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*Research article*

# Downscaling global land-use/land-cover projections for use in region-level state-and-transition simulation modeling

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**Abstract:** Global land-use/land-cover (LULC) change projections and historical datasets are typically available at coarse grid resolutions and are often incompatible with modeling applications at local to regional scales. The difficulty of downscaling and reapportioning global gridded LULC change projections to regional boundaries is a barrier to the use of these datasets in a state-and-transition simulation model (STSM) framework. Here we compare three downscaling techniques to transform gridded LULC transitions into spatial scales and thematic LULC classes appropriate for use in a regional STSM. For each downscaling approach, Intergovernmental Panel on Climate Change (IPCC) Representative Concentration Pathway (RCP) LULC projections, at the 0.5 × 0.5 cell resolution, were downscaled to seven Level III ecoregions in the Pacific Northwest, United States. RCP transition values at each cell were downscaled based on the proportional distribution between ecoregions of (1) cell area, (2) land-cover composition derived from remotely-sensed imagery, and (3) historic LULC transition values from a LULC history database. Resulting downscaled LULC transition values were aggregated according to their bounding ecoregion and "cross-walked" to relevant LULC classes. Ecoregion-level LULC transition values were applied in a STSM projecting LULC change between 2005 and 2100. While each downscaling methods had advantages and disadvantages, downscaling using the historical land-use history dataset consistently apportioned RCP LULC transitions in agreement with historical observations. Regardless of the downscaling method, some LULC projections remain improbable and require further investigation.

**Keywords:** Representative Concentration Pathways (RCP); downscaling; state-and-transition simulation modeling; scenarios; land-use

## 1. Introduction

Global land-use/land-cover (LULC) change projections generated by the integrated assessment and climate modeling communities are used for a wide variety of applications including modeling carbon dynamics, water use, and land-change [1-3]. While increasingly sophisticated models are becoming available, applying global projections of LULC change at regional scales remains a challenge requiring further research [4,5]. Typically, global LULC models produce LULC projections at broad regional scales or at coarse grid resolutions [4,6]. However, modeling at local to regional scales is often of greater relevance for informing management decisions and mitigation strategies. For LULC change in particular, local factors have important and direct influence on land-use patterns necessitating modeling at finer scales where local data is available [7].

The climate modeling community has been moving towards a scenario framework in an effort to explore implications of alternative climate futures and mitigation outcomes [8]. Applying global-scale scenario data to regional-scale scenario modeling of LULC change has two important benefits: (1) it allows for the incorporation of global climate scenarios into regional-scale research, and (2) facilitates relevant comparisons between LULC modeling efforts [9]. Using global LULC data in regional assessments requires data downscaling to scales relevant for analysis. Downscaling refers to the process of translating data from a coarse scale to a more detailed scale while maintaining a degree of consistency between datasets [10,11].

Previous approaches to downscaling LULC projections have relied largely on finer scale classified LULC products derived from remote sensing sources to facilitate the downscaling of LULC data. Dendoncker et al. [12], used the Coordinated Information on the European Environment (CORINE) land cover map as a starting point for projecting land-use at fine spatial scales. West et al. [13], used Moderate Resolution Imaging Spectroradiometer (MODIS) land-cover data to facilitate land-use downscaling from a 0.5 degree grid to a 0.05 degree grid for the United States. Other approaches have used finer scale models to downscale global land-cover data [14,15]. Sleeter et al. [16] and Sohl et al. [17] used an integrated assessment model combined with land-use histories and expert knowledge to drive downscaling.

Representative concentration pathways (RCPs) are the latest set of climate scenarios used for the Intergovernmental Panel on Climate Change's (IPCC) Fifth Assessment Report (AR5) [18]. The RCPs are a set of trajectories of land use, air pollutants, and greenhouse gas levels leading to total radiative forcing targets of 2.6, 4.5, 6.0, and 8.5 in $W/m^2$ in the year 2100 [9]. Each RCP is named after the radiative forcing target value (e.g. RCP 2.6, etc.). Global RCP land-use transition projections (i.e. LULC change amounts) are available annually between 2005 and 2100 at $0.5 \times 0.5$ degree grid cells [9]. While LULC transition values at this resolution may be suitable for global modeling efforts, local to regional scale land-use modeling often requires RCP LULC transition values summarized at the regional scale to maintain data consistency.

Regional scale RCP LULC transition values can be created by simply aggregating RCP grid cell LULC transition values to a regional boundary of interest. However, a strategy is needed for dealing with coarse grid cells overlapping into two or more regions. For these cells, LULC transition values must first be downscaled to region boundaries before they can be summarized by region of interest. Since RCP cells are quite large (~ 3000 $km^2$) the method used to downscale RCP boundary cells to regions may have a large impact on the resulting LULC projections.

We present three approaches for downscaling RCP land-use projections to Level III Ecoregions [19] in the Pacific Northwest, USA: (1) using area proportions ("area-based"), (2) using proportions of LULC from a classified remote sensing dataset ("composition-based") and (3) using a historic LULC transition dataset ("transition-based"). Ecoregions are useful for regional scale analysis as they represent areas of similar biotic, abiotic, physical and aquatic characteristics [19,20] and have been proven useful in examining historical [3] and potential future land use change [21]. For RCP 6.0 [22] we used LULC projections from the RCP database [4] to derive ecoregion-scale projections of LULC change for each of the three downscaling approaches. We then used a state-and-transition simulation model (STSM) to project changes in LULC between 2005 and 2100 based on each downscaling outcome. Below we describe the three downscaling methods and compare the results of each simulation. Our goal was to assess the most effective downscaling technique for regional applications of RCP data.

## 2. Methods

### *2.1. Study area*

Seven Level III Ecoregions in the Pacific Northwest, USA were analyzed in this study including the Puget Lowland, Coast Range, Eastern Cascades Slopes and Foothills (hereafter East Cascades), Willamette Valley, Klamath Mountains, Cascades, and North Cascades. The total study area is comprised of approximately 266,734 $km^2$ (Figure 1). The LULC mosaic in the Pacific Northwest is characterized by the forested mountainous terrain of the Cascades and Coast Range, agriculture and urban dominated land-use in Willamette Valley and Puget Lowland and grass/shrub dominated areas of the East Cascades. Historical LULC change rates within the Pacific Northwest are high with the greatest change rates found in the Puget Lowland, Coast Range and Willamette Valley ecoregions [23]. Logging, urbanization, and changes in agriculture are all important regional land change processes.

