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Assessment of Climate Change and Atmospheric CO_2 Impact on Winter Wheat in the Pacific Northwest Using a Multimodel Ensemble

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Simulations of crop yields under climate change are subject to uncertainties whose quantification is important for effective use of projected results for adaptation and mitigation strategies. In the US Pacific Northwest (PNW), studies based on single crop models and weather projections downscaled from a few general circulation models (GCM) have indicated mostly beneficial effects of climate change on winter wheat production for most of the twenty-first century. In this study we evaluated the uncertainty in the projection of winter wheat yields at seven sites in the PNW using five crop growth simulation models (CropSyst, APSIM, DSSAT, STICS, and EPIC) and daily weather data downscaled from 14 GCMs for 2 representative concentration pathways (RCP) of atmospheric CO_2 (RCP4.5 and 8.5). All crop models were calibrated for high, medium, and low precipitation dryland sites and one irrigated site using 1979–2010 as the baseline period. All five models were run from years 2000 to 2100 to evaluate the effect of future conditions (precipitation, temperature and atmospheric CO_2) on winter wheat grain yield. Simulations of future climatic conditions and impacts were organized into three 31-year periods centered around the years 2030, 2050, and 2070. All models predicted a decrease of the growing season length and crop transpiration, and increase in transpiration-use efficiency, biomass production, and yields, but with substantial variation that increased from the 2030s to 2070s. Most of the uncertainty (up to 85%) associated with predictions of yield was due to variation among the crop models. Maximum uncertainty due to GCMs was 15% which was less than the maximum uncertainty associated with the interaction between the crop model effect and GCM effect (25%). Large uncertainty associated with the interaction between crop models and GCMs indicated that the effect of GCM on yield varied among the five models. The mean of the ensemble of all crop models and GCMs provided a robust indication of positive effects of future environmental conditions on winter wheat yield during this century at all sites studied, with greater beneficial effect under water stressed conditions than under well-watered conditions, and under RCP8.5 than RCP4.5.

Keywords: climate change, CO_2 fertilization, crop-climate models, multimodel ensemble, uncertainty, winter wheat

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INTRODUCTION

Climate change is a major concern for crop productivity. The chief elements of climate change include rising temperature, modified frequency, and severity of extreme events, and elevated atmospheric concentration of CO_2 (Rosenzweig and Tubiello, 2007). Concentrations of CO_2 are now significantly higher than in earlier years and they have been increasing continuously and rapidly (Siegenthaler et al., 2005). Agriculture is one of the sensitive sectors to climate variability and change (Slingo et al., 2005; Osborne et al., 2013). Climate change has affected crop growth, development and yield over the past few decades across the globe directly or indirectly (Nicholls, 1997; Lobell and Asner, 2003; Challinor and Wheeler, 2008a; Teixeira et al., 2013). Direct effects are due to increased CO_2 fertilization which leads to higher photosynthetic rate and water use efficiency (Challinor and Wheeler, 2008b). Indirect effects include crop responses to variability in temperature and precipitation. Higher seasonal temperature increases the risk of water stress, limits photosynthesis, and reduces light interception by accelerating crop phenological development (Tubiello et al., 2007).

Wheat is the third largest crop globally, which has shown particular sensitivity to climate change (Porter and Semenov, 2005), yet increased wheat yield has also been reported for some regions of the world because of increased growth rates and a shift of the grain filling period to a wetter part of the season (Xiao et al., 2010).

Mechanistic process-based crop models are common tools for assessing the impact of climate change on crop productivity, incorporating physiological responses of crop growth and development to environmental and management variables. Different crop models have been used to study climate change impact on crop production across the globe but with mixed results (Lobell and Burke, 2010). The assessment of climate change impacts on agriculture often has been conducted using

TABLE 1 | Modeling approaches of five models used for a study of climate change effects on crop performance in the Pacific Northwest.

Model characteristic	Crop model				
	CropSyst	**APSIM**	**DSSAT**	**EPIC**	**STICS**
Crop phenology[a]	f (TPV)	f (TPVW)	f (TPV)	f (TPV)	f (TPVO)
Leaf area development and Light interception[b]	S	D	D	S	D
Light utilization/Biomass production[c]	TE /RUE	RUE/TE	RUE	RUE	RUE
Biomass partitioning[d]	None	PCD	PCD	None	PCD
Yield formation[e]	B, HI	Prt, B, Gn, LHI	B, Gn, HI	B, HI	B, Gn, HI
Root distribution over depth[f]	LIN	EXPO	EXPO	EXPO	SIG
Stresses[g]	WNH	WAH	WN	WNO	WNH
Water stress type[h]	E	S	E	E	S
Heat stress type[i]	VR	V	–	V	VR
Water dynamics[j]	C	C	C	C	C
Water relation[k]	S	D	D	S	D
Plant N budget[l]	S	D	D	S	D
Evapotranspiration[m]	PM	PT	PM	PM	PT
Soil CN model[n]	CNP(1)	CNP(3)B	CNP(4)B	CNP(5)	CNP(3)B
CO_2 effects[o]	RUE/TE/T	RUE/TE	RUE/TE	RUE/TE	RUE
Model relative[p]	CRS	C	C	C	C
Model type[q]	P	P	P	PG	P

[a] *Crop phenology is a function (f) of: T, temperature; P, photoperiod; V, vernalization; W, water stress; O, other water stress or nutrient stress.*
[b] *Leaf area development and Light Interception: S, simple; D, detailed approach.*
[c] *Light Utilization/Biomass Production: RUE, radiation use efficiency; TE, transpiration-use efficiency.*
[d] *Biomass partitioning: PCD, detailed partitioning coefficients and more organs.*
[e] *Yield Formation: B, total above ground biomass; HI, fixed harvest index; Prt, partitioning during reproductive stages; LHI, linear increase in harvest index; Gn, grain number.*
[f] *Root distribution over depth: LIN, linear; EXPO, exponential; SIG, sigmoidal.*
[g] *Stresses: W, water; N, nitrogen; H, heat; A, air (Oxygen); O, others (e.g. EPIC model considers stresses for both above ground (water, temperature, nitrogen, phosphorus and potassium stresses) and below ground growth [Bulk density, aluminum tolerance (Soil acidity), salinity, temperature and soil aeration)].*
[h] *Water stress type: E, Eta/Etp; S, soil available water in root zone.*
[i] *Heat stress type: V, vegetative (source); R, reproductive (sink).*
[j] *Water Dynamics: C, Tipping bucket capacity approach.*
[k] *Water relation: S, simple approach includes linear increase in root depth; D, detailed approach includes root growth and water absorption.*
[l] *Plant N budget: S, simple from nitrogen dilution curve; D, detailed concentration curves for different organs over growth period.*
[m] *Evapotranspiration: PM, Penman-Monteith; PT, Priestley-Taylor.*
[n] *Soil CN model: N, nitrogen mode; P(x), x number of organic matter pools; B, microbial biomass pool.*
[o] *CO_2 effects: RUE, radiation use efficiency; TE, transpiration efficiency; T, stomatal conductance.*
[p] *Model relative: CRS, CropSyst; C, CERES.*
[q] *Model type: P, point model (site specific); G, global or regional model.*

a combination of weather downloaded from general circulation models (GCM) and crop responses evaluated with cropping systems models (CSM), often one crop model and a few GCM projections. This approach has been applied to the US Pacific Northwest (PNW) with projections suggesting mostly beneficial effects of climate change on wheat production, especially winter varieties (Thomson et al., 2002; Stöckle et al., 2010). However, recent studies (e.g., Asseng et al., 2013; Martre et al., 2015; Ruane et al., 2016) have shown large variation in both GCM and CSM projections, which can introduce significant uncertainty in assessments of climate change impact on agriculture.

