainfed Canola</u>						<u>Irrigated Canola</u>					
Minimum	0.93	2.62	0.04	0.7	3.43	0.01	1	4.64	0.06	0.7	3.85	0.03
Maximum	1	5.06	0.12	1	8.2	0.17	1	7.5	0.06	1	7.3	0.14
Average	0.97	3.46	0.07	0.91	5.97	0.06	1	5.99	0.06	0.9	5.88	0.09

322

323 **3.2 Spatially explicit distribution of Y and VWC**

324 Historical and future Y, and the projected changes for rainfed wheat, barley, and canola in Alberta  
 325 are shown in Fig. 3. Overall, simulated average canola Y was lower (1.68 tonnes/ha) for the historic  
 326 period, followed by barley (2.93 tonnes/ha) and wheat (3.15 tonnes/ha), although there were some  
 327 sub-basins where barley Y is projected to be more than 5 tonnes/ha in the future period. Simulated  
 328 Y of all rainfed crops for the historic period was higher in the central and northern parts of Alberta  
 329 followed by low Y in the south-eastern province. Rainfed Y is projected to substantially increase  
 330 for both RCP scenarios (2.6 and 8.5) by up to 80% in many sub-basins with some others decreasing  
 331 by up to 20%. On average, wheat, barley, and canola Y are projected to increase by 11, 25 and  
 332 33% for RCP 2.6 and 31, 65 and 69% for RCP 8.5, respectively. The spatial pattern showed that

333 wheat Y is expected to increase more uniformly over the study domain than other crops, and such  
 334 results are in agreement with other global scale studies on wheat production (e.g., Iizumi et al.,  
 335 2017). Canola Y was projected to increase less than the other two crops, however, the projected Y  
 336 differences were noticeable between RCP 2.6 and 8.5 having significantly higher magnitudes for  
 337 the latter scenario.

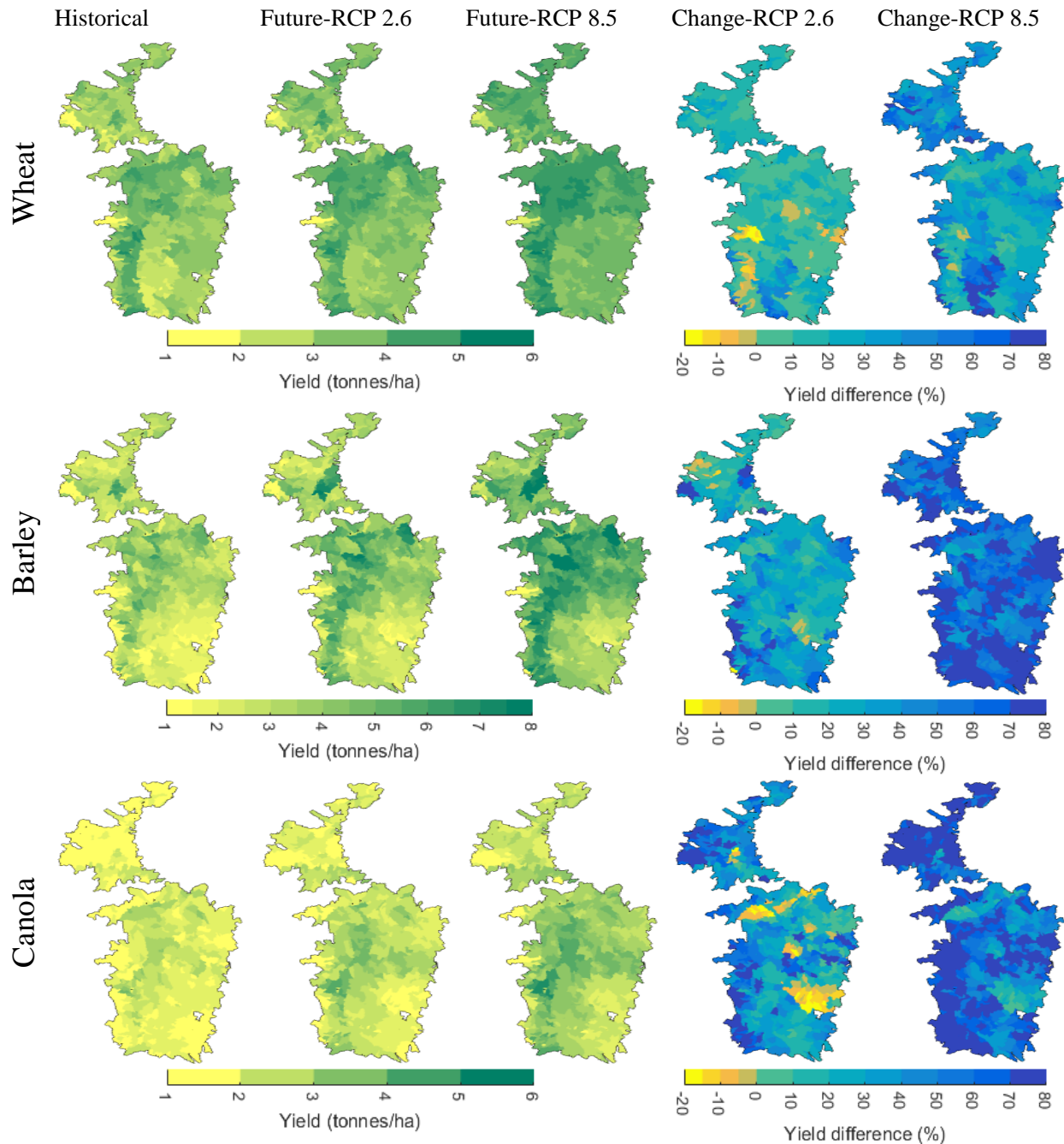


Fig. 3. Simulated long-term average rainfed yield (Y) (tonnes/ha) for historical (1985-2009) and future (2040-2064) periods and their projected changes (%).

