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

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REACCH Agroecological Classes (AECs)

Land use classification often relies on biophysical variables hypothesized to be key drivers or determinants of land use/cover. Weak relationships, however, can occur between delineated land use classification and actual land use. On the other hand, classification based on land use/cover that has emerged as a consequence of determinants may be advantageous as the actual land use can then be used for identifying important driving variables.

Huggins et al., 2011 developed a methodology to delineate the REACCH ("Regional Approaches to Climate Change for Pacific Northwest Agriculture") study area into four major agroecological classes (AECs) using National Agricultural Statistical Service (NASS) cropland data-layer of actual land use/cover (Fig. 1). The proportion of fallow was used to define the dryland farming AECs (Table 1). The irrigated AEC was defined as an annual cropping region (<10% fallow) where mean annual precipitation was <330 mm.

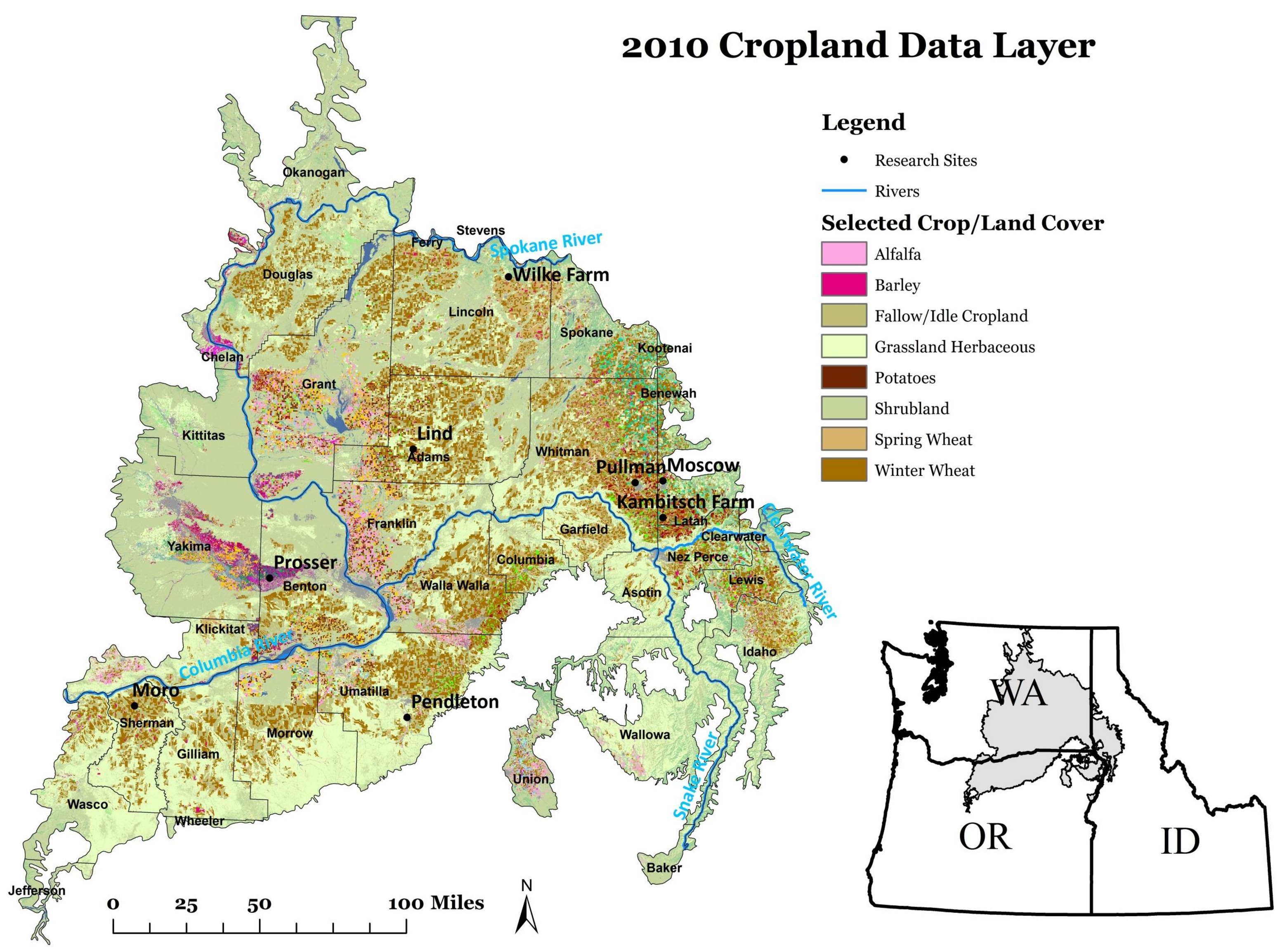

Fig. 1. Cropland data layer for the REACCH study area (NASS, 2010).