Based on results of a 27-wheat model comparison study, Asseng et al. (2013) reported that crop models were able to produce acceptable yield estimates compared to observations from single-year experiments for four diverse sites when properly calibrated. However, when changes in precipitation combined with increases in temperature and atmospheric CO_2 concentration were imposed on the same sites, a large variation in yield projections was obtained. Thus, Asseng et al. (2013) recommended the use of crop model ensembles, particularly when limited information about the crops and cropping systems involved is available, suggesting that at least five models should be used for reliable assessment of yield impacts for temperature increases up to 3°C and 540 ppm of CO_2, with fewer models needed for lower temperature increases and vice versa. Similar results have been reported for maize models (Bassu et al., 2014) and rice models (Li et al., 2015), where model ensembles appeared to perform better than individual models when compared with observations. Martre et al. (2015) concluded that there was no additional advantage of a model ensemble including more than 10 models. Bassu et al. (2014), in a study involving 23 maize models, concluded that a single model may not be able to simulate well absolute yields while an ensemble of 8–10 models is more likely to perform better if a small amount of information is available for calibration. Li et al. (2015) evaluated 13 rice models against experimental information and found that individual models were not consistent in reproducing observed yields, but an ensemble of five models properly calibrated was able to approximate measured yields within the uncertainty of well-controlled experiments.

Studies such as those of Asseng et al. (2013), Bassu et al. (2014), and Li et al. (2015) that include a large number of crop models for a given crop species are possible by the direct involvement of modelers and user groups. The customary use of large crop model ensembles as a standard practice in climate change assessments would be time consuming and costly (at least for now), and will require significant cooperation. In the meantime, securing adequate information on some key crop characteristics such as crop phenology, canopy cover [e.g., maximum leaf area index (LAI)], and rooting depth along with the use of a few models, well-documented and tested under a large range of conditions around the world, appears to be a reasonable approach.

With the interest of corroborating or disputing previous findings regarding climate change impacts on wheat production in the PNW, USA, in this study we evaluated the uncertainties in yield projections related to crop-climate models using 5 CSMs and 14 GCMs. Our primary focus was on the usefulness of applying a multimodel ensemble in the examination of future climate change in the IPNW. Toward this end, we excluded consideration of rotational effects and other effects related to farm management decisions.

MATERIALS AND METHODS

The impacts on winter wheat productivity at six dryland and one irrigated sites were evaluated using five well-established CSM (CropSyst, APSIM-Wheat, DSSAT CERES Wheat, EPIC, and STIC) and downscaled weather projections from 14 GCMs and 2 RCPs (RCP4.5 and 8.5).

TABLE 2 | General circulation models used to study dryland crop response to future climate change in the Inland Pacific Northwest.

General Circulation Model	Source	References
BCC-CSM1.1	Beijing Climate Center	Wu et al., 2014
BNU-ESM	Beijing Normal University Earth System Model	Ji et al., 2014
CanESM2	Canadian Centre for Climate Modeling and Analysis	Chylek et al., 2011.
CNRM-CM5	Centre National de Recherches Me'te'orologiques—Groupe d'e'tudes de l'Atmosphe're Me'te'orologique and Centre Europe'en de Recherche et de Formation Avance'e	Voldoire et al., 2013
CSIRO-Mk3-6-0	Commonwealth Scientific and Industrial Research Organisation and Queensland Climate Change Centre of Excellence	Jeffrey et al., 2013
GFDL-ESM2G	Geophysical Fluid Dynamics Laboratory Earth System Models	Dunne et al., 2013
GFDL-ESM2M	Geophysical Fluid Dynamics Laboratory Earth System Models	Delworth et al., 2006
HadGEM2-CC	Hadley Global Environment Model 2—Carbon Cycle	Martin et al., 2011
HadGEM2-ES	Hadley Global Environment Model 2—Earth System	Martin et al., 2011
INMCM4	Institute for Numerical Mathematics, Moscow, Russia	Voldin et al., 2010
MIROC5	Model for Interdisciplinary Research on Climate	Watanabe et al., 2010
MIROC-ESM	Model for Interdisciplinary Research on Climate, Earth System Model	Watanabe et al., 2011
MIROC-ESM-CHEM	Model for Interdisciplinary Research on Climate, Earth System Model	Watanabe et al., 2011
MRI-CGCM3	Meteorologcical Research Institute	Yukimoto et al., 2012

TABLE 3 | Characteristics of seven study sites used for a study of climate change effects on crop performance in the Pacific Northwest.

Characteristics	Study site						
	Pullman	**Kambitsch**	**Wilke**	**St. John**	**Lind**	**Moro**	**Moses Lake (irrigated)**
Position latitude/longitude/altitude m.a.s.l	46°78′/−117°09′/ 796.75	46°58′/−116°95′/ 848.86	47°65′/−118°14′/ 743.71	47°09′/−117°58′/ 598.00	47°00′/-118°56′/ 505.35	45°48′/-120°72′/ 566.92	47°31′/−119°54′/ 389.00
Average annual precipitation (mm year^{-1})	590.3	685.2	354.7	437.4	261.1	296.3	205.0
Simulation period precipitation (mm)	474.7	561.6	323.0	407.6	216.1	229.5	192.7
Average annual temperature (°C)	7.2	6.9	5.5	6.6	7.1	7.1	8.7
Soil texture	Silty Clay Loam	Silty Clay Loam	Coarse Silt Loam	Coarse Silt Loam	Coarse Silt Loam	Coarse Silt Loam	Sandy Loam
Sand (%)	12.0	7.6	11.0	11.0	21.7	14.2	48.9
Silt (%)	69.3	63.6	68.6	68.6	70.8	71.8	21.1
Clay (%)	18.7	28.7	20.4	20.4	7.5	14.0	30.0
Bulk density (g cm^{-3})	1.3	1.3	1.3	1.3	1.3	1.4	1.4
Soil water at field capacity in the root zone (m^3 m^{-3})	0.3	0.3	0.3	0.3	0.3	0.3	0.3
Soil water at wilting point in the root zone (m^3 m^{-3})	0.2	0.2	0.1	0.1	0.1	0.1	0.1
Soil name	Mollisol	Mollisol	Mollisol	Mollisol	Aridisol	Aridisol	Aridisol

TABLE 4 | Target results for a series of five cropping system models used in a study of climate change effects on crop performance at several locations in the Pacific Northwest.