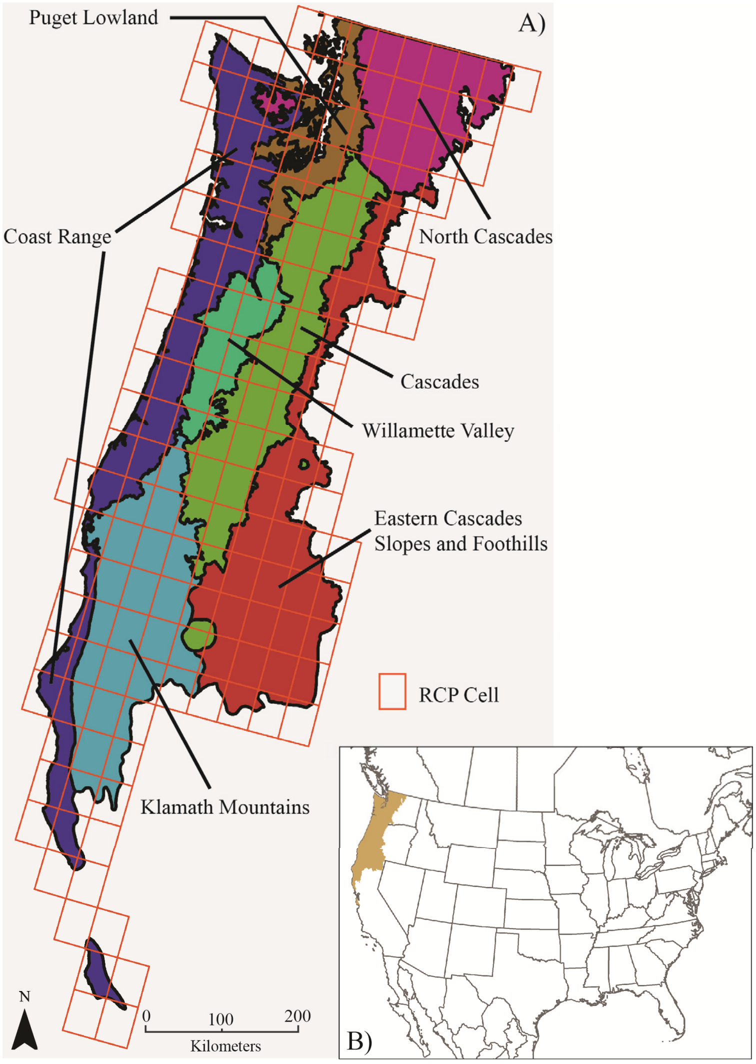


**Figure 1. A) Study area with ecoregions and RCP cells (in orange). B) Study site in the context of the USA.**

*2.2. Methods overview*

Global LULC projections from 2005 to 2100 for the RCP 6.0 scenario were available from the RCP database hosted by the International Institute for Applied Systems Analysis (IIASA) [24]. RCP 6.0 is a medium to high emission pathway scenario where radiative forcing stabilized at 6.0 W/m$^2$ in the year 2100. Mitigation efforts in this scenario were implemented around 2060 in an effort to reduce global greenhouse gas emissions, resulting in a decrease in fossil-based fuels and an increase in renewable energy sources [22]. Globally, land use change was characterized by increased area devoted to agriculture and development; however regional variation occurred in land-use patterns. A complete description of RCP 6.0 can be found in Masui et al. [22]. A total of 21 RCP land-use transitions were considered for downscaling (Table 1). RCP projections provide LULC transitions as a percentage of total cell area within a 0.5 × 0.5 degree cell.

**Table 1. RCP transitions considered for downscaling and the average annual amount of transition over the study region between 2005 and 2100.**

| RCP "from" Class | RCP "to" Class | Average Annual Transition ($km^2$) |
|---|---|---|
| Crop | Pasture | 57.9 |
| Crop | Primary land | 0.0 |
| Crop | Secondary land | 25.4 |
| Crop | Urban | 30.7 |
| Pasture | Crop | 144.3 |
| Pasture | Primary land | 0.0 |
| Pasture | Secondary land | 551.4 |
| Pasture | Urban | 62.3 |
| Primary land | Pasture | 348.7 |
| Primary land | Crop | 8.1 |
| Primary land | Secondary land | 1278.1 |
| Primary land | Urban | 0.0 |
| Secondary land | Pasture | 158.8 |
| Secondary land | Crop | 4.6 |
| Secondary land | Urban | 135.2 |
| Urban | Pasture | 0.0 |
| Urban | Crop | 0.0 |
| Urban | Secondary land | 0.0 |
| Mature secondary forested land | Harvested biomass | 21871.8 |
| Primary forested land | Harvested biomass | 0.0 |
| Young secondary forested land | Harvested biomass | 0.0 |

RCP grid cells within or partially overlapping the study area were selected for use in our downscaling methods. Large bodies of water within the study site were extracted and consolidated as a separate region so that water areas could be excluded when applying area-based reapportioning. Ecoregion and RCP cell layers were merged so that sub-cell zones were created at ecoregion boundaries. For the purpose of explaining our three downscaling approaches, we define the following terms in relation to Figure 2. Cells are 0.5 × 0.5 degree RCP cells (Figure 2A), regions refer to ecoregion boundaries (Figure 2B), and zones are sub-cell areas created by the intersection of a cell and region (Figure 2C–D).

Regional level transition values were created by aggregating cell transition values to regional boundaries. However, for RCP cells overlapping more than one ecoregion, RCP cell LULC transitions must be downscaled to zones before summarizing at the ecoregion level. Three methods: area-based, composition-based, and transition-based downscaling were tested. In order to use RCP transition values in our STSM, broad RCP classes were cross-walked into LULC classes consistent with remote sensing imagery and historical data. For the area and composition-based reapportioning methods, this process was done following aggregation of RCP transitions to the ecoregion level. For the transition-based method, cross-walking was required prior to RCP transition reapportioning, so that transition classes were consistent with the historical Land Cover Trends dataset [25] used in the downscaling process. Table 2 provides an overview of our three downscaling methods and crosswalking approaches.

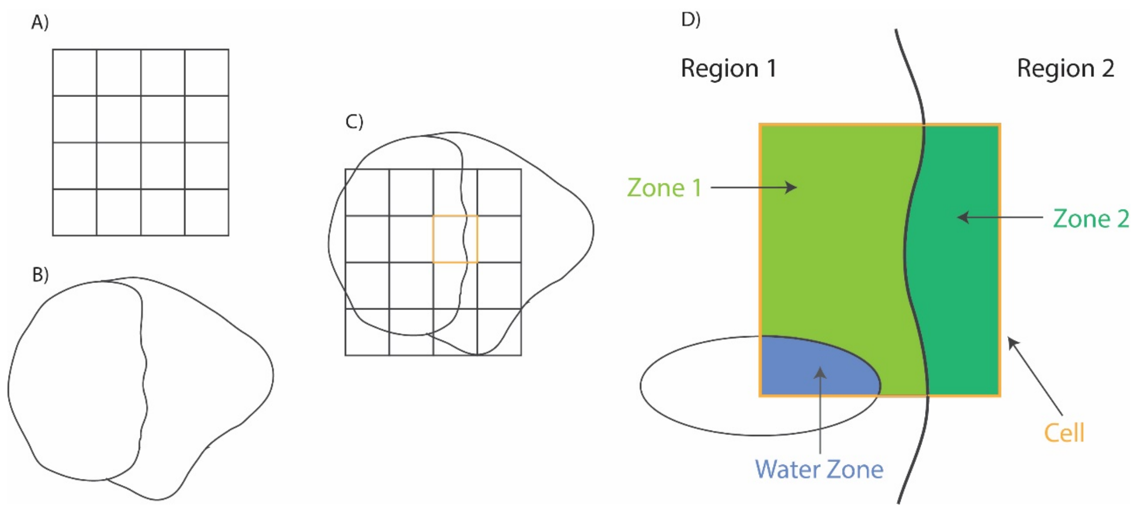


**Figure 2. A representation of A) an RCP 0.5 × 0.5 degree cell grid, B) two adjacent regions, C) a cell grid overlaid and merged with regions, and D) an RCP cell with sub-cell zones including a water zone.**