338 Our results suggest a larger increase in wheat and canola yield under irrigated conditions  
339 as compared to rainfed Y. However, this is opposite for barley (Fig. A2). A possible reason could  
340 be a larger Y gap in Wheat and Canola under the irrigated condition that is the difference between  
341 actual and potential Y. The large historical Y gap can then be closed in the future due to more  
342 favorable conditions (Schierhorn et al., 2014). On the other hand, historical barley Y gap is already  
343 meager, therefore, more water or temperature may not help to boost up yield under irrigated  
344 conditions. Overall, the complex interaction of growing season precipitation, temperature,  
345 antecedent spring and winter soil moisture status influence the Y difference in the future (Kukul  
346 and Irmak, 2018). These results are consistent with Lu et al. (2018) who used empirical models to  
347 study crop Y response to climate variability.

348 Simulated VWC of rainfed crops for the historical period shows that canola has the highest  
349 VWC followed by wheat and barley (Fig. 4), implying a higher volume of water to produce a unit  
350 of canola than the other two crops. In general, maximum VWC was found in southern parts of the  
351 province as this area experienced higher temperature inducing higher ET. Projected future VWC  
352 shows a decreasing trend from RCP 2.6 to RCP 8.5. One possible reason could be the lower ET  
353 under RCP 8.5 scenario, where a higher CO<sub>2</sub> concentration reduces crop stomatal closure, hence  
354 decreases actual crop ET by reducing plant transpiration (Deryng et al., 2016). Similar to rainfed  
355 crops, the VWC of irrigated crops is projected to decrease in the future (Fig. A3). The magnitude  
356 of VWC in irrigated crops is more than rainfed crops in southern Alberta. This is due to a higher  
357 (atmospheric) evaporative demand in the southern part of the province that needs to be  
358 supplemented by irrigation. Overall, the magnitude of VWC and the projected changes (i.e.,  
359 decrease) are highest for canola followed by barley and wheat.