Study site	Crop trait	Predicted					
		Target range	APSIM	CropSyst	DSSAT	EPIC	STICS
Pullman	Emergence (DOY)†	295	295	295	295	295	295
	Anthesis time (DOY)	162	160	162	162	–	160
	Maturity time (DOY)	215	214	216	215	215	214
	$LAI^{\dagger}_{max}$	4.5–6.0	4.5–6.9	2.2–6.3	3.5–6.5	4.8–5.4	4.5–6.2
	Biomass at harvest (t ha^{-1})	11.2–16.0	10.0–16.3	6.3–17.6	8.8–16.3	12.9–15.0	9.4–15.9
	Grain yield (t ha^{-1})	4.5–7.2	3.5–7.8	2.6–7.8	3.1–7.5	5.4–6.2	5.0–7.5
	HI†	0.40–0.45	0.35–0.45	0.41–0.44	0.36–0.45	0.40–0.42	0.35–0.46
Wilke	Emergence (DOY)	260	260	260	260	260	260
	Anthesis time (DOY)	150	149	150	150	–	150
	Maturity time (DOY)	200	199	200	200	200	200
	LAI_{max}	3.5–5.0	2.1–5.0	3.0–5.7	2.5–6.0	3.3–4.2	3.2–5.4
	Biomass at harvest (t ha^{-1})	9.0–12.0	8.0–15.2	5.4–14.3	8.1–15.5	5.3–13.8	8.5–12.5
	Grain yield (t ha^{-1})	3.3–5.00	2.69–7.2	2.2–6.2	2.5–7.2	2.1–5.8	3.5–7.0
	HI	0.38–0.43	0.30–0.49	0.41–0.44	0.30–0.46	0.40–0.42	0.39–0.44
Lind	Emergence (DOY)	251	251	250	251	251	251
	Anthesis time (DOY)	143	143	143	143	143	143
	Maturity time (DOY)	191	191	191	191	191	191
	LAI_{max}	2.5–3.5	1.6–3.4	2.5–3.5	2.5–3.0	2.5–3.8	2.5–3.3
	Biomass at harvest (t ha^{-1})	2.6–8.0	1.7–9.5	2.1–9.0	2.1–8.5	2.4–11.9	2.7–8.9
	Grain yield (t ha^{-1})	1.0–3.5	0.7–4.0	1.0–4.0	0.8–3.6	0.9–5.0	1.1–4.0
	HI	0.38–0.43	0.38–0.46	0.40–0.43	0.39–0.42	0.38–0.42	0.38–0.44
Moses Lake	Emergence (DOY)	251	251	251	251	251	251
	Anthesis time (DOY)	143	143	143	143	–	143
	Maturity time (DOY)	191	191	191	191	191	192
	LAI_{max}	6.0–7.0	4.5–6.5	4.9–7.0	5.5–6.5	4.6–5.3	5.9–7.0
	Biomass at harvest (t ha^{-1})	16.5–20.0	14.4–22.2	14.5–21.7	12.3–21.9	14.2–21.0	16.0–20.6
	Grain yield (t ha^{-1})	7.5–9.5	6.0–9.0	6.5–11.4	5.0–10.6	6.0–8.9	7.1–8.2
	HI	0.45–0.48	0.35–0.45	0.44–0.45	0.38–0.48	0.41–0.42	0.37–0.49

† *DOY, day of year; LAI_{max}, maximum leaf area index; HI, harvest index.*

Crop Models

CropSyst

CropSyst is a multi-year, multi-crop, daily time-step cropping system model developed as an analytical tool to study the effect of climate, soil, and management on the productivity and environmental impact of cropping systems (Stöckle et al., 2003). The model can simulate crop development, growth and yield in response to weather, atmospheric CO_2 concentration, and management (crop rotations, fertilization, irrigation, tillage), and soil processes such as soil water dynamics, nitrogen budgets, soil erosion by water, and salinity. Details on the use, parametrization and execution of CropSyst are given on the website (http://modeling.bsyse.wsu.edu/CS_Suite_4/CropSyst/index.html).

APSIM

The APSIM (Agricultural Production Systems Simulator) is a modeling framework developed by the Agricultural Production Systems Research Unit (APSRU) in Australia (Keating et al., 2003). APSIM was developed to simulate biophysical processes in farming systems, in particular where there is interest in the economic and ecological outcomes of management practice in the face of climatic risk (Keating et al., 2003). It was constructed on a modular modeling framework based on biophysical processes in farming systems with many plant, soil and management modules for a diverse range of crops, pastures and trees, soil processes including water balance, nitrogen and phosphorus transformations, soil pH, erosion, and a full range of management controls. Details of the model are included on the APSIM web site (https://www.apsim.info/Documentation.aspx). The APSIM-Wheat model version 6.1 (Wang et al., 2002; Keating et al., 2003) was used in this study.

DSSAT_CERES_Wheat

The CERES wheat model included in the DSSAT (Decision Support System for Agrotechnology Transfer) family of models is a complex model used to integrate knowledge about crops, soil, climate, and management for making appropriate decisions under a wide range of climatic conditions. It can be used to design

TABLE 5 | Performance of five crop models under historical weather conditions (1979–2010) in simulating mean maximum leaf area index (LAI_{max}), above-ground biomass, grain yield and harvest index (HI) with standard deviation and coefficient of variation at three sites not used for model calibration in the Pacific Northwest.

Study site	Crop trait	APSIM			CropSyst			DSSAT			EPIC			STICS		
		Mean	SD	CV	Mean	SD	CV	Mean	SD	CV	Mean	SD	CV	Mean	SD	CV
Kambitsch	LAI_{max} (m^2 m^{-2})	5.8	0.4	0.1	6.0	0.3	0.1	5.5	2.3	0.4	5.8	1.1	0.2	5.5	1.2	0.2
	Biomass (t ha^{-1})	13.9	2.5	0.2	16.4	2.1	0.1	13.6	3.2	0.2	14.0	2.7	0.2	14.6	2.1	0.2
	Yield (t ha^{-1})	5.8	1.2	0.2	7.2	1.0	0.1	6.0	1.2	0.2	5.7	1.1	0.2	6.6	1.0	0.2
	HI	0.42	0.04	0.10	0.44	0.01	0.02	0.45	0.05	0.11	0.40	0.01	0.02	0.46	0.06	0.13
Moro	LAI_{max} (m^2 m^{-2})	2.9	0.4	0.2	3.5	1.5	0.4	2.7	2.4	0.9	3.2	0.4	0.1	3.3	1.4	0.4
	Biomass (t ha^{-1})	6.5	1.6	0.3	6.2	2.6	0.4	6.7	3.3	0.5	6.7	2.6	0.4	6.3	2.6	0.4
	Yield (t ha^{-1})	2.7	0.7	0.3	2.6	1.1	0.4	2.8	1.5	0.5	2.8	1.1	0.4	2.9	1.6	0.6
	HI	0.42	0.02	0.04	0.42	0.01	0.02	0.42	0.05	0.12	0.42	0.05	0.11	0.47	0.19	0.40
St. John	LAI_{max} (m^2 m^{-2})	5.0	0.9	0.2	4.9	1.0	0.2	4.5	1.3	0.3	4.6	0.7	0.2	4.7	0.8	0.2
	Biomass (t ha^{-1})	15.2	1.4	0.1	11.0	2.7	0.3	12.0	2.6	0.2	10.4	2.3	0.2	11.7	1.4	0.1
	Yield (t ha^{-1})	6.2	1.1	0.2	4.7	1.2	0.3	5.3	1.3	0.2	4.3	1.0	0.2	4.7	0.8	0.2
	HI	0.41	0.04	0.10	0.43	0.01	0.03	0.45	0.08	0.18	0.41	0.01	0.02	0.40	0.04	0.10

optimum crop management practices, precision agriculture, and pest management. Similarly, it can be used to quantify responses to climate change and variability impacts on crop yield and to study long term sustainability, environmental pollution and genomics (Hoogenboom et al., 2012; http://dssat.net/).