**Table 2. Overview of methods for the area-based, composition-based, and transition-based downscaling approaches.**

| Area-based | Composition-based | Transition-based |
|---|---|---|
| 1. Areas for zones covered by water proportionally redistributed to land-based zones within each RCP cell.<br>2. RCP transitions apportioned to zones based on each zone's proportion of area, relative to its cell.<br>3. Zone transitions summed across regions.<br>4. RCP transition classes cross-walked to STSM transition classes. | 1. Landcover composition derived for each cell and zone from a classified remote sensing product.<br>2. RCP transitions apportioned to zones based on each zone's landcover area of the "from" class of the transition, relative to its cell.<br>3. Zone transitions summed across regions.<br>4. RCP transition classes cross-walked to STSM transition classes. | 1. RCP transition classes cross-walked to STSM transition classes.<br>2. Region level transition data from the Trends dataset distributed to zones based on zone area relative to the region.<br>3. RCP transitions apportioned to zones based the proportion of Trends transition occurring within each zone relative to its cell.<br>4. Zone transitions summed across regions. |

### *2.3. Area-based downscaling*

For the area-based downscaling approach, cell transition values were downscaled based on the proportional area of each zone within a cell. Since LULC transitions cannot occur where water bodies are present, the relative proportion of land area (not total area) of each zone within a cell was used to determine RCP downscaling. RCP cell transitions were downscaled to zones as follows:

$$A_{i,j,z}(t) = P_{i,j,c}(t)\, A_c \frac{(A_z - W_z)}{(A_c - W_c)} \qquad (1)$$

Where $A_{i,j,z}(t)$ represents the area transitioning from class i to class j for zone z in timestep t. $P_{i,j,c}(t)$ represents the RCP proportion of area transitioning from class i to j for cell c in timestep t. Variables $A_c$, $A_z$, $W_c$, and $W_z$ represent the area of cell c, the area of zone z, the water area of cell c, and the water area of zone z respectively. Thus, $P_{i,j,c}(t)\, A_c$ represents the total area of transition in a cell, and $\frac{(A_z - W_z)}{(A_c - W_c)}$ represents the ratio of zone land area to cell land area. Transitions downscaled to zones were then aggregated to regions.

*2.4. Composition-based downscaling*

Our composition-based downscaling approach assumes the relative presence of a particular LULC type determines the share of corresponding RCP transition apportioned between ecoregions. This method relied on a classified LULC map to facilitate the downscaling of RCP transitions to zones. The baseline LULC composition map must have a sufficiently high resolution to disaggregate RCP cells, offer a classification scheme capturing all of the RCP classes, and provide good spatial and temporal correspondence with the study region. The National Land Cover Database (NLCD) 2006 dataset with a resolution of 30 m and 16-class classification scheme met these requirements (Table 3) [26].

**Table 3. NLCD 2006 classes and percent of study region area.**

| NLCD Class | Percent of Study Area (2006) |
|---|---|
| Open water | 1.32 |
| Perennial ice/snow | 0.22 |
| Developed, open space | 2.76 |
| Developed, low intensity | 1.55 |
| Developed, medium intensity | 0.69 |
| Developed high intensity | 0.25 |
| Barren land (rock/sand/clay) | 1.68 |
| Deciduous forest | 1.54 |
| Evergreen forest | 53.36 |
| Mixed forest | 4.56 |
| Shrub/scrub | 18.52 |
| Grassland/herbaceous | 6.50 |
| Pasture/hay | 3.37 |
| Cultivated crops | 1.93 |
| Woody wetlands | 1.02 |
| Emergent herbaceous wetlands | 0.72 |

Land-cover composition was derived for each cell and respective zone from the NLCD map. NLCD landcover classes were generalized to RCP LULC classes. RCP cell transition values were then downscaled to zones based on the NLCD area of the RCP transition “from” class. For example, the RCP transition “crop to urban” was reapportioned based on the area of the NLCD class “crop”. Each transition is apportioned as follows:

$$A_{i,j,z}(t) = P_{i,j,c}(t)\, A_c \, \frac{C_{i,z}}{\sum_{z \in c} C_{i,z}} \tag{2}$$

where $A_{i,j,z}(t)$ represents the area transitioning from class i to class j for zone z in timestep t. $P_{i,j,c}(t)$ represents the RCP proportion of area transitioning from class i to j for cell c in timestep t. $A_c$ is the area of the cell and $C_{i,z}$ is the NLCD area of the LULC class i in zone z. Transitions downscaled to zones were then aggregated to regions.

*2.5. Transition-based downscaling*

The transition-based downscaling approach utilized the USGS Land Cover Trends (hereafter referred to as "Trends") dataset [25] of ecoregion-level LULC transitions to disaggregate RCP cells to zones. Trends data include LULC transition values for transitions between 11 LULC classes for four temporal periods between the years 1973 and 2000, for each Level III Ecoregion in the conterminous United States. The dataset was created using a statistical sampling method and manual interpretation of Landsat imagery [3,27]. RCP land-use transitions were crosswalked to transition classes used in our STSM as described in section 2.6. Average annual transition values for 9 Trends transitions corresponding to STSM transition classes were used to facilitate the disaggregation of crosswalked RCP cell values (Table 4).

**Table 4. Trends transitions and average annual transition amount over the study region between 1973 and 2000.**

| Trends "from" Class | Trends "to" Class | Annual Transition (km$^2$) |
|---|---|---|
| Agriculture | Developed | 25.9 |
| Agriculture | Forest | 7.6 |
| Agriculture | Grass/shrub | 7.5 |
| Forest | Agriculture | 13.8 |
| Forest | Developed | 55.0 |
| Forest | Grass/shrub | 59.2 |
| Grass/shrub | Agriculture | 5.1 |
| Grass/shrub | Developed | 2.7 |
| Grass/shrub | Forest | 0.0 |

Ecoregion-based transition values from Trends were distributed to zones based on the proportional area of each zone relative to its region. Crosswalked RCP transitions were matched with Trends transitions and apportioned to zones as follows:

$$A_{i,j,z}(t) = P_{i,j,c}(t)\, A_c \, \frac{T_{i,j,z}}{\sum_{z \in c} T_{i,j,z}} \tag{3}$$

where $A_{i,j,z}(t)$ represents the area transitioning from class i to class j for zone z in timestep t. $P_{i,j,c}(t)$ represents the RCP proportion of area transitioning from class i to j for cell c in timestep t. $A_c$ is the area of the cell and $T_{i,j,z}$ is the Trends area transitioning from class i to j in zone z. Transitions downscaled to zones were then aggregated to regions.