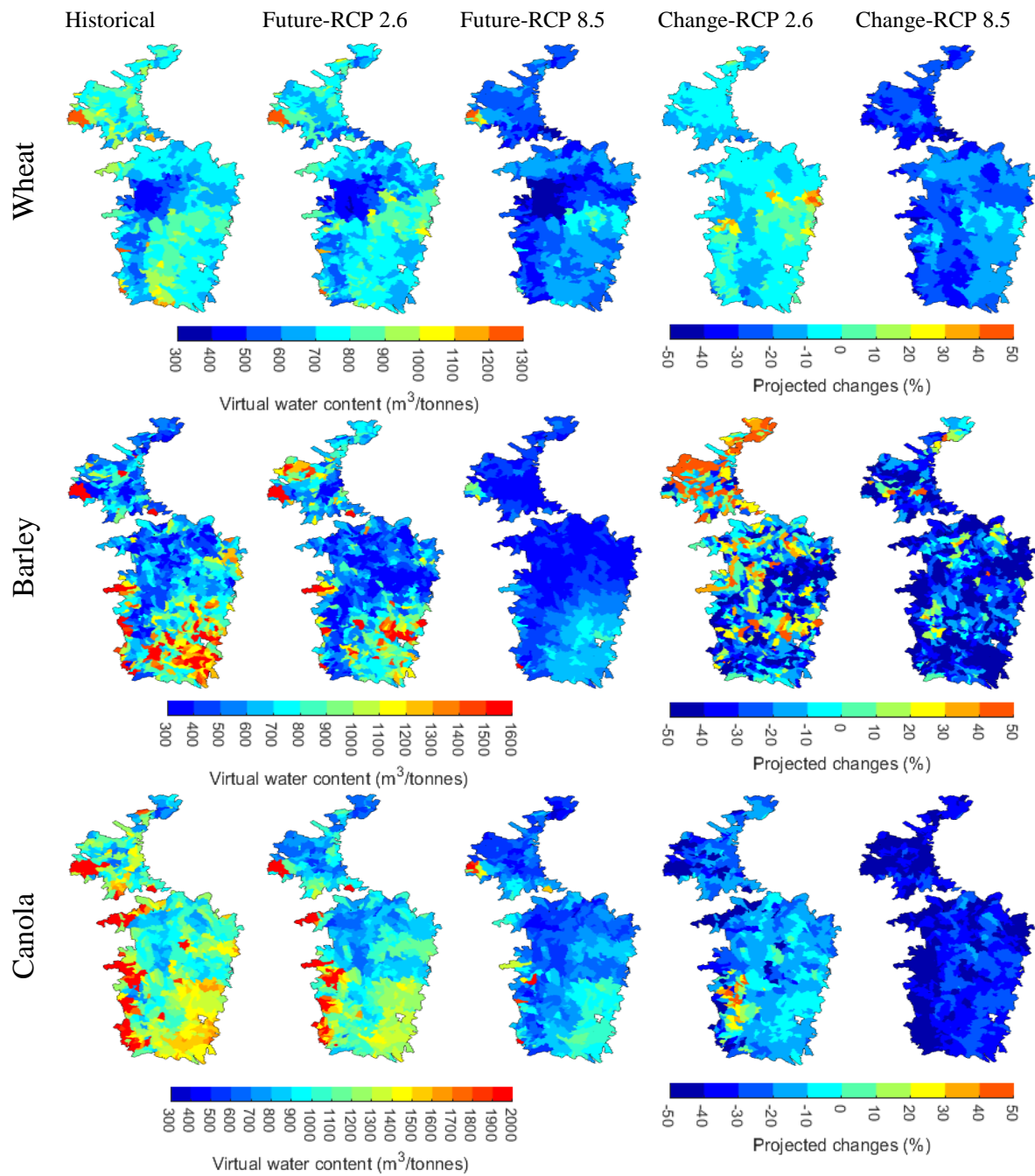


Fig. 4. Simulated long-term average pattern of virtual water content (VWC) for historical (1985-2009) and future (2040-2064) periods for the rainfed crops ( $m^3/tonnes$ ) and their projected changes (%).

### 360 3.3 VWC at the provincial level

361 Temporal variation of simulated VWC at the provincial level is shown in Fig. 5 for wheat, barley,  
362 and canola for the 1985-2009 period. VWC exhibits substantial temporal variation in the historical  
363 period. It is noticeable from Fig. 5 and 6 that VWC varied for different crop types (wheat, barley,  
364 and canola), production conditions (rainfed vs. irrigated), and geographical locations in different  
365 parts of the province (north vs. south). Our models captured the temporal fluctuation of VWC due  
366 to interactive feedback between local agro-hydrologic, climate, and management factors. In global  
367 studies (e.g., Mekonnen and Hoekstra, 2010; Konar et al., 2013), such variation in rainfed and  
368 irrigated conditions may not be adequately considered, since global models are not adopted to  
369 represent the regional/local conditions. This often causes large uncertainty in the overall estimation  
370 of crop Y, ET, and VWC. Further, we aggregated our sub-basin based simulated data and  
371 calculated the weighted average VWC (Prov\_AVG) of wheat, barley, and canola at the provincial  
372 level (see Eq. 2). The time-averaged provincial VWC of wheat, barley, and canola, weighted for  
373 both rainfed and irrigated conditions, are 797, 835 and 1239 m<sup>3</sup>/tonnes, respectively (Fig. 6).  
374 Hereafter, we will discuss VWT and VWF based on the weighted average of VWC.

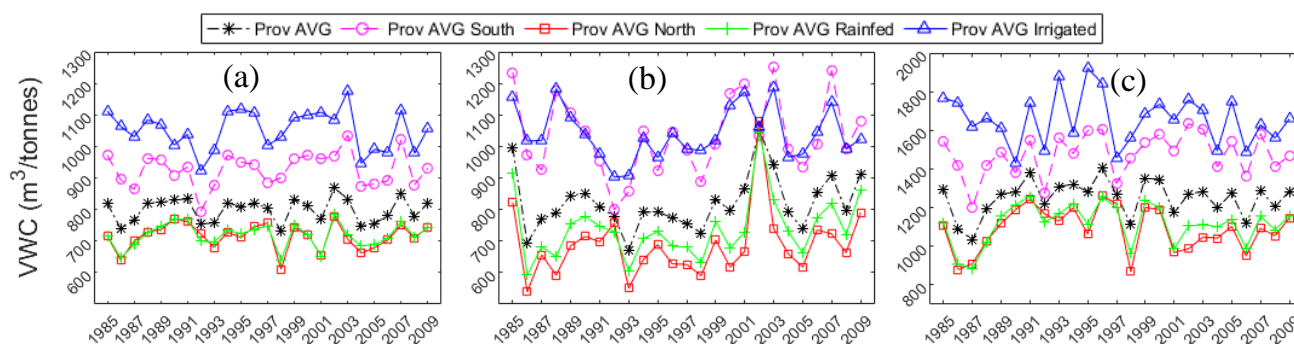


Fig. 5. Temporal variation of virtual water content (VWC) of wheat (a), barley (b), and canola (c) aggregated to the provincial level. Definition of acronyms in the legend: Prov\_Avg: Entire agricultural area (both rainfed & irrigated); Prov\_Avg\_South: Both rainfed & Irrigated, only for sub-basins those are located in the irrigated districts; Prov\_Avg\_North: Excluding the Irrigated districts;

Prov\_Avg\_Rainfed: Purely rainfed for entire agricultural area; Prov\_Avg\_Irrigated: Purely irrigated (irrigated districts).

