

Bioclimatic Predictors of Dryland Agroecological Classes and Projected Shifts under Climate Change

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Introduction

Climatic variables play an important role in determining the present/current status of dryland agriculture land use. Thus, future changes in climate variables will likely influence future dryland agriculture land use.

Huggins et al. (2011) developed a methodology to delineate the REACCH (Regional Approaches to Climate Change for Pacific Northwest Agriculture) study area into agroecological classes (AECs): three dryland and one irrigated AEC (Table 1) using National Agricultural Statistical Service (NASS) cropland data-layer of actual land use/cover (Fig. 1).

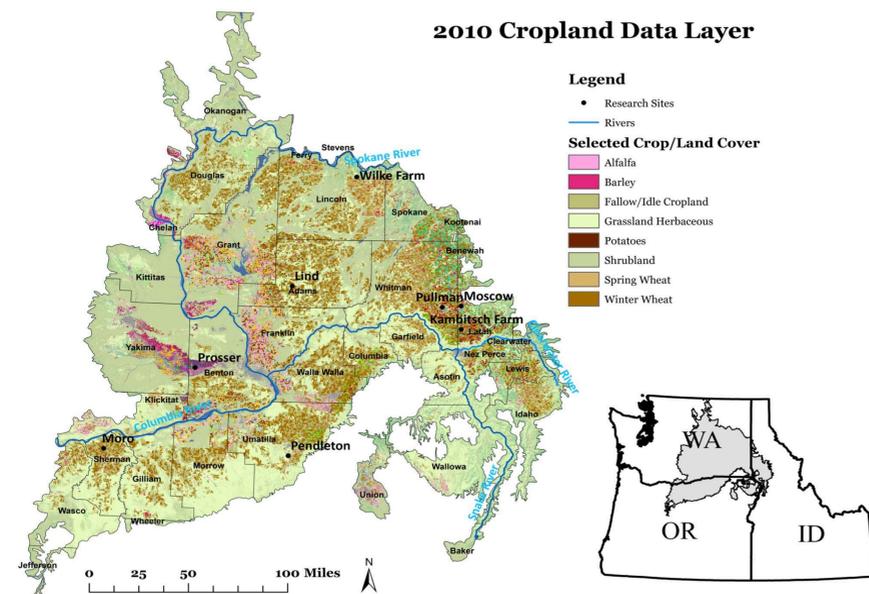


Fig. 1. Cropland data layer for the REACCH study area (NASS, 2010).

Agroecological Classes (AECs)	Fallow %
Annual Crop (AC) (limited annual fallow)	<10%
Annual Crop-Fallow Transition (AC-T) (e.g. rotations with fallow every 3rd year)	10 to 40%
Grain-Fallow (GF), 2-year	>40%
Irrigated	<10% ; Mean annual precipitation of <310 mm

Table 1. Percentage of fallow as criterion to delineate AECs.

The same methodology has been used every year to classify each 30-m pixel into one of the four AECs (Fig. 2, Table 1) and to detect spatial changes in AECs over time. Dryland AECs from year 2007 to 2014 were used in this study.

The defined AECs, representing actual land use information, were used in different statistical variable selection processes at a 4-km resolution to identify bioclimatic variables that are empirically related to actual land use.

Identified bioclimatic predictors were then used to assess changes that would occur in AECs under different future climate change scenarios, given current agricultural production systems.

References:

- Abatzoglou JT (2012) *International Journal of Climatology*. 33: 121–131.
 Abatzoglou JT and Brown TJ (2012) *International Journal of Climatology*. doi: 10.1002/joc.2312
 Huggins D, Rupp R, Gessler P, Pan W, Brown D, Machado S, Abatzoglou J, Walden V and Eigenbrode S (2011) *American Geophysical Union, Fall Meeting 2011*.
 NASS. 2010. <http://nassgeodata.gmu.edu/CropScape/>
 Peinado M, Díaz G, Delgado J, Ocaña-Peinado FM, Macías MÁ, Aguirre JL and Aparicio A (2012) *American Journal of Plant Sciences* 3:1430-1450.