*2.6. Crosswalk to STSM classes*

In order to utilize the downscaled RCP projections within our STSM approach, we first had to convert the broad RCP classification scheme into transition classes more consistent with remote sensing derived LULC maps. For example, the RCPs classify vegetation as either "primary" or "secondary", where "primary" land refers to land that has not been altered by human activity and "secondary" land is land that is recovering from human disturbance [4]. On the other hand, remote sensing-based LULC maps most often classify vegetation according to basic functional types, such as whether a cell is dominated by forest or grass/shrub. To account for discrepancies between classification schemes, we cross-walked the RCP scheme to the classification system used for the STSM (Table 5).

**Table 5. RCP classes and corresponding STSM classes excluding forest to biomass transition classes.**

| RCP Class | STSM Classes |
|---|---|
| Pasture | Agriculture, Grass/shrub |
| Primary Land | Forest, Grass/shrub, Wetland |
| Secondary Land | Forest, Grass/shrub, Wetland |
| Crop | Agriculture |
| Urban | Developed |

Translating from RCP transitions to STSM transitions would have been straight forward had each RCP class corresponded to a unique STSM class. However, the "primary-land", "secondary-land", and "pasture" RCP classes potentially encompass more than one STSM class. The "primary-land" and "secondary-land" RCP classes were split between STSM classes "grass/shrub", "forest", and "wetland". Cross-walking the "pasture" RCP class was especially problematic since the RCP definition of "pasture" included rangeland, which encompasses both grazing lands dominated by natural vegetation as well as croplands producing forage. Since no unique STSM equivalent was available, the RCP class "pasture" was split between STSM classes "grass/shrub" and "agriculture".

RCP transitions into and out of "pasture", "primary-land", and "secondary-land" classes were allocated among possible STSM transitions based on landcover area derived from an NLCD 2006 map. RCP transitions were first matched to corresponding STSM transitions. For example the RCP transition *primary-land to pasture* potentially encompasses five possible STSM transitions: *wetland to agriculture*, *wetland to grass/shrub*, *grass/shrub to agriculture*, *forest to agriculture* and *forest to grass/shrub* (Figure 3). The RCP transition was allocated among STSM transitions considering both the "from" class and "to" class of each crosswalked STSM transition. For each STSM transition the proportion of NLCD area of the "from" class of the transition relative to the NLCD area of all STSM classes crosswalked from the RCP "from" class was calculated. Next the proportion of NLCD area of the "to" class of the transition relative to the NLCD area of all STSM classes crosswalked from the RCP "to" class was calculated. RCP transition was allocated to STSM transitions based on the "from" class and "to" class proportions of each STSM transition.

The three RCP *forest to harvested biomass* transitions uniquely represent the STSM transition *forest harvest* and were simply aggregated into a single STSM *forest harvest* transition. All transitions out of "developed" land were not relevant to our effort and were ignored.

*Primary-to-secondary* transitions were also ignored since the intent of our modeling effort was to examine LULC change, rather than natural environmental transitions.

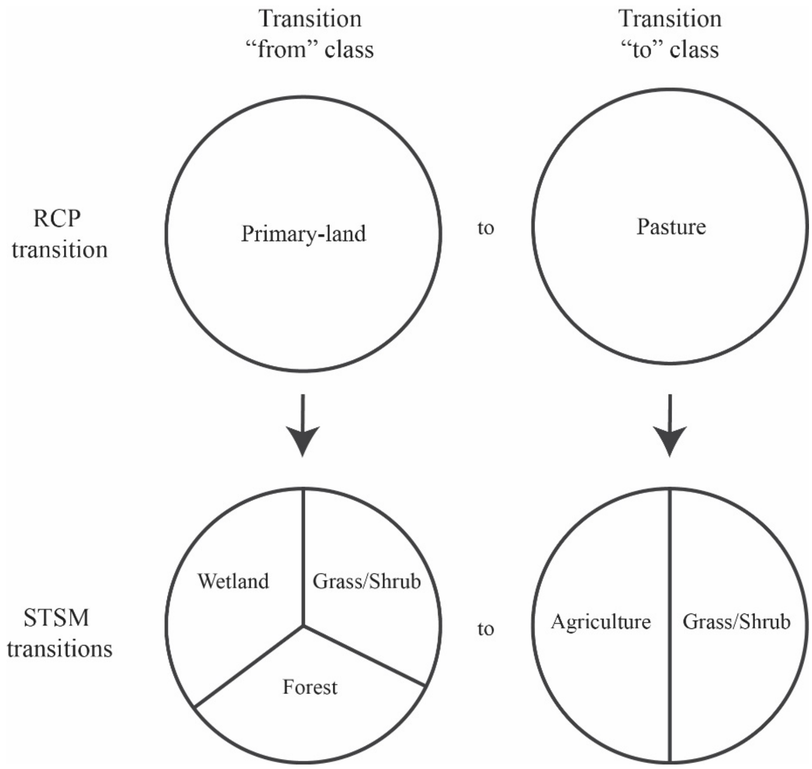


**Figure 3. Crosswalking primary-land to pasture RCP transition to all potential STSM transition classes.**

*2.7. State-and-transition simulation modeling*

State-and-transition simulation models (STSMs) have been used in a variety of applications including simulating landscape level vegetation and fire dynamics, modeling the progression of invasive species, and projecting habitat suitability [28-30]. STSMs use an adaptive Markov chain approach to simulate changes in state class (e.g. vegetation, land use class) over time and can be used to model succession, disturbance, and management interactions [31]. An STSM splits the landscape into a set simulation cells which are each given an initial state class. State class transition pathways can be assigned either stochastic probabilities of occurrence or deterministic transition values [31]. More recently STSM's have been designed to incorporate a spatial dimension, such as a region level stratification, or to be run in a spatially explicit fashion where transition probabilities are assigned by cell location [32]. While STSMs are suitable for modeling probability driven scenarios, only a few efforts have explicitly incorporated climate change scenarios into STSMs [33,34].

We developed three, probabilistic LULC change downscaling scenarios (i.e. Area scenario, Composition scenario, and Transition scenario) for use in an STSM in order to test our three downscaling approaches. We converted the STSM transition class data from annual area targets into annual transition probabilities from 2005–2100 for each scenario. Annual transition probabilities were calculated from transition target values by dividing the transition target value by the total amount of the transition "from" class within each ecoregion for each timestep. Unlike transition targets, probabilities are driven by the amount of land available for transition.

LULC change scenario modeling was done in the ST-Sim environment [35]. All scenarios were run using Level III Ecoregions as the spatial strata. Simulations were run annually from 2005 to 2100 using a 10 $km^2$ cell size and 100 Monte Carlo replicates over the 266,730 $km^2$ study area. Initial land-cover state class values were derived from a harmonized classified LULC product. The harmonized dataset was developed using a pixel-based data fusion process combining a collection of fifteen land classification datasets into a single product and validated with remotely sensed imagery [36].