EPIC

The EPIC (Environmental Policy Integrated Climate) model is a field scale soil and crop model originally designed to quantify the effects of erosion on soil productivity (Williams et al., 1984). It is a complete agroecosystem model that can simulate crop growth under different rotations while simulating detailed soil management operations. EPIC version 0810 was used in this study. Additional information on the EPIC model can be found at http://epicapex.tamu.edu/epic/.

STICS

The STICS crop growth model was developed by INRA, France (Brisson et al., 2003). The model can simulate carbon, water and nitrogen dynamics as well as a number of different environmental and agricultural variables in response to weather, soil, crop, and management practices. STICS is a generic model that can simulate various kinds of crops and environmental conditions. Options for plant parameters associated with detailed ecophysiological characteristics are adjusted to define a specific crop. Additional parameters are used to simulate physical and biological processes occurring in the soil-crop system and define soils, crop management and climate. In this work, we used STICS version v8.4. The detailed description of all parameters used in the model is available in the document freely downloadable with the model from http://www6.paca.inra.fr/stics_eng/.

A general description of the approaches used by each of the five crop models is presented in **Table 1**.

General Circulation Models (GCMs)

Many GCMs have been evaluated for use in climate change studies (Randall et al., 2007; Flato et al., 2013). The fourteen GCMs listed in **Table 2** were used in this study due to their suitability for use in North America (Rupp et al., 2013; Sheffield et al., 2013). The methodology used for generation of the weather data for these GCMs is found in Abatzoglou (2013) and Abatzoglou and Brown (2012). Specific datasets are available at http://thredds.northwestknowledge.net:8080/thredds/reacch_climate_MET_catalog.html.

Emission Scenarios

Representative concentration pathways (RCP) are climate change research scenarios that contain trajectories of emissions, GHG concentrations and land-use patterns based on alternative responses of future socio-economic, technological, energy use, and emissions patterns (Van Vuuren et al., 2011). Four RCPs have been developed that provide distinct trajectories of radiative forcing and GHG concentrations (Moss et al., 2010). For this research, we used RCP4.5 which stabilizes at a radiative forcing of 4.5 W m^{-2} and 650 ppm CO_2-equiv in the year 2100, and RCP8.5 which develops a radiative forcing of 8.5 W m^{-2} and 1,370 ppm CO_2-equiv at 2100 (Moss et al., 2010). RCP4.5 is characterized by policies that, among other things, reduce energy use, reduce fossil fuel use, increase renewable and nuclear energy, employ CO_2 capture and storage, expand forests, and reduce beef consumption by a world population of 8.7 billion in 2100 (Thomson et al., 2011). RCP8.5 is characterized by minimal climate change policies, global population of 12 billion in 2100, slow income growth, high energy demand mostly from fossil fuels and declines in forested area (Riahi et al., 2011).

Study Sites

Seven diverse agro-ecological sites were selected for CSM and GCM models ensemble study. These sites are in the main

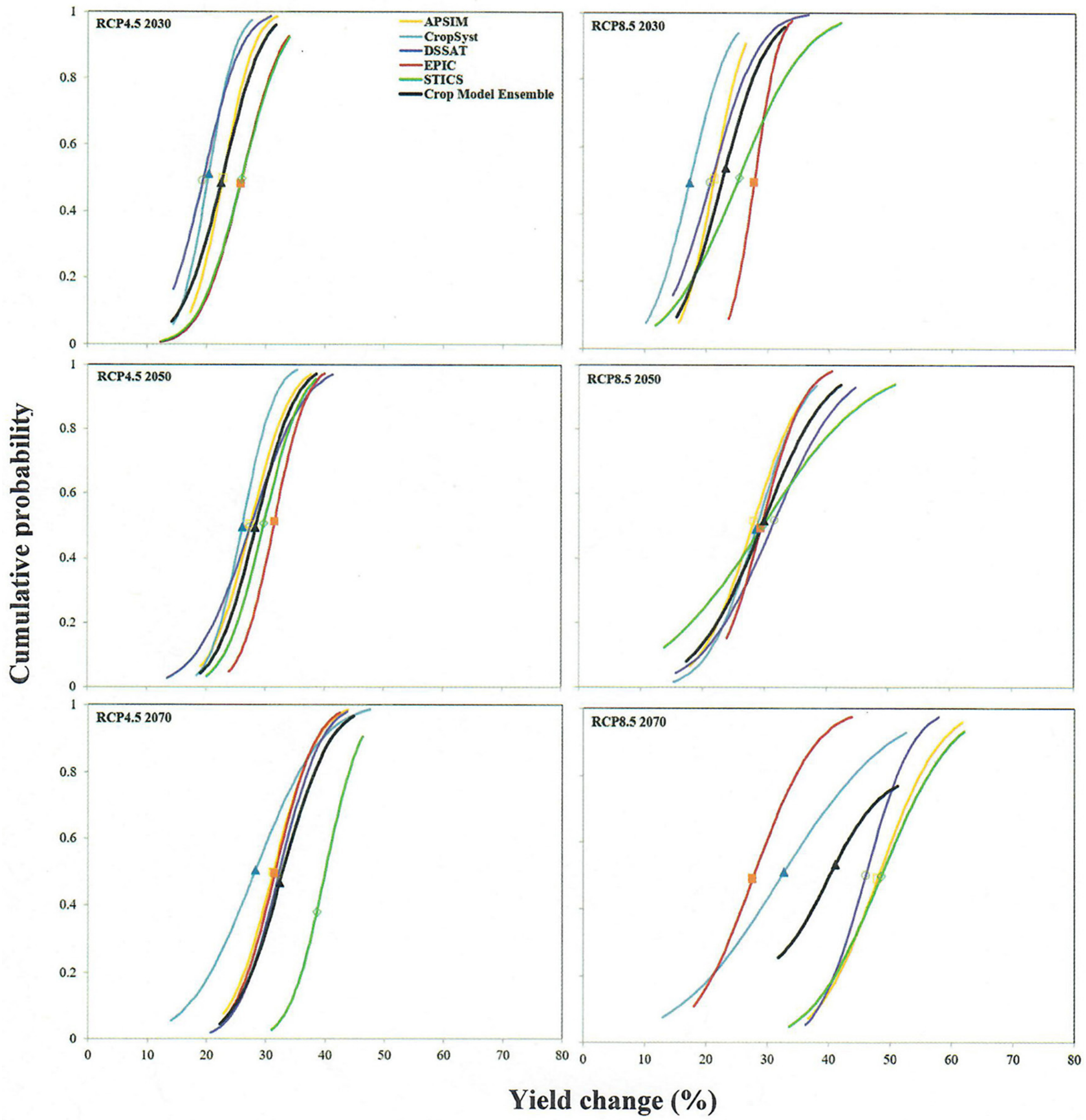

FIGURE 1 | Cumulative probability distribution for simulated winter wheat yield changes during three 31 year time periods, centered on 2030, 2050, and 2070, relative to the baseline period (1979–2010) under two representative concentration pathways (RCP4.5 and 8.5) and five crop models with ensembles of crop models at high rainfall site Pullman. Symbols on curves are at the curve's inflection point and represent the most probable yield change.

winter wheat production region in the IPNW. Average annual precipitation ranges from 125 to 700 mm on moving from west to east (Schillinger et al., 2010). Basic features of the study sites are summarized in **Table 3**.