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Objectives

- Identify important bioclimatic predictors which can discriminate between current dryland AECs and;
- Use identified bioclimatic predictors with future climate scenarios to evaluate changes in dryland AECs given current production technology.

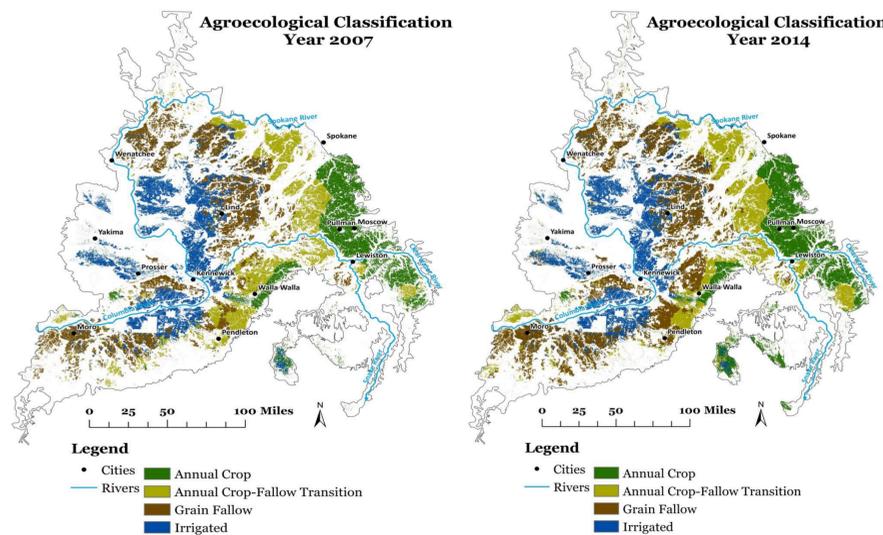


Fig. 2. Agroecological Classes for years 2007 and 2014.

Methodology

- Computed 44 bioclimatic predictors (Peinado et al., 2012) using climate data (1981–2010) of precipitation and temperature (Abatzoglou, 2012)
- Subcategorized AECs into stable and dynamic AECs (Fig. 3) in ArcGIS
- Selected important predictors using different variable selection methods in “R”
- Assess shifts in AECs using Random forest model with selected significant bioclimatic predictors under three different time periods (2030, 2050, 2070) and two different climate change scenarios (Representative Concentration Pathway) RCP 4.5 and RCP 8.5 (Abatzoglou and Brown, 2012)