## 3. Results

### 3.1. Pacific Northwest

Under RCP 6.0, the Pacific Northwest was projected to see increases in developed land through the year 2100, with gains highly concentrated in the Willamette Valley, Puget Lowland, and Coast Range ecoregions. Large declines in forest cover and agriculture were largely the result of demand for developed land use, although agriculture increases were found in the East Cascades, North Cascades, Klamath Mountains, and Coast Range ecoregions (Figure 4). Forest harvest increased sharply by the year 2100 across all downscaling scenarios.

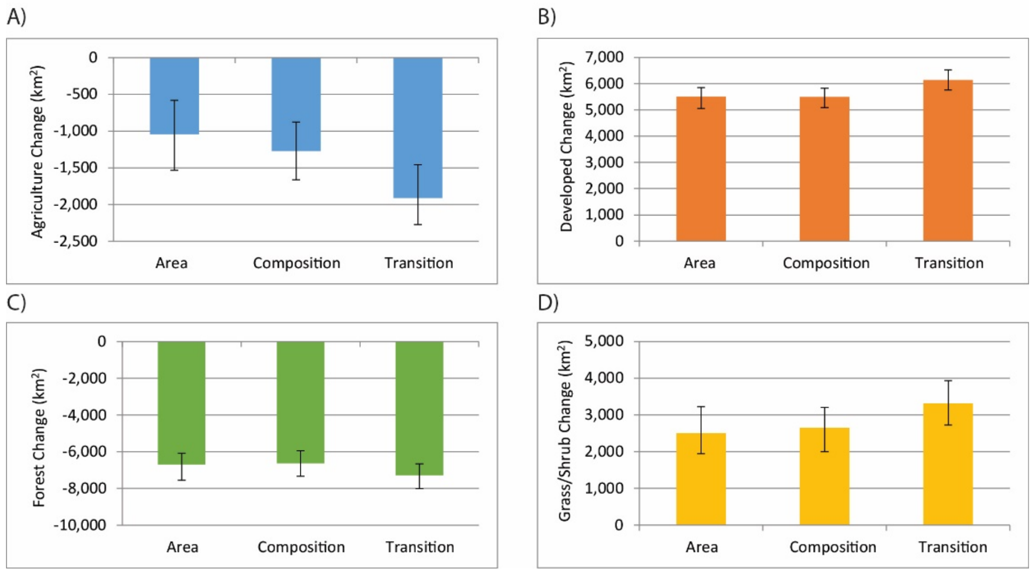


**Figure 4. Projected LULC change by downscaling scenario between 2005 and 2100 over all ecoregions for A) Agriculture, B) Developed, C) Forest, and D) Grass/Shrub.** Error bars represent the 95th percentile of Monte Carlo simulations.

Downscaling scenarios were compared based on the mean and 95th percentile of Monte Carlo replicates. The difference between two scenarios was only considered important if each scenario's mean value of Monte Carlo replicates fell outside the range of variation of the other scenario's Monte Carlo replicates. Average LULC change totals for the Pacific Northwest between the Area and Composition scenarios were within each other's ranges of variation and thus were not found to be large enough to be important (Figure 4). However, several differences in projected LULC emerged between the Transition scenario and the Area and Composition scenarios. Projected agriculture loss, as well as developed and grass/shrub and gains were greater under the Transition scenario (Figure 4). Important differences between projected forest changes were not found between scenarios (Figure 4).

Differences between Transition scenario projections and Area and Composition scenario projections over the study site were driven by the downscaling of transitions for cells on the study site border. The impact of the Columbia Plateau ecoregion, an ecoregion outside the study site, explains a great deal of the difference seen in agriculture and grass/shrub change between downscaling methods. The Columbia Plateau ecoregion has a much higher Trends transition value for the *grass/shrub to agriculture* transition than neighboring ecoregions. Both the North Cascades and East Cascades ecoregions were apportioned less *grass/shrub to agriculture* transition than the neighboring Columbia Plateau when applying transition-based downscaling compared to the composition or area-based downscaling (Figure 5). Since the Columbia Plateau ecoregion lies outside of the study site, *grass/shrub to agriculture* transition is effectively removed from the study site. This contributed to an increase in total grass/shrub and a decrease in total agriculture area for the Transition scenario compared to the Composition scenario. When combined, differences between reapportionment of RCP cells bordering ecoregions outside of the study site accounted for most of the differences in projected LULC totals.

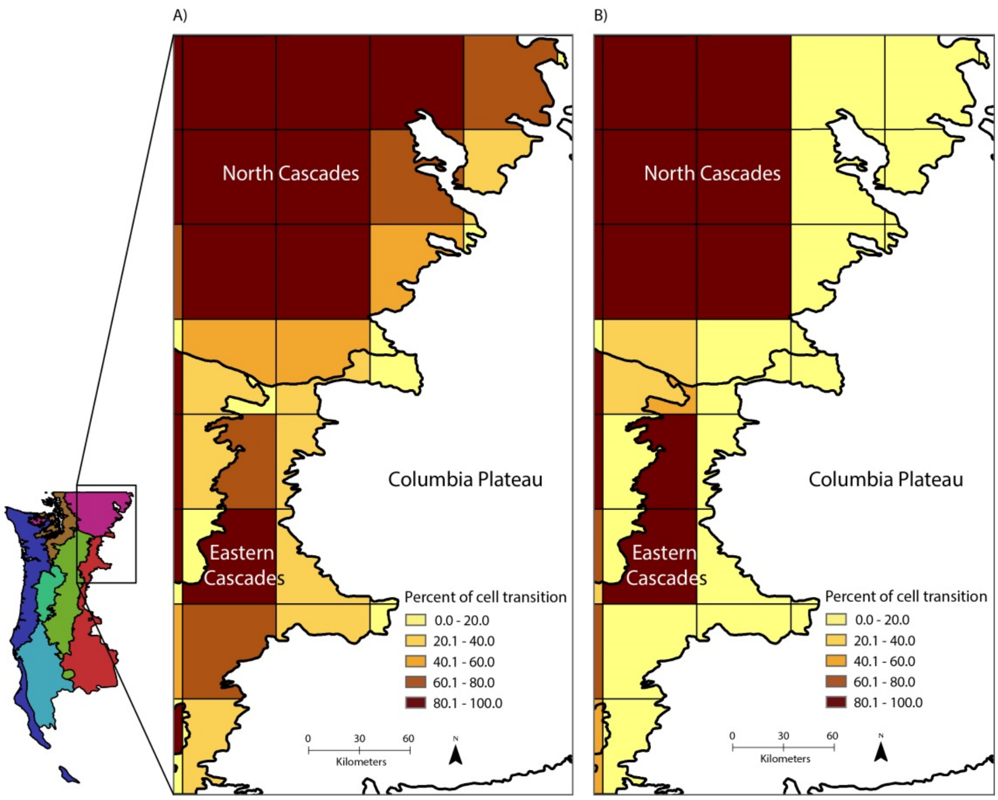


**Figure 5. Total zone transition as a percent of total cell transition for the grass/shrub to agriculture transition in the North Coast, Eastern Cascades and Columbia Plateau ecoregions between 2005–2100, for A) composition-based downscaling, B) transition-based downscaling.**

### 3.2. Ecoregion variability

#### 3.2.1. Developed change

Developed land-use totals increased over all ecoregions by the year 2100, with the largest increases occurring in the Cascades, Coast Range, Puget Lowland and Willamette Valley ecoregions (Figure 6). Of these ecoregions, the largest difference between downscaling methods occurred in the Puget Lowland ecoregion, where the Transition scenario projected nearly twice the amount of developed land than Area or Composition scenarios (Figure 6). The Transition scenario also differed from the Area and Composition scenarios in the Cascades, North Cascades and Willamette Valley ecoregions (Table 6). Between Area and Composition scenarios no important differences were found since the means of simulation runs were within the range of variability of each method (Figure 6).