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 <330 mm

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

The same methodology is used every year to classify each 30-m pixel into one of the four AECs (Fig. 2) and to detect spatial changes in AECs over time.

Thus, the actual land use classification derived from the cropland data layer was used in the present study to identify the key predictors of REACCH AECs.

Objectives

- Identify important bioclimatic predictors which can discriminate between current dryland AECs and;
- Use identified bioclimatic predictors with future climate scenarios to predict potential shifts in dryland AECs.

Defined AECs, representing actual land use information, were used in the statistical variable selection process to identify bioclimatic variables that significantly affect actual land use. Identified AEC bioclimatic predictors were then used to predict future land use under different climate change scenarios. Dryland AECs from year 2007 to 2013 were used in this study.

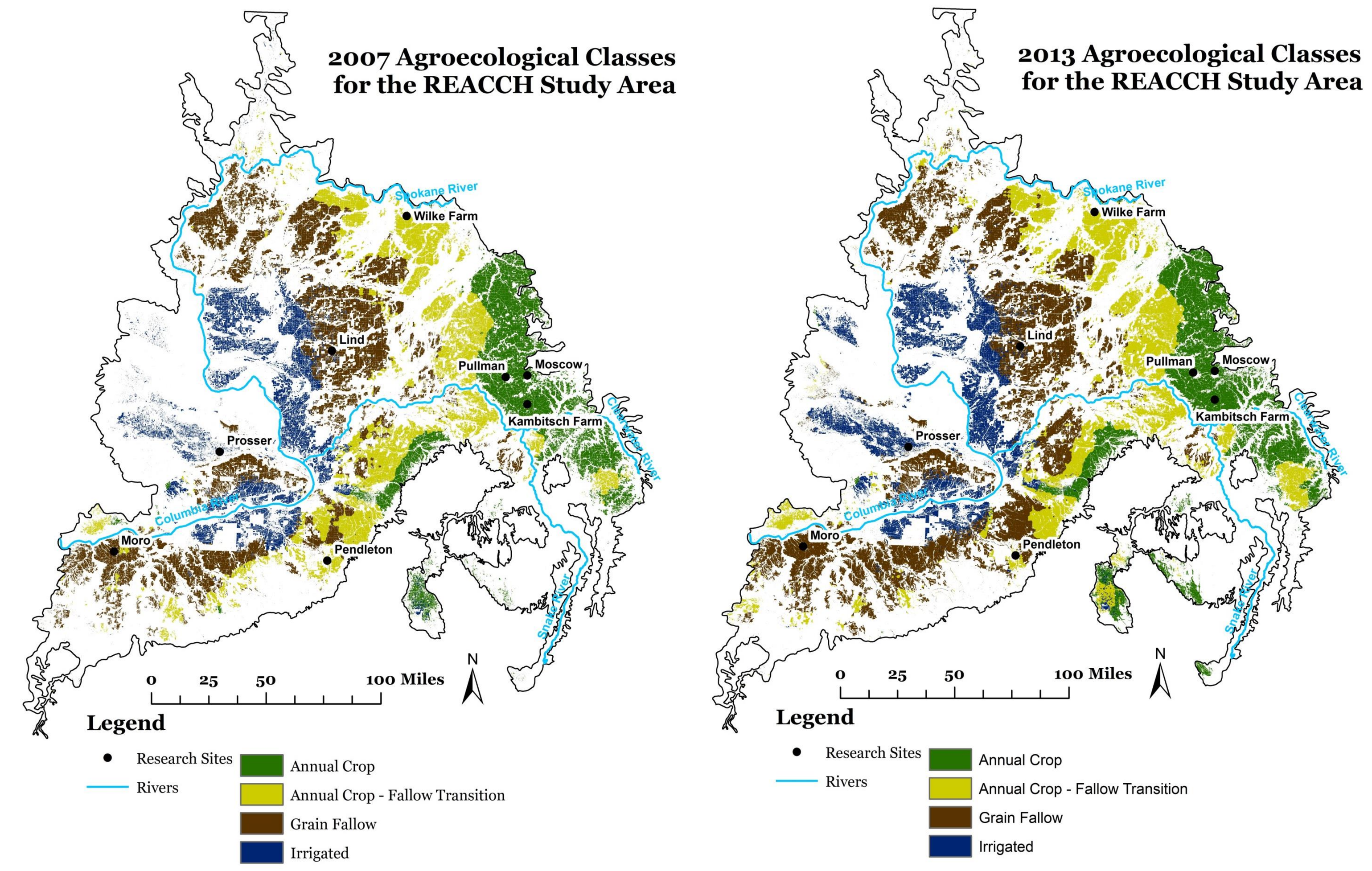

Fig. 2. Agroecological Classes for years 2007 and 2013.

Methodology

Geographic information system software (ArcGIS) was integrated with statistical software "R" to process the AEC and climate data. The methodology is explained in the following steps:

Climate data processing

Climate layers (Abatzoglou, 2012) of precipitation, maximum and minimum temperature (4 × 4 km) from 1981-2010 were used to calculate 38 bioclimatic predictors (Peinado et al., 2012)

AEC data processing

Conversion of AECs to climate data scale

Subcategorizing AECs into stable and dynamic AECs (Fig. 3)

Extraction of AEC data and bioclimatic predictors at 4 × 4 km scale

Statistical Analysis in "R"

Variable selection using "Recursive Feature Elimination", training random forest on selected predictors and estimating predictive capacity of model

Future climate data extraction

Future climate data from 14 different Global Climate Models were used to calculate the identified variables for three different time periods (2026-2035, 2056-65 and 2086-2095) and two different climate change scenarios (Representative Concentration Pathway) RCP 4.5 and RCP 8.5 (Abatzoglou and Brown, 2012).

Prediction of AECs under different future scenaios

Random forest model with selected significant bioclimatic predictors was used to predict shifts in stable and dynamic AECs under different future climate change scenarios.