375

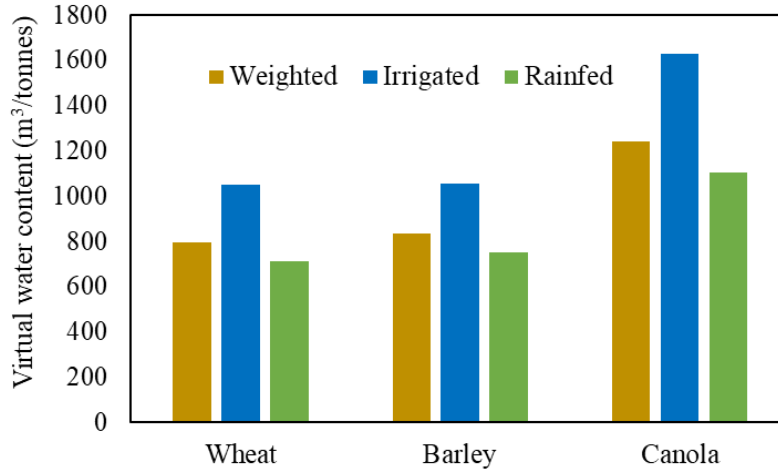


Fig. 6. Long-term average (1996-2005) modeled virtual water content (VWC) of cereal crops at the provincial level.

376 **3.4 Provincial status of virtual water trade (VWT)**

377 Based on the available data on the volume of the three cereal crops imported and exported during  
378 the 1996-2005 period, we calculated the status of VWT of the province (Fig. 7). Among these  
379 crops, wheat accounts for on average 65% of virtual water export followed by canola and barley  
380 that accounted for 25% and 10%, respectively (Fig. 7a). There was a decline in the export during  
381 2000-2003 as the province experienced a significant drought (Masud et al., 2017a). The average  
382 annual VW export was 3.76, 0.57 and 1.44 billion m<sup>3</sup> for wheat, barley, and canola, respectively  
383 with a total of 5.77 billion m<sup>3</sup> per year. Overall, the results show that total virtual water import to  
384 the province was marginal with only about 0.05 billion m<sup>3</sup> annually (Fig. 7b). However, an  
385 increased amount of VW of barley was imported during the drought years, since Alberta is among  
386 the largest beef producing jurisdictions around the world and barley is used as the main feed crop.  
387 Out of total average annual net virtual water exports of 5.71 billion m<sup>3</sup>, about 66%, 9%, and 25%  
388 were traded through wheat, barley and canola in the form of grain crops (Fig. 7c). Other processed

389 or consumed crops (e.g., beef, cattle, calve, poultry, and beverage) in our VWF calculations will  
 390 further increase the volumes (see section 3.5). As the VWT analyses depend on the existing import-  
 391 export data, we projected future VWF rather than the VWT in the following section.