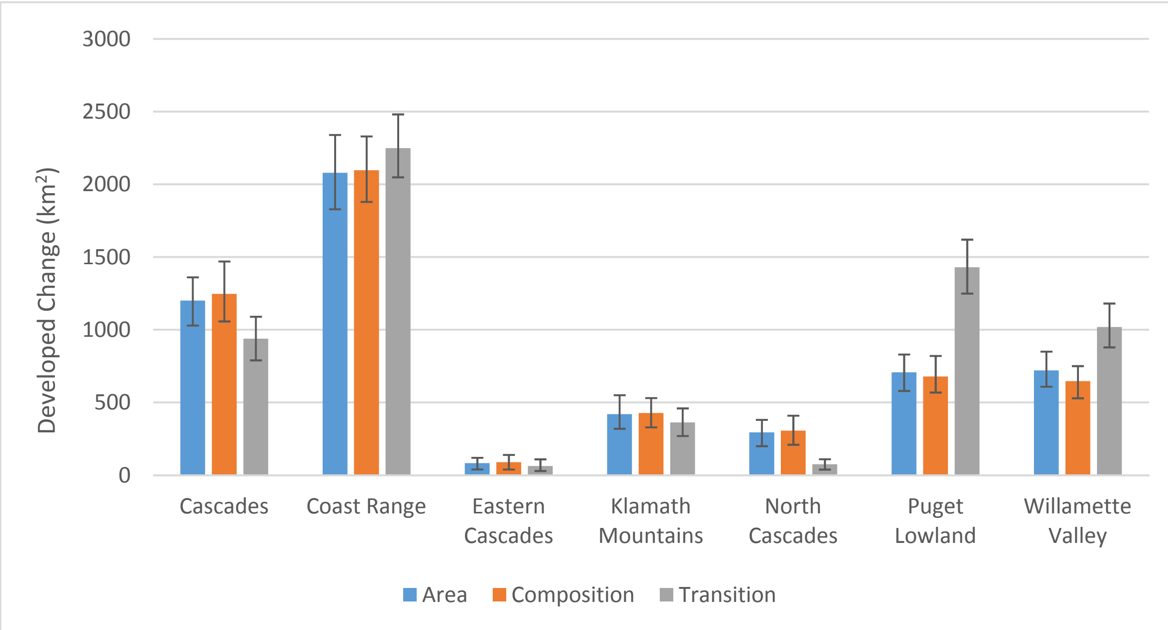


**Figure 6. Projected total developed area change by ecoregion and downscaling scenario between 2005–2100 (average over 100 Monte Carlo replicates).** Error bars represent the 95th percentile of Monte Carlo simulations.

The transitions *forest to developed* and *agriculture to developed* drove most of the change in developed land over our study site as transitions out of developed were not included in the scenarios and *grass/shrub to developed* transitions were small. For composition-based downscaling, the amount of the "from" class of the transition determines how border cells are reapportioned. Therefore, the amount of forest and agriculture land at border cells drives reapportioning, not the amount of developed land. However, in the Puget Lowland we expected the presence of existing developed land in the greater Seattle Metropolitan area would influence patterns of future development (Figure 7) since new development is likely to occur near existing developed areas [37]. Compared to the Transition scenario, the Composition scenario led to less *forest to developed* transition in the Puget Lowland (Figures 7B–C). Apportioning transitions into developed land without incorporating historic patterns of development may lead to an under-allocation of transition in the Puget Lowland.

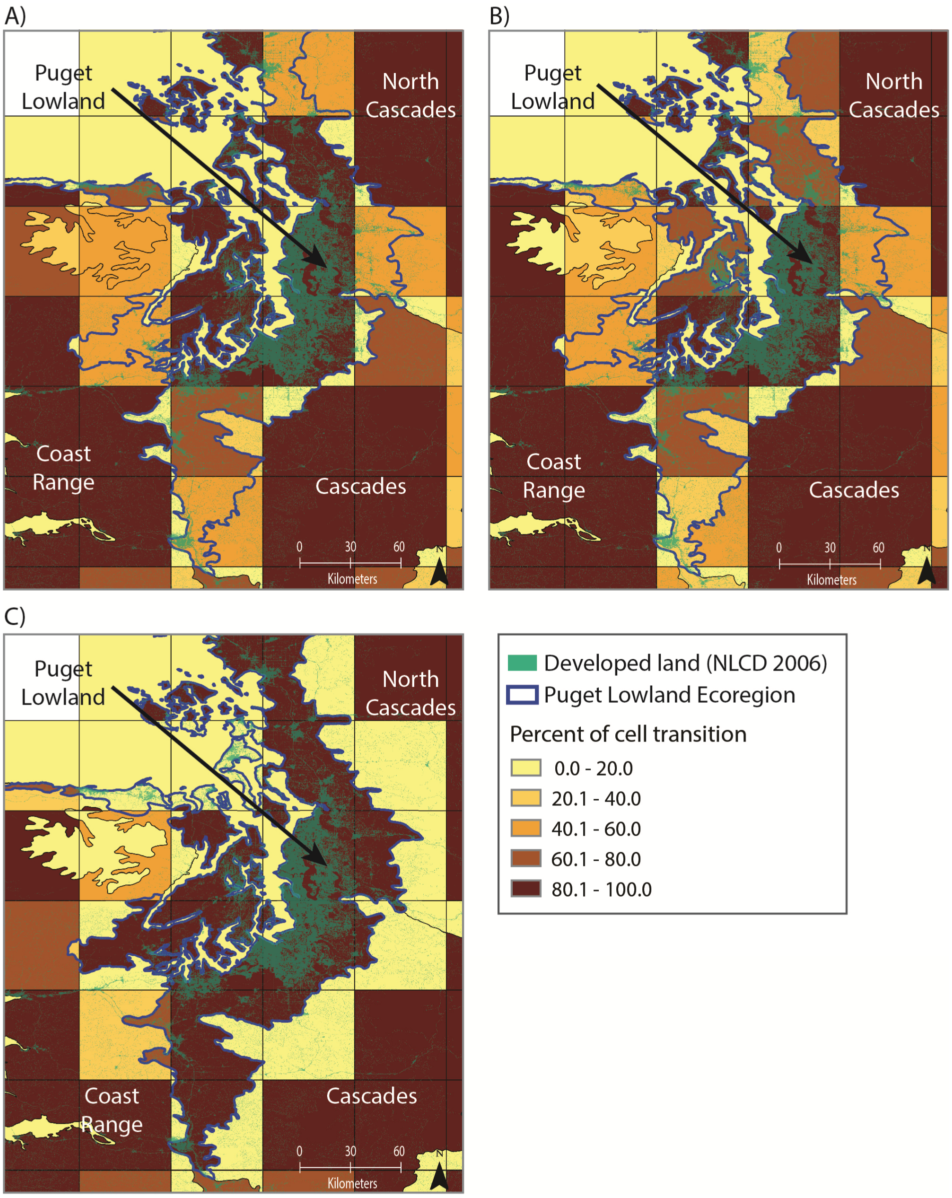


**Figure 7. Total zone transition as a percent of total cell transition for the forest to developed transition in the Coast Range, Puget Lowland, Cascades, and North Cascades ecoregions, for A) area-based downscaling B) composition-based downscaling and C) transition-based downscaling.**