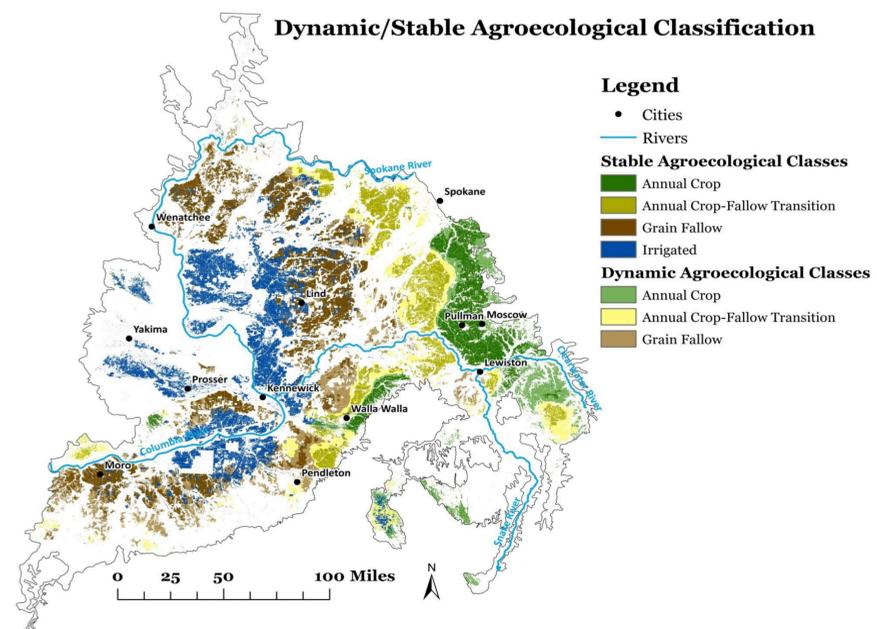


Fig. 3. Agroecological Classes for years 2007 through 2014.

Results and Discussion

The best identified bioclimatic predictors for stable and dynamic AECs were:
 (1) Holdridge evapotranspiration index
 (2) Precipitation during June, July and August
 (3) Precipitation of the warmest four-month season (June, July, August, September)
 (4) Percent spring precipitation (March, April, May)
 (5) Percent precipitation during February, March, April and May
 Overall classification accuracy and kappa were 72% and 66% for current stable and dynamic AECs.

Time period	Stable AECs			Dynamic AECs		
	AC	AC-T	GF	AC	AC-T	GF
Present	276	271	455	205	235	262
Accuracy (%)	80	74	88	61	55	59
Reliability (%)	74	70	84	72	58	63
Future scenario (RCP -4.5)						
2030	167	192	530	242	205	368
2050	150	163	570	266	168	387
2070	165	130	524	224	213	448
Future scenario (RCP -8.5)						
2030	184	173	488	205	179	475
2050	169	99	499	205	191	541
2070	94	96	533	228	179	574

Table 2. Number of pixels (4 × 4 km) classified in each AEC for present and future scenarios.

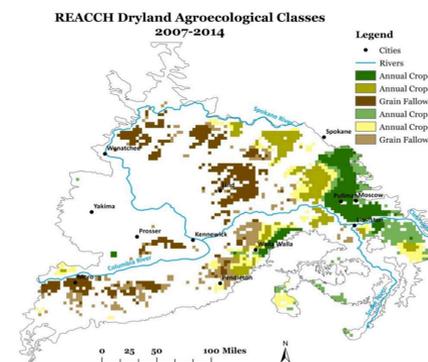


Fig. 4. Present dryland AECs.

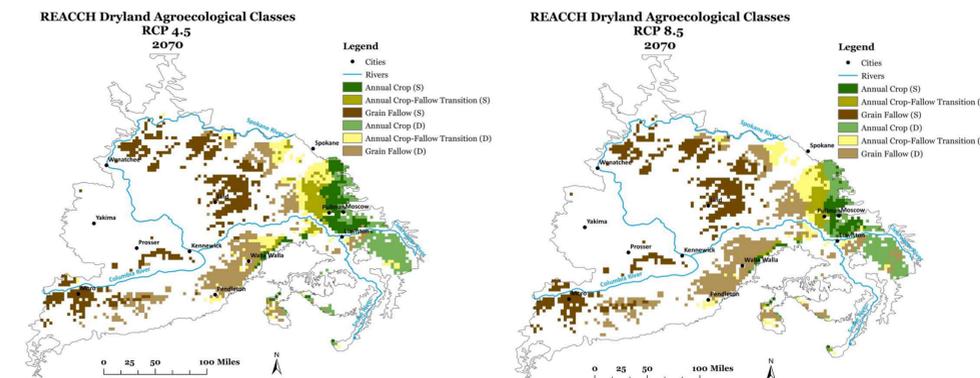


Fig. 5. Shifts in REACCH dryland AECs for 2070 for RCP 4.5 and 8.5.

Imposing future climate scenarios on current AECs suggests there will be shifts:

- (1) from stable to more dynamic AECs with notable increases in GF;
- (2) to less area as stable AC and AC-T and with more area as stable GF;
- (3) to more area as dynamic AC and GF with less area as AC-T (Table 2; Fig. 5).