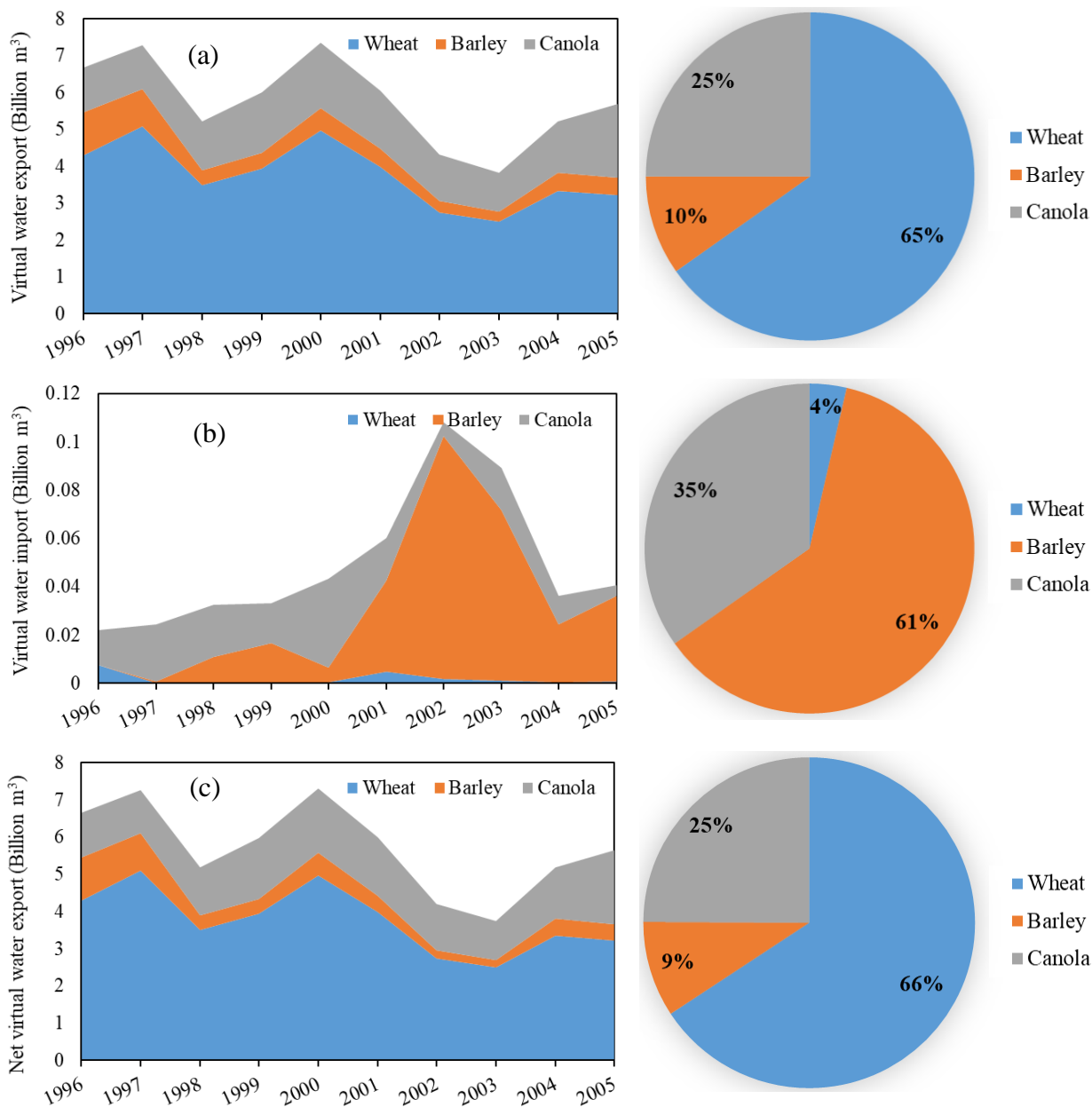


Fig. 7. Modeled annual virtual water export (a), import (b), and the net virtual water export (c) from Alberta. Pie charts show their corresponding shares.

392



### 393 **3.5 Future potential of virtual water flow (VWF)**

394 Figure 8 shows the future export potential of wheat, barley, and canola regarding production and  
395 associated VWF. Here we calculated the export potential for each year and then averaged for the  
396 entire simulation period. The future potential of exporting these cereal crops have been determined  
397 after meeting local demands based on the cropping area, Y, and per capita consumption and  
398 population. We used the simplified assumption by considering the local demands only from the  
399 demographic sector, while there are other sectors including beef-cattle, poultry and beverage  
400 industries, where cereal crops are consumed in their production processes. Since the majority of  
401 these commodities are exported, we assumed that they are exported in the form of crops rather  
402 than consumed crops. Future alterations in demand from these sectors are not considered, which  
403 requires a comprehensive assessment of future local consumption and production patterns based  
404 on socio-economic and demographic changes. Figure 8a demonstrates that Alberta has a great  
405 potential to export wheat and barley followed by canola. Overall, Alberta is projected to export  
406 70, 60, 52 million tonnes of wheat, barley, and canola, respectively. Results also revealed that  
407 Alberta is projected to export a large volume of virtual water by exporting canola followed by  
408 wheat and barley, as the VWC of canola is the largest among all three crops. A larger difference  
409 between RCP 2.6 and RCP 8.5 in potential VWT of canola is due to a higher Y and lower crop  
410 water use in RCP 8.5 than RCP 2.6 that resulted smaller VWC in RCP 8.5 (Fig. 4). Overall, average  
411 annual trade of wheat, barley, and canola is projected to lead the export potential of 44, 32 and 62  
412 billion m<sup>3</sup> of virtual water, respectively that amounts to a total of 138 billion m<sup>3</sup>. Earlier studies  
413 (Faramarzi et al., 2017, 2015) found a provincial level long-term average annual precipitation,  
414 water yield (surface water availability), and actual ET of 289.62, 66.14, and 224.36 billion m<sup>3</sup> for  
415 the historic period (1983-2007), respectively. Our projected total VWF through the export of  
416 wheat, canola and barley, in the form of both crop and processed foods, would outweigh the total

417 historical water yield and will account for about 47% of total precipitation and 61% of total ET  
 418 due to ET from all vegetation and crop types. This imbalance between total provincial water yield  
 419 and projected VWF has implications for long term sustainable VWT (see section 4).