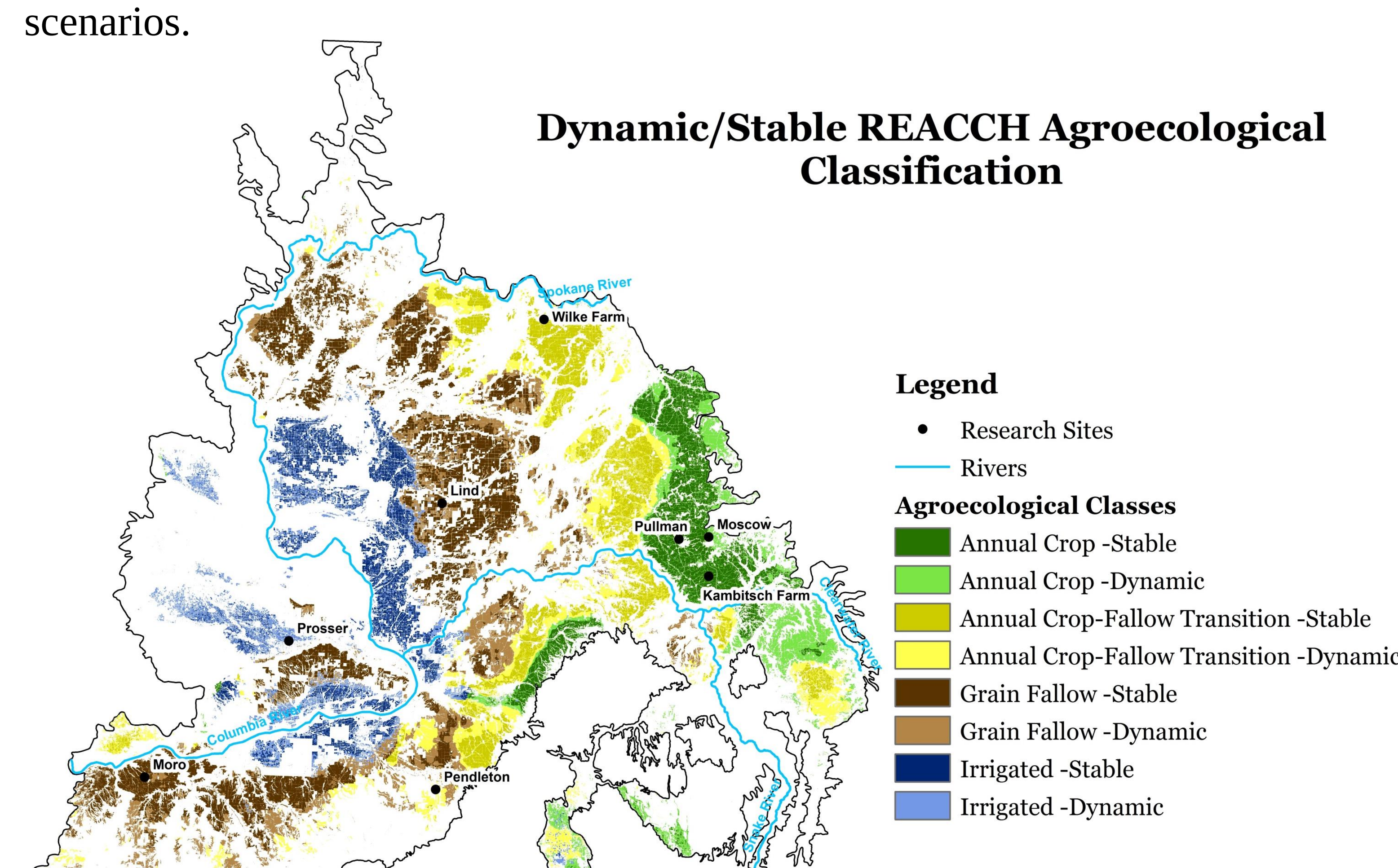

Fig. 3. Agroecological Classes for years 2007 through 2013.

Results and Discussion

	Stable AECs			Dynamic AECs		
Time period	**AC**	**AC-T**	**GF**	**AC**	**AC-T**	**GF**
Present Test set	52	65	134	57	67	80
Predicted Test set	47	52	132	43	48	61
Correctness (%)	90.4	80.0	98.5	75.4	71.6	76.3
Future scenario (RCP -4.5)						
2026-2035	169	190	483	155	172	356
2056-2065	165	175	502	128	204	351
2086-2095	158	164	520	130	191	362
Future scenario (RCP -8.5)						
2026-2035	157	179	506	137	191	355
2056-2065	145	165	532	112	205	366
2086-2095	127	142	573	54	255	374