Model Simulation Targets

To establish reasonable historical baselines for all five CSMs, four study sites were selected: Pullman (high precipitation), Wilke (intermediate precipitation), Lind (low precipitation), and Moses Lake (irrigated). Baseline simulations (1979–2010) were conducted for all models to meet targets for crop phenology (emergence, anthesis, and maturity dates), maximum LAI, biomass at maturity, and yield derived from literature and extension reports focused on winter wheat in the study region (Papendick, 1996; Schillinger et al., 2006; Schillinger, personal communication; WSU Extension variety trials). The model parameters used were as suggested for winter wheat by the respective models, with adjustments to phenology, and minor adjustments to leaf area development and biomass production parameters within the range provided by each model so as to conform to the targets, with the same set of parameters (except for phenology) used in all sites.

Although, winter wheat in the region is rotated with other cereals and legumes, to avoid adding complexity to

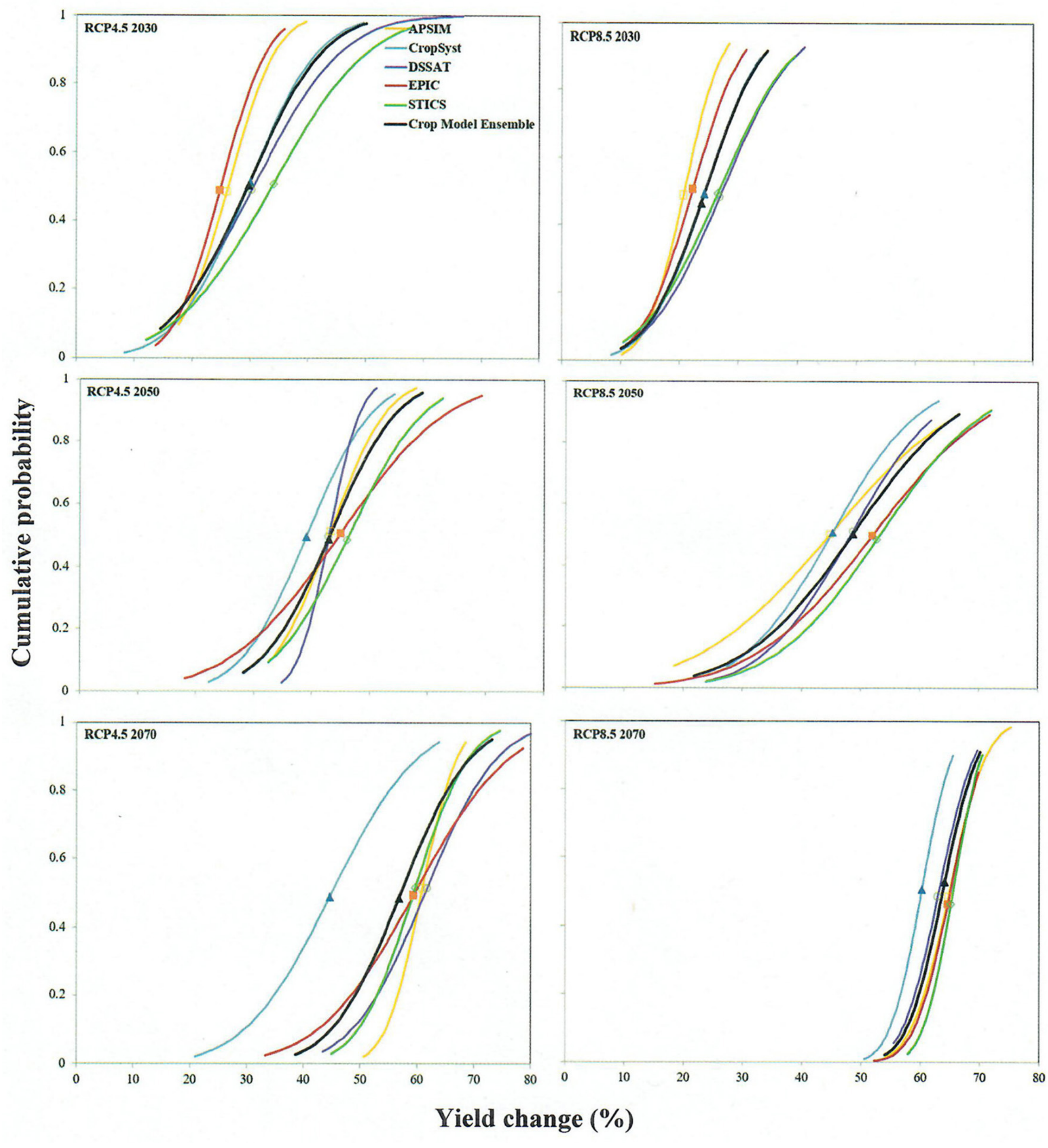

FIGURE 2 | Cumulative probability distribution for simulated winter wheat yield changes during three 31-year time periods, centered on 2030, 2050, and 2070, relative to the baseline period (1979–2010) under two representative concentration pathways (RCP4.5 and 8.5) and five crop models with ensembles of crop models at low rainfall site Lind. Symbols on curves are at the curve's inflection point and represent the most probable yield change.

the comparison of models and to focus on the simulated responses of wheat to climate variation and atmospheric CO_2, continuous winter wheat was simulated. The profile soil water content was reset to a set low value at the end of the summer each year, so that cumulative effects were not a factor. To focus our concern only on CSM and GCM, we removed the confounding effects of crop rotation and carryover. **Table 4** shows targets and baseline results after parameter adjustments.