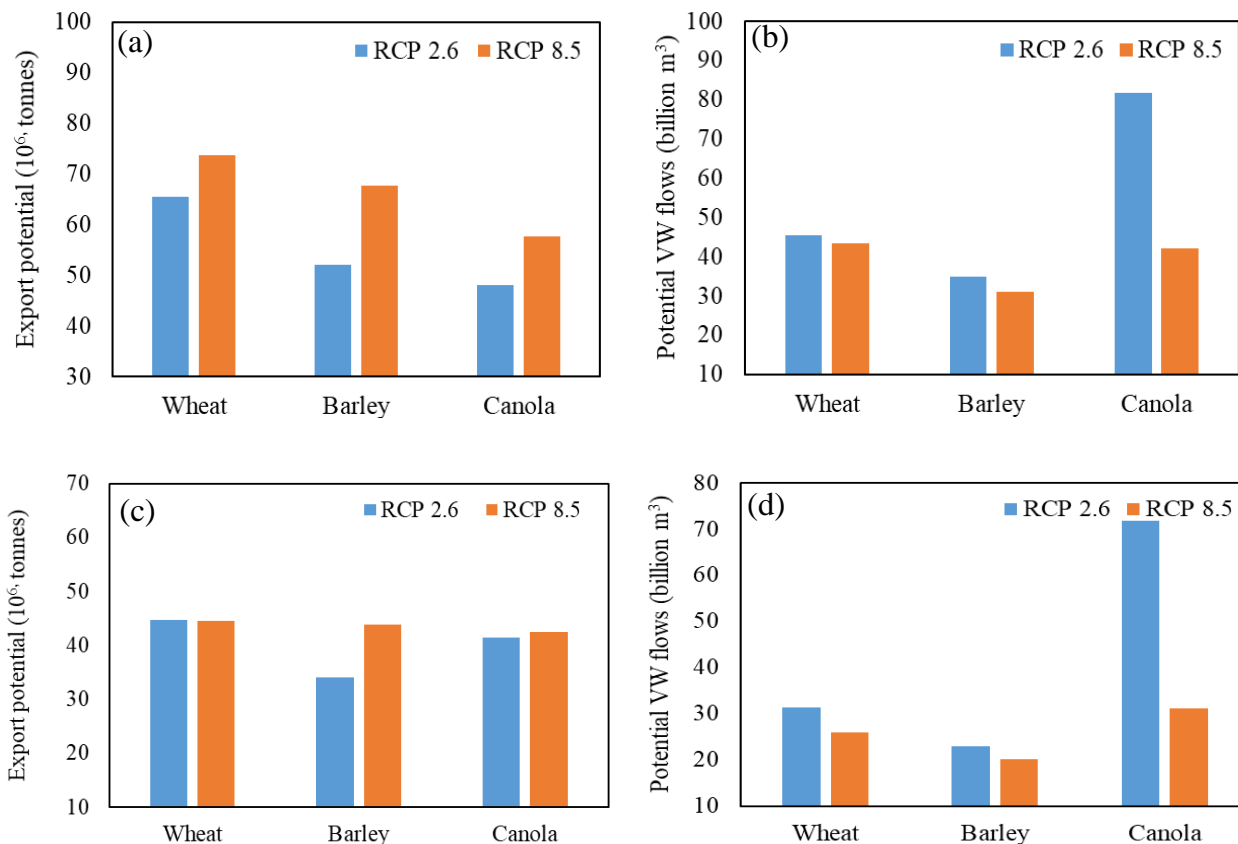


Fig. 8. Projected annual export potential of cereal crops (a), and their corresponding virtual water flows (b) for the 2040-2064 period. (c) and (d) show the same results for the scenario, where only the top 90% of density values in the crop density maps were considered for future cropping areas.

420 It is worth mentioning that we assumed future cropping area remains the same as the  
 421 historical acreage. Here, we also evaluated the potential crop export, and their corresponding VWF  
 422 based on the assumption that only grid-cells with >10% crop density values will be considered for  
 423 cropping areas. Therefore, the area under cultivation for each sub-basin was decreased with the  
 424 highest reduction obtained for barley crop (Fig. A1). As a result, the volume of export potential  
 425 and VWF were reduced for all cereal crops. Overall, the projected annual export potential for  
 426 wheat, barley, and canola are 45, 39, and 42 million tonnes (Fig. 8c). The corresponding annual

427 VWF are 29, 21, and 51 billion m<sup>3</sup> for wheat, barley, and canola, respectively (Fig. 8d). The  
428 reduction in area coverage of cereal crops resulted in a total of 101 billion m<sup>3</sup> VWF and indicated  
429 a reduction of about 27% as compared to the use of full area coverage based on the crop density  
430 map of Fig. A1.

## 431 **4. Discussion**

### 432 **4.1 Comparison with previous studies**

433 Historical regional studies on the VWF demonstrate substantial variation in VWC of a given crop  
434 in a geographic location. In this study, our simulated VWC of rainfed and irrigated crops fall below  
435 the range reported in other large-scale studies. In a global study by Hoekstra and Hung (2002), the  
436 long-term average (1995-1999) VWC of wheat and barley for Canada were reported to be 1441  
437 and 1098 m<sup>3</sup>/tonne, respectively. Similarly, other global scale studies reported a wide range from  
438 1057 to 2209 m<sup>3</sup>/tonne for VWC of wheat in Canada (Chapagain et al., 2006; Aldaya et al., 2009;  
439 Hanasaki et al., 2010; Mekonnen and Hoekstra, 2014; Tuninetti et al., 2015). While global studies  
440 ignore important information at a local scale and often simplify the representation of the key  
441 processes, our predicted VWC based on a locally adapted large-scale SWAT model was 797  
442 m<sup>3</sup>/tonnes for Alberta. Inadequate consideration of local climate and soil conditions, and  
443 inaccurate reflection of local management practices, as well as poor calibration and validation of  
444 the models, may be attributed to the uncertainty in estimating VWC in earlier regional and global  
445 studies (Mekonnen and Hoekstra, 2014). Variations also existed among studies for the estimation  
446 of VWC for barley and canola. For barley, the ranges found in the literature (546-1029 m<sup>3</sup>/tonne)  
447 (Mekonnen and Hoekstra, 2014) overlap well with the overall average value (835 m<sup>3</sup>/tonne) found  
448 in this study. However, results from our study indicated large variations in the VWC estimation in  
449 different sub-basins within Alberta (Fig. 4). This suggests that the estimation of VWC is sensitive