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

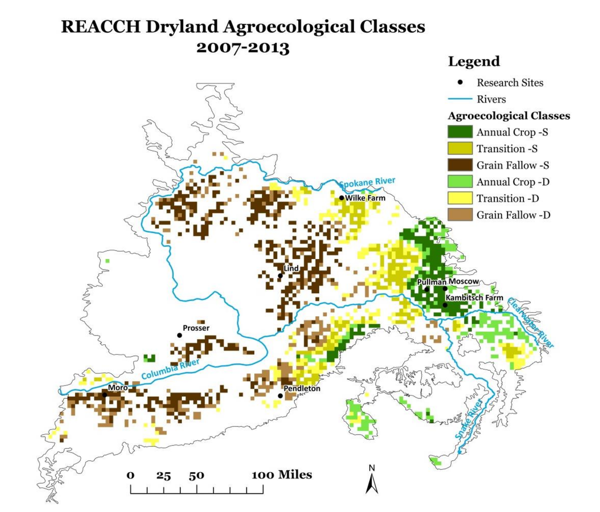

Fig. 4. Present dryland AECs.

Top identified bioclimatic predictors for stable and dynamic AECs were Aridity index, Precipitation of the warmest four-month season (June, July, August, September), Holdrige evapotranspiration index, precipitation during June, July and August, Annual precipitation and Precipitation of the two warmest consecutive months (July & August). Overall classification accuracy were 92% and 75% and kappa statistics were 0.87 and 0.61 for stable and dynamic AECs, respectively.