Simulations and Analysis

In total, 140 simulations were generated for each study site (14 GCMs × 5 crop models × 2 RCPs), with outputs separated into three time periods (2030s, 2015–2045; 2050s, 2035–2065; and 2070s, 2055–2085). PROC ANOVA in SAS, Version 9.2 (SAS Institute Inc., 2010), was used to obtain the sums of squares for targeted effects, and an Uncertainty Index (UI) was calculated by dividing the treatment sums of squares by the total sums of squares (Holzkämper et al., 2015). The resulting UI is a measure

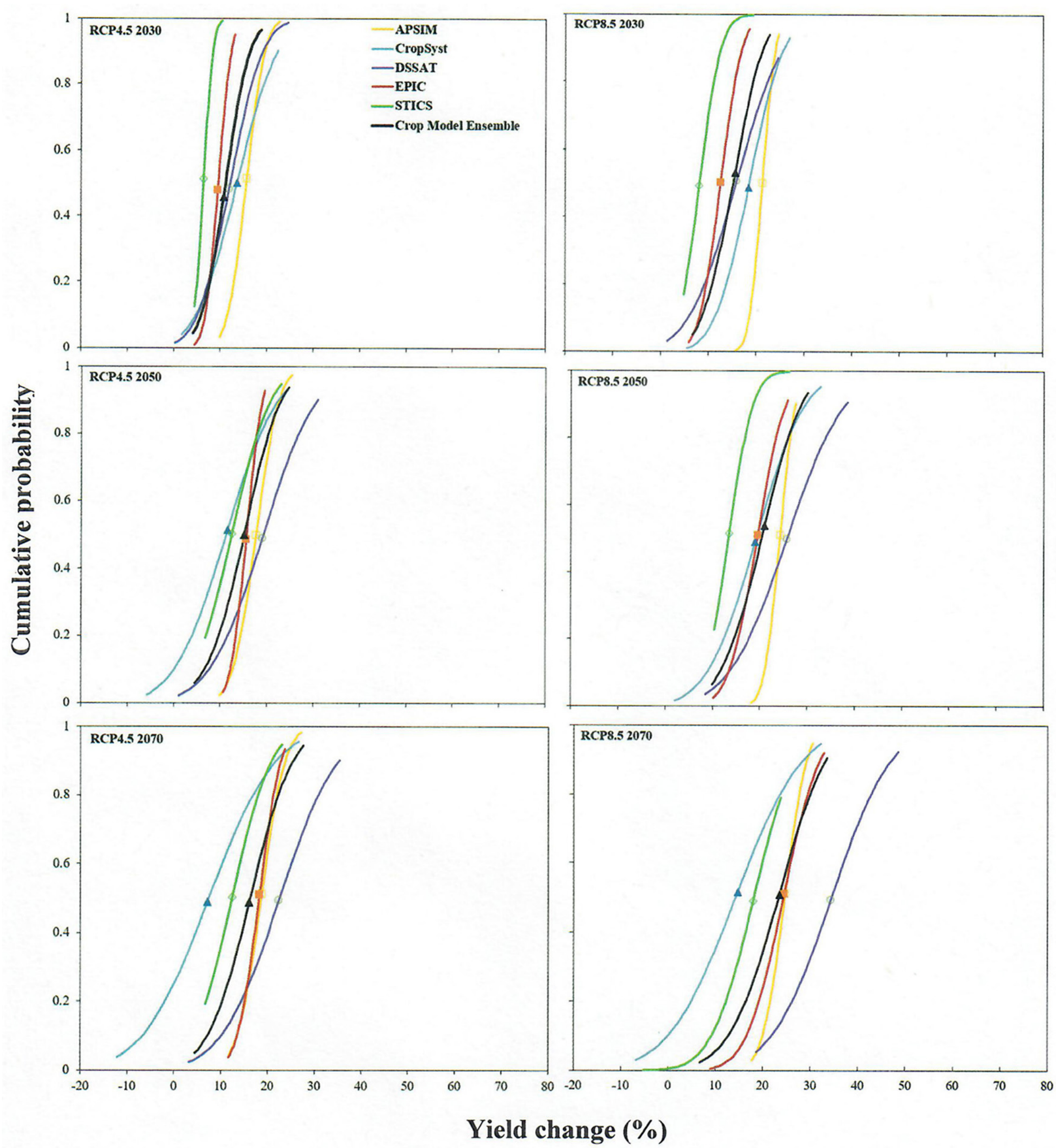

FIGURE 3 | Cumulative probability distribution for simulated winter wheat yield changes during three 31-year time periods, centered on 2030, 2050, and 2070, relative to the baseline period (1979–2010) under two representative concentration pathways (RCP4.5 and 8.5) and five crop models with ensembles of crop models at an irrigated site, Moses Lake, WA. Symbols on curves are at the curve's inflection point and represent the most probable yield change.

of the proportion of the total variation explained by the effect of interest.

The cumulative probability distributions (CPDs) for yield changes (see Section Results) were generated using a multi-step process. First the average yield was calculated for the historic period within location for each CSM. Then the average yield over all GCMs was calculated within location, CSM and year. The percentage change between this average projected yield (within location, CSM, and year) and its respective baseline yield was calculated, [percent change = ((future yield/baseline yield)−1) × 100]. This last calculation resulted in 41 percentage yield changes, one for each year within a given time period, location and CSM. The mean and standard deviation of these 41 values were used to generate the normal density distribution for the values and the CPD by applying the NORMDIST function in Microsoft Excel. The maximum value on the normal density distribution thus represents the percentage yield change with the highest probability of occurrence and

TABLE 6 | Percent changes with respect to baseline (1979–2009) values of selected process components contributing to changes in winter wheat yield during the 2070 period (2055–2085) and representative concentration pathway 8.5.

Study site	Response variable	Crop model				
		CropSyst	DSSAT	APSIM	STICS	EPIC
		(Percentage change from baseline)				
Lind	Length of growing season	−34.8	−16.9	−20.6	−30.9	−33.6
	$LAI_{max}^{\dagger}$	1.8	44.0	6.9	21.7	5.9
	Transpiration	−7.2	−2.3	−6.8	−2.2	−8.6
	Biomass	34.4	49.2	44.1	52.2	53.4
	Transpiration-use efficiency	41.8	46.8	39.8	33.0	36.3
Pullman	Length of growing season	−21.0	−15.7	−13.6	−20.2	−17.5
	$LAI_{max}^{\dagger}$	2.8	11.6	5.6	16.9	9.9
	Transpiration	−2.1	−5.3	−4.6	−5.7	−0.4
	Biomass	20.0	24.1	4.2	32.1	21.2
	Transpiration-use efficiency	25.0	25.6	20.9	23.0	18.3
Moses Lake	Length of growing season	−6.6	−12.6	−21.8	−12.7	−5.5
	$LAI_{max}^{\dagger}$	13.1	9.8	11.1	4.8	3.5
	Transpiration	−7.5	−10.8	−8.9	−2.1	−7.2
	Biomass	15.7	23.8	17.8	6.5	19.2
	Transpiration-use efficiency	18.4	22.8	16.5	10.8	16.6

† *LAI_{max}, maximum leaf area index.*

corresponds to the inflection point on the CPD. Rather than present both the normal and cumulative curves, we present only the cumulative curve with its inflection point identified.

RESULTS AND DISCUSSION

Baseline Period (1979–2010)

Three sites, Kambitsch, Moro and St. John, were not used for parameter adjustments/calibration. The relative performance of the five crop models using historical weather at these three sites is shown in **Table 5**. The results showed that the simulated LAI fluctuated within a relatively narrow range, while biomass and grain yields showed more variation among the models, except at the driest site, Moro, where better agreement existed. Nevertheless, most models were still within a narrow range of biomass and yield values at Kambitsch and St. John.