450 to time, crop parameters, input data, and geographic location in the modeling framework (Hanasaki  
451 et al., 2010). Sun et al. (2013) found the local agricultural management practices as the most  
452 influential factor in calculating the VWC, followed by the regional climate and its variation.  
453 Similar discrepancies have been found by Shtull-Trauring and Bernstein (2018) who compared  
454 global and local scale datasets in calculating VWC and suggested the use of local datasets. Higher  
455 resolution and accurate data are essential for the development of appropriate local, regional and  
456 national agricultural policy.

457         According to our analysis, Alberta has enormous potential to export virtual water through  
458 grain export to the rest of the world (Fig. 8). Previous studies supported our results by estimating  
459 the historical trade record of Canada, which is one of the top five countries with net virtual water  
460 export (Hoekstra and Hung, 2005; Hanasaki et al., 2010). However, local water renewals and  
461 demands of other water use sectors and environment should be taken into account for a  
462 comprehensive understanding of the future risks and opportunities for food production. Therefore,  
463 developing a locally adapted modeling framework for simulation and projection of both VWF  
464 potentials and local water renewals, similar to this study, is necessary for both regional and global  
465 water-food policy and planning in support of sustainable agriculture.

#### 466 **4.2 Global and regional policy implications of VWT**

467 The net VW export from Alberta, due to the trade of grain wheat, to other countries is presented  
468 in Fig. 9. Alberta has exported wheat to more than a hundred countries in the world (Table A7).  
469 According to our results, the largest virtual water importers from Alberta are Japan, China, USA,  
470 Indonesia, Mexico, Italy, Colombia, Peru, Nigeria, and Bangladesh (Fig. 9); and altogether these  
471 countries import more than 50% of the total virtual water. We also calculated the magnitude of  
472 virtual water requirements if the importing countries would have produced grain wheat on their

473 own soil. VWC of the importing countries was obtained from Hoekstra and Chapagain, (2006) and  
 474 Mekonnen and Hoekstra (2011), and the global average VWC was used for Indonesia as there is  
 475 no data available for this country. The results showed that during 1996-2005, Japan, China and  
 476 USA have annually imported 0.342, 0.303 and 0.293 billion m<sup>3</sup> of virtual water by importing grain  
 477 wheat from Alberta. This revealed a VW saving of 0.516, 0.616 and 0.512 billion m<sup>3</sup>, respectively  
 478 (Fig. 9). Overall, we found the global water savings due to the export of grain wheat from Alberta  
 479 to other countries was 4.897 billion m<sup>3</sup>. This supports the fact that regional and global WUE can  
 480 be increased if countries use their comparative advantages and disadvantage regarding water  
 481 availability and water use (Chapagain et al., 2006).