Area-based downscaling split RCP transitions between ecoregions based solely on the proportion of cell area within respective ecoregions. This method does not follow any spatial pattern; instead, the relative size of each zone determines the amount of transition apportioned to each ecoregion. Again, the high apportionment of transitions into developed land that we would expect to see in the Puget Lowland based on the historical presence of developed land did not occur in the area-based scenario (Figure 7A). Like composition-based reapportioning, area-based reapportioning leads to an under-allocation of transitions into developed land in the Puget Lowland.

When applying transition-based downscaling, greater Trends transition values for transitions into developed land in the Puget Lowland compared to adjacent ecoregions led to a greater apportionment of the RCP transitions into developed in the Puget Lowland and subsequently a higher amount of change into developed land (Figure 7C). Transition-based downscaling led to an apportionment of developed land more consistent with historical, empirical patterns.

### 3.2.2. Agriculture change

Between 1973 and 2000, agriculture in the Pacific Northwest was largely concentrated in the Eastern Cascades, Puget Lowland, and Willamette Valley ecoregions [23]. Under each of the three downscaling scenarios, agriculture was projected to increase in the Eastern Cascades, and decline in the Puget Lowland and Willamette Valley ecoregions (Figure 8). Differences between downscaling scenarios were small for most ecoregions. In the Cascades and Willamette Valley ecoregions, the Composition scenario mean was outside the range of variability of both the Area and Transition Scenarios (Figure 8). Differences were also found between the Area and Transition scenarios in the Coast Range and Puget Lowland ecoregions.

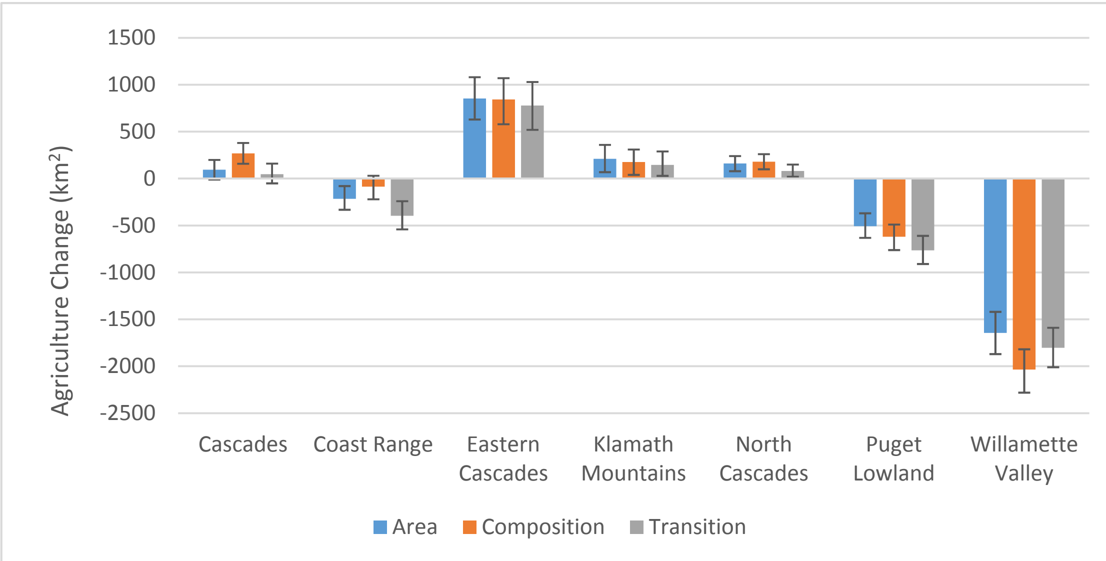


**Figure 8. Projected total agriculture change by ecoregion and downscaling scenario between 2005–2100 (average over 100 Monte Carlo replicates).** Error bars represent the 95th percentile of Monte Carlo simulations.

In the Willamette Valley the Composition scenario led to the highest projected decline in agriculture. Agriculture in the Willamette Valley constitutes a much higher percentage of the landscape (16% from NLCD 2006), than in surrounding ecoregions, and follows the ecoregion border closely (Figure 9). As a result, most of the agricultural loss in border cells (e.g. *agriculture to forest*) was allocated to the Willamette Valley (Figure 9B). The apportionment of agriculture transitions in this case demonstrates a typical problem with composition-based downscaling approach. Composition-based downscaling apportions transitions based on the presence of a transition's "from" class. However, the presence of a land-use is not necessarily indicative of future change. In some cases transitions out of a land-use will more likely occur in areas where land-use is rare since conditions are likely to be less suitable. Composition-based reapportioning may lead to an over-apportionment of the *agriculture to forest* transition to the Willamette Valley and subsequent overestimation of the agricultural decline.

Another problem with composition-based downscaling is that all transitions out of a LULC class are reapportioned equally. While agriculture is available for transition to forest in the Willamette Valley ecoregion, agriculture will likely transition to developed land given a high demand for developed land. In contrast, in the forest-dominated Coast Range, agricultural land may be more likely to transition back to forest. Potential differences between the likelihood of transitioning into the "to" class are not well distinguished in composition-based downscaling and may lead to implausible results.