Probability Distribution of Crop-Climate Model Projections

The CPD of future winter wheat yield changes projected by the 14 GCMs for the five CSMs and three sites (Pullman, Lind, and Moses Lake) are presented in **Figures 1–3**, where the thicker line is the mean of the CSMs ensemble. All CSMs projected a positive impact of climate change and atmospheric CO_2 concentration on future winter wheat yields, but with significant variation. This variation was larger for RCP8.5 (more warming and higher atmospheric CO_2) than RCP4.5, and increased significantly with increasing time periods. The most probable yield change for the CSMs in Pullman (**Figure 1**), identified by the inflection point on the curves, ranged from 19 to 26% (RCP4.5) and from 17 to 28% (RCP8.5) for the 2030s, with the range increasing to 28 to 39% (RCP4.5) and 27 to 49% (RCP8.5) for the 2070s. The range of yield increases spanned by the CPD curves tended to increase from the 2030s to the 2070s, indicating increasing spread among GCM projections later in the century. The most probable yield change of the ensemble of all CSMs and CGMs indicated a 23% (2030s), 30% (2050s), and 41% (2070s) increase in projected vs. baseline yields for RCP8.5 (**Figure 1**). A similar pattern of increasing yield gains was obtained for RCP4.5.

Figure 2 shows the CPDs for Lind, the site with the lowest precipitation. Inflection points ranged from 25 to 34% yield increase for RCP4.5 in the 2030s, and from 21 to 27% for RCP8.5 in the 2030s. By the 2070s, the range had increased to 45–62% under RCP4.5 and 61–66% under RCP8.5. The tighter clustering of models under RCP8.5 late in the century in Lind was probably due to the dominant effect of water stress, and the high percent yield increase was likely due to the direct effect of CO_2 having a higher relative impact under more limited water supply. The crop-climate model ensemble at Lind projected increased yield under both RCPs but the effect was greater under RCP8.5 than RCP4.5 (**Figure 2**). The percentage yield increase under RCP8.5 was substantial, jumping from 23% in the 2030s to 64% in the 2070s (**Figure 2**).

At the wettest site, Moses Lake, the ensemble of all crop model and GCMs projected a wheat yield increase for both RCP4.5 and RCP8.5 (**Figure 3**) but the increase was not as large as at the

TABLE 7 | Uncertainty Index (UI) for projected winter wheat yield at seven sites in the Pacific Northwest modeled under 14 general circulation models (GCMs) averaged over 2 representative concentrations pathways in each of 5 cropping system models (CSMs).

Study site	Source of variation	Time period		
		2030 (UI)	2050 (UI)	2070 (UI)
Lind	GCMs	0.091	0.063	0.050
	CSMs	0.509	0.684	0.630
	GCMs*CSMs	0.223	0.075	0.046
Moro	GCMs	0.127	0.077	0.089
	CSMs	0.549	0.510	0.351
	GCMs*CSMs	0.175	0.161	0.183
Wilke	GCMs	0.073	0.064	0.126
	CSMs	0.530	0.652	0.564
	GCMs*CSMs	0.302	0.194	0.165
St. John	GCMs	0.034	0.067	0.107
	CSMs	0.791	0.662	0.576
	GCMs*CSMs	0.141	0.207	0.217
Pullman	GCMs	0.011	0.021	0.048
	CSMs	0.858	0.792	0.710
	GCMs*CSMs	0.086	0.105	0.116
Kambitsch	GCMs	0.029	0.053	0.101
	CSMs	0.695	0.625	0.520
	GCMs*CSMs	0.203	0.201	0.192
Moses Lake	GCMs	0.050	0.130	0.155
	CSMs	0.733	0.550	0.381
	GCMs*CSMs	0.135	0.180	0.252

Results are presented for three 31-year time periods, centered on 2030, 2050, or 2070.

rainfed sites. The ensemble yield change under RCP8.5 went from 15% in the 2030s to 24% in the 2070s. This smaller increase was due to a lower direct effect of CO_2 when water was not a limiting factor. The effect of the different CO_2 responses among models is perhaps evident in these responses under irrigation. Free-Air CO_2 Enrichment (FACE) experiments have demonstrated well-watered wheat yield increases of 7–9% when CO_2 was elevated from 350 to 550 ppm (Tubiello et al., 1999), and ~10% when CO_2 was elevated from 365 to 645 ppm (Manderscheid and Weigel, 2007). Photosynthetic response to CO_2 follows a typical saturation response, and biomass gain of wheat shows a similar response saturating (plateau response) at about 25% gain (compared to 370 ppm) when CO_2 exceeds 1,000 ppm (Reuveni and Bugbee, 1997). For the conditions during the 2070s and RCP8.5, atmospheric CO_2 concentration fluctuated from 570 to 801 ppm, while baseline conditions were set at 360 ppm. Thus, it is unlikely that yield gains greater than ~15% should be obtained with these CO_2 concentrations for the 2070s, particularly when the effect of warming is considered. However, the 50% CPD of most models and the ensemble exceeded this figure, implying that not only differences in temperature responses but also in CO_2 responses contribute to the spread of projections among CSMs.

In all crop-climate model ensembles, the most probable yield increase was shifted rightward with time, indicating a high probability of yield increase. Although results for only the wettest (Moses Lake, Pullman), and the driest (Lind) sites are presented here, all seven sites evaluated showed similar responses, modulated mainly by the extent of water limitations. Overall, the behavior of all CSMs was similar in terms of direction of change in process components leading to yield estimations but with variations in magnitude, as shown in **Table 6** for the 2070s period and RCP8.5 compared to baseline values. The growing season was shorter during the 2070s at all sites as predicted by all CSMs, with the percentage reduction being largest at Lind and smallest under irrigation at Moses Lake. These differences reflect the different magnitude of projected temperature changes in these contrasting environments. All CSMs predicted increased biomass at all sites late in the century under RCP8.5. This increase was due in part to the CO_2 fertilization effect and to the warmer winter temperatures. Not surprisingly, with more biomass, all CSMs predicted higher LAI at all locations (**Table 6**). As expected under higher atmospheric CO_2 concentrations (Ainsworth and Rogers, 2007) and warmer temperatures (shorter growing season), all CSMs projected a decrease in transpiration, fluctuating from 0.4 to 11%. On the other hand, consistent with increased biomass and decreased transpiration, transpiration use efficiency increased at all locations and with all CSMs (**Table 6**), being greatest in the driest location, Lind, and least in the wettest.

Partitioning of Projection Uncertainties

Substantial uncertainty/variation was found among GCM and CSM projections. We present here results of the uncertainty analysis for yield only (**Table 7**). The UI revealed that the uncertainty attributable to CSMs was substantially larger than that from GCMs at all study sites during all three time periods. This is in agreement with previous finding by Asseng et al. (2013). The maximum UI for CSM was over 0.85 during the 2030s at Pullman whereas the maximum UI for GCM was 0.15 during the 2070s at Moses Lake. At a majority of locations, the UI associated with GCM tended to increase with time, but the UI for CSM tended to decrease with time at most locations (**Table 7**). Although the largest proportion of uncertainty was associated with CSM, the relatively large UI associated with the interaction of GCM and CSM indicated that the amount of uncertainty associated with GCM depended on which of the five models was under consideration.