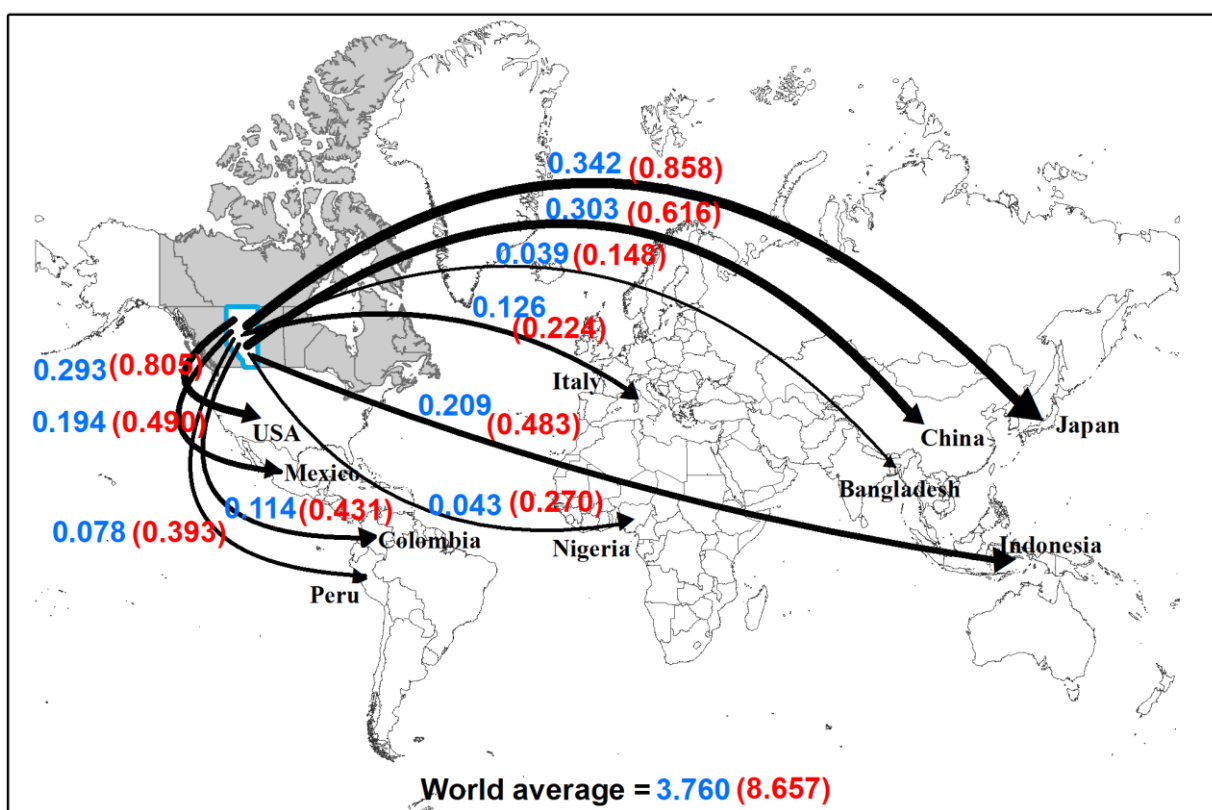


Fig. 9. Global water saving (billion m<sup>3</sup>/yr) related to the wheat export from Alberta to selected countries during 1996-2005 (all countries listed in SI). Values in the parentheses indicate the amount of virtual water required if the importing countries produced those imports on their own soil.

482           It is important to note that irrigation in Alberta is unquestionably a significant part of the  
483 agricultural industry contributing to more than 19% of the gross provincial production and  
484 covering 6% of the total cultivated lands in southern part of the province (Alberta Agriculture and  
485 Forestry, 2018b). Although importing countries have benefited by importing wheat grain from  
486 Alberta, the local water resources in Alberta and their low renewal rates in southern parts of the  
487 province may become a barrier to long-term production and trade opportunities. This is evident  
488 from our earlier studies (Faramarzi et al., 2015, 2017), where a large historical water scarcity was  
489 found for agricultural crop growing months in irrigated districts of southern sub-basins. This also  
490 indicated by Goswami and Nishad (2015) that the net virtual water export alone can lead to loss  
491 of water sustainability of a nation (e.g., India) by less than 300 years. Canada has the highest  
492 negative balances of water, mainly due to wheat exports and the associated water consumption  
493 that is more than 50% of total water consumption to produce export goods (Fader et al., 2011).  
494 Therefore, local water security challenges need to be considered in future VWF calculations to  
495 ensure a sustainable trade pattern in the future.

496           On the contrary, Aldaya et al. (2009) reported that precipitation and rainfed agriculture is  
497 by far the largest share of VWC in wheat export from Canada. Given the low opportunity cost of  
498 rainfed agriculture as compared to irrigated, Alberta might be in a relatively good future condition  
499 regarding VWF due to the projected increases in precipitation (Masud et al., 2017b), larger Y, and  
500 higher production as shown in this study. However, the long-term environmental impacts (e.g., on  
501 soil and water quality), and the imbalance between local water yields and water consumption (e.g.,  
502 if the future VWF potentials exceed local water yields), may require landuse change and a proper  
503 water-food, and land management. All these important factors need to be taken into account for a

504 sustainable and an environmentally informed VWT strategy. These are subjects of our future  
505 studies.

### 506 **4.3 Limitations**

507 In this framework, some limitations are worthy of further improvements. A crop consumption  
508 component in the production and export processes of other commodities than grain crops (e.g.,  
509 beef, poultry, and beverages) would enhance the VWF accounting. The VWT can be influenced  
510 by socioeconomic factors like food prices which play a significant role in the consumption pattern  
511 and quantity of crops. The international trade efficiency of crops is also highly dependent on other  
512 factors than water alone, including land scarcity, cost of labor, comparative advantages, domestic  
513 and international subsidies and taxes (Chapagain et al., 2006). Moreover, the bilateral political  
514 relationship between countries may considerably influence the trade pattern and overall efficiency.

### 515 **5. Conclusions**

516 This study developed a framework to project future VWF related to cereal crops and corresponding  
517 water savings under different climate change scenarios. Our results for the historical 1985-2009  
518 and future 2040-2064 periods revealed that:

- 519 • Future climate change leads to an increase in cereal crop yields and a decrease in VWC.
- 520 • The VWC varied substantially in time and space and for different production conditions  
521 (rainfed and irrigated).
- 522 • The area-based weighted average VWC of both rainfed and irrigated crops at provincial  
523 level revealed that the VWF of wheat grain from Alberta to more than a hundred countries  
524 in the world has led to a global annual water saving of 4.897 billion m<sup>3</sup> during 1996-2005.
- 525 • Future climate change may provide opportunities for increases in the export of virtual water  
526 through export of cereal crops. However, it may exceed some hydrologic water balance

527 components and be affected by local water resources availability and low renewal rates.  
528 Our results indicated that total VWF through the export of cereal crops, in the form of both  
529 grain and processed foods, would outweigh the total historical water yield and will account  
530 for about 47% of total precipitation and 61% of total ET due to ET from all vegetation and  
531 crop types.

- 532 • For a sustainable VWT strategy, future water renewals, as well as environmental impacts,  
533 should be predicted using locally adapted modeling tools.

#### 534 **Acknowledgment**

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