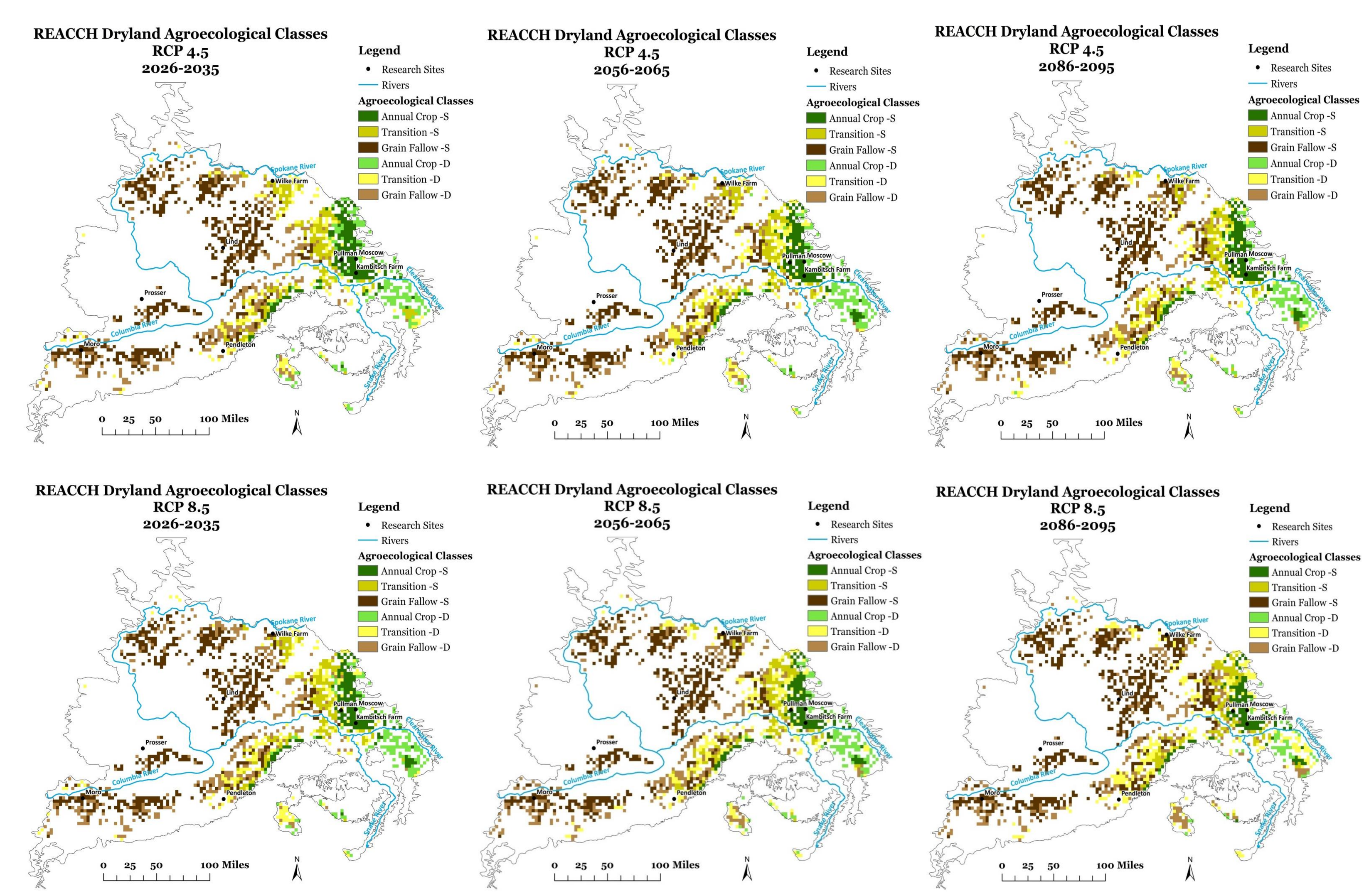

Fig. 5. Shifts in REACCH dryland AECs under different future scenarios.

Future prediction analysis showed that Annual Crop AEC area would decrease and convert into Annual Crop-Fallow Transition AEC. In a similar way, Annual Crop-Fallow Transition AEC area would also convert into relatively stable Grain-Fallow AEC, the least affected dryland AEC in future climate change scenarios (Table 2; Fig. 5).

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