Model (CSM and GCM) Ensemble Projection of Winter Wheat Biomass Production and Yield

An ensemble of all GCMs and CSMs showed a consistent trend of beneficial effects of climate change on biomass production and wheat yields in all sites studied under the two RCP scenarios (**Figure 4**). The model ensemble depicted increasing trends for biomass and grain yields under RCP4.5 at the seven study sites, but the increasing trend was more prominent at low

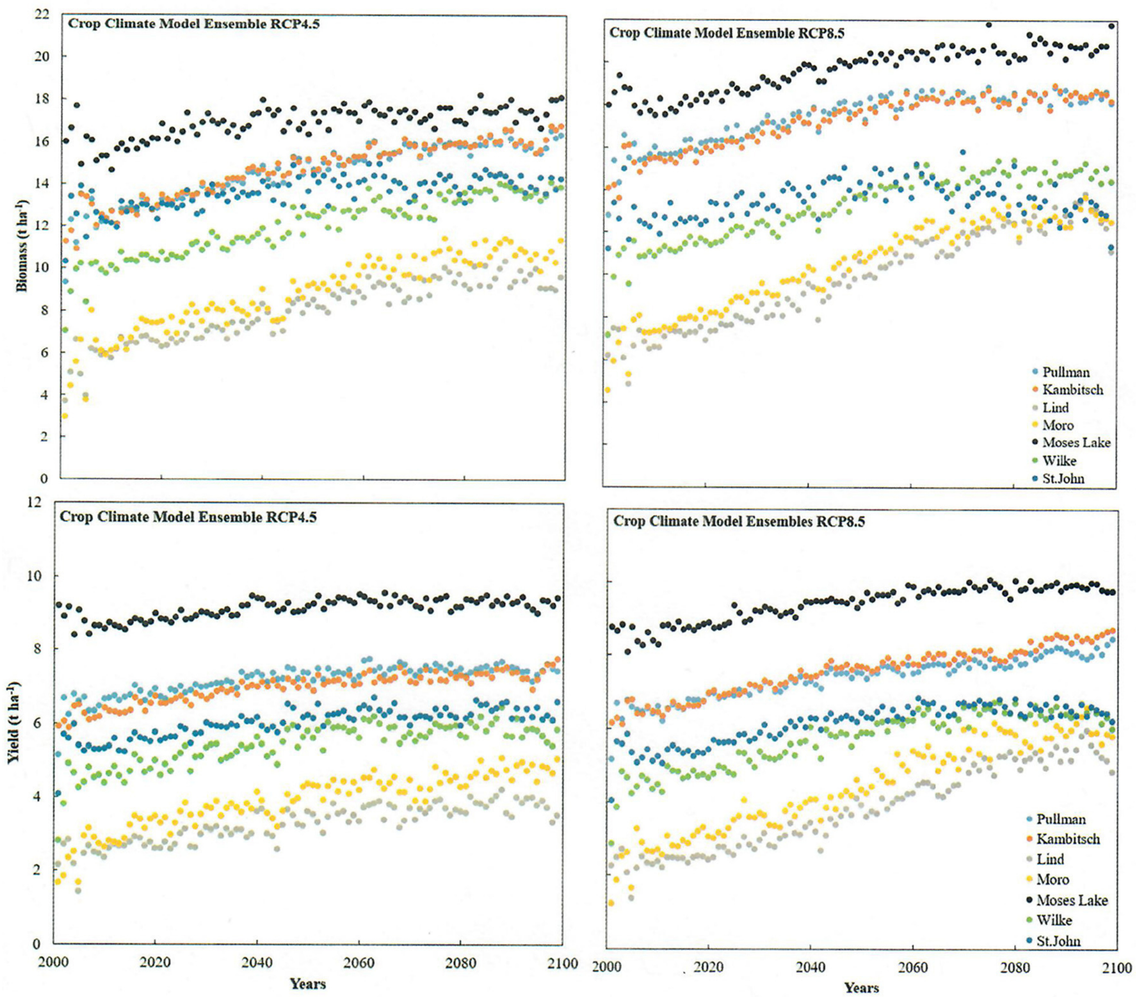

FIGURE 4 | Winter wheat biomass (t ha^{-1}) and grain yield (t ha^{-1}) trends by the crop climate model ensemble approach using two representative concentration pathways (RCP4.5 and 8.5) at seven diverse agroecological sites in the Inland Pacific Northwest.

rainfall sites (Lind and Moro) than at the wetter sites, Pullman, Kambitsch, and Moses Lake. A somewhat steeper increasing trend was observed under RCP8.5 for all sites. Over the twenty-first century, the benefit to yield of climate change appeared to be positively correlated to water stress. The driest site, Lind, saw a benefit of over 3 t ha^{-1} under RCP 8.5 whereas the least water-stressed sites, Pullman, Kambitsch and Moses Lake, experienced yield increases of at most about 2 t ha^{-1} (**Figure 4**). Also, there was a trend for biomass and yields to plateau toward the end of the century, more so for wetter sites.

There is certainly large uncertainty (**Table 7**) associated with each trajectory in **Figure 4**, implying many possible pathways toward future crop performance in the region. But the overall beneficial trend resulting from the combination of climate change and elevated CO_2 appears strong and in agreement with previous studies conducted in the region (Thomson et al., 2002; Stöckle et al., 2010). Overall, positive effects have been also projected for the northern Great Plains of the US (Izaurralde et al., 2003). Similar findings indicating increased suitability for wheat production under climate change of high northern Europe latitudes have been reported (Eckersten et al., 2001; Richter and Semenov, 2005; Balkovič et al., 2014). The winter wheat producing region of China is also expected to move northward (Sun et al., 2015).

Many additional factors will affect crop production in the future. Weeds, insect pests and diseases (Rosenzweig and Tubiello, 1996; Scott et al., 2014; Junk et al., 2016) will all influence crops, and these influences will all be impacted one way or another by climate change. Additionally, management decisions made by farmers in response to climate change will certainly affect future crop production.

CONCLUSIONS

In this study we assessed climate change impacts on winter wheat crop yield in the PNW using five CSMs and 14

GCMs. It was found that the uncertainty due to the variability of GCM and CSM projections can be substantial with the uncertainty attributed to CSMs being larger than that attributed to GCMs. Nevertheless, despite substantial variations, all CSMs consistently projected decrease in growing season length and transpiration and increase in transpiration-use efficiency, biomass, and yields. Overall, the mean of the ensemble of all CSMs and GCMs provided a robust indication of positive effects of future environmental conditions on winter wheat yield during this century at all sites studied, with greater beneficial effect under water stressed conditions than under well-watered, less stressed conditions.

AUTHOR CONTRIBUTIONS

MA conduct simulations, data reduction, draft manuscript; CS project conception and supervision, manuscript revision, RN programming, project realization; SH advise analyses, manuscript revision.

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