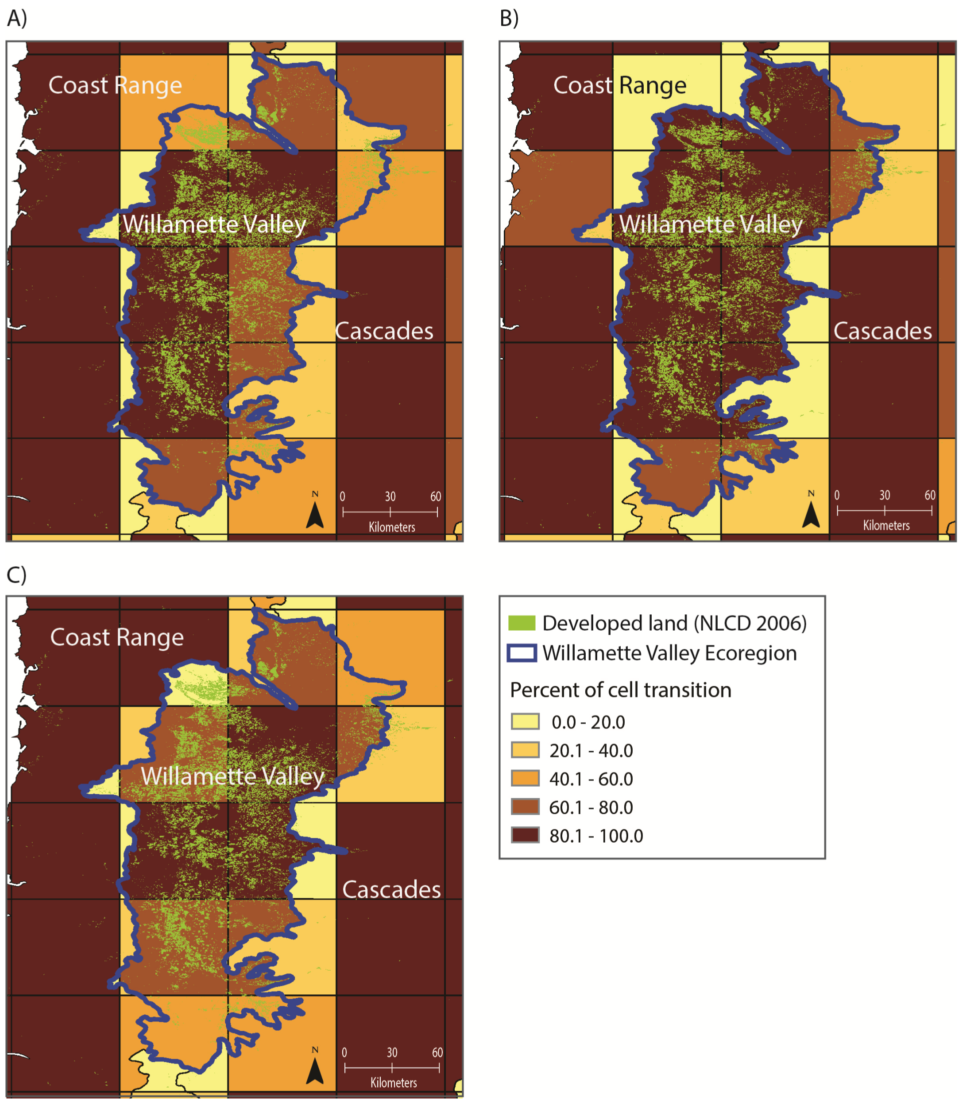


**Figure 9. Total zone transition as a percent of total cell transition for the agriculture to forest transition in the Coast Range, Willamette Valley, and Cascades ecoregions, for A) area-based downscaling, B) composition-based downscaling, and C) transition-based downscaling.**

The Transition scenario resulted in lower amounts of agriculture returning to forest in the Willamette Valley, the result of capturing recent historical LULC conversions occurring in the neighboring Coast Range ecoregion [23].

### 3.2.3. Forest change

Large reductions in forest were projected for all ecoregions except for the Willamette Valley where forests were projected to increase by 339 $km^2$, 619.1 $km^2$ and 131.0 $km^2$ for the Area, Composition, and Transition scenarios respectively (Figure 10). The Transition scenario projected higher total forest loss in the Puget Lowland ecoregion and less forest loss in the Cascades ecoregion than the Area or Composition scenarios (Figure 10). In the Willamette Valley the Composition scenario led to greater forest gains than the Area or Transition scenarios (Figure 10).

In the Puget Lowland greater forest loss projected by the Transition scenario was largely driven by two factors. First, a high Trends transition value for the *forest to developed* transition in the Puget Lowland, relative to surrounding ecoregions, led to a greater apportionment of the transition into the Puget Lowland when applying transition-based downscaling opposed to area or composition-based downscaling. Secondly, forest area constitutes a smaller percentage of total area in the Puget Lowland (40% from NLCD 2006) than in the forest dominated Coast Range (66% from NLCD 2006) and Cascades (75% from NLCD 2006) ecoregions [23]. Since, composition-based downscaling apportions transition values based on the “from” class of the transition, less transition out of forest was apportioned to the Puget Lowland when applying composition-based downscaling than for area or transition-based downscaling. Combined, these factors led to a large difference in projected forest change between the Transition and Composition scenarios.

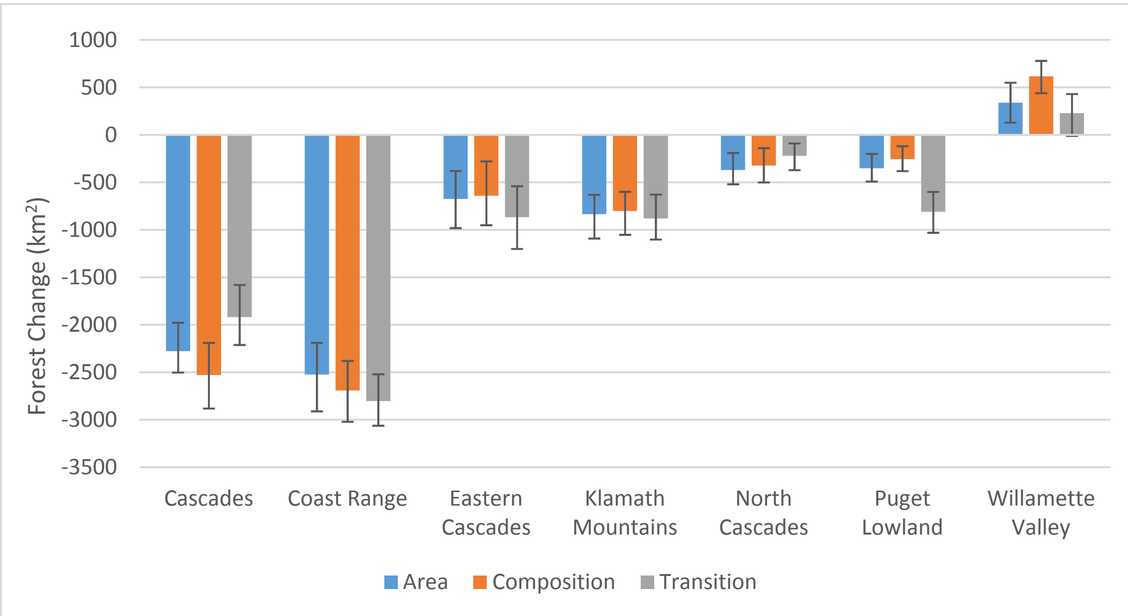


**Figure 10. Projected total forested area change by ecoregion and downscaling scenario between 2005–2100 (average over 100 Monte Carlo replicates).** Error bars represent the 95th percentile of Monte Carlo simulations.

Large amounts of forest harvest are projected by 2100, with most harvest occurring the in Cascades, Coast Range and Klamath Mountains ecoregions. However, differences between downscaling scenarios were within each other's range of variability and not large enough to be considered important (Figure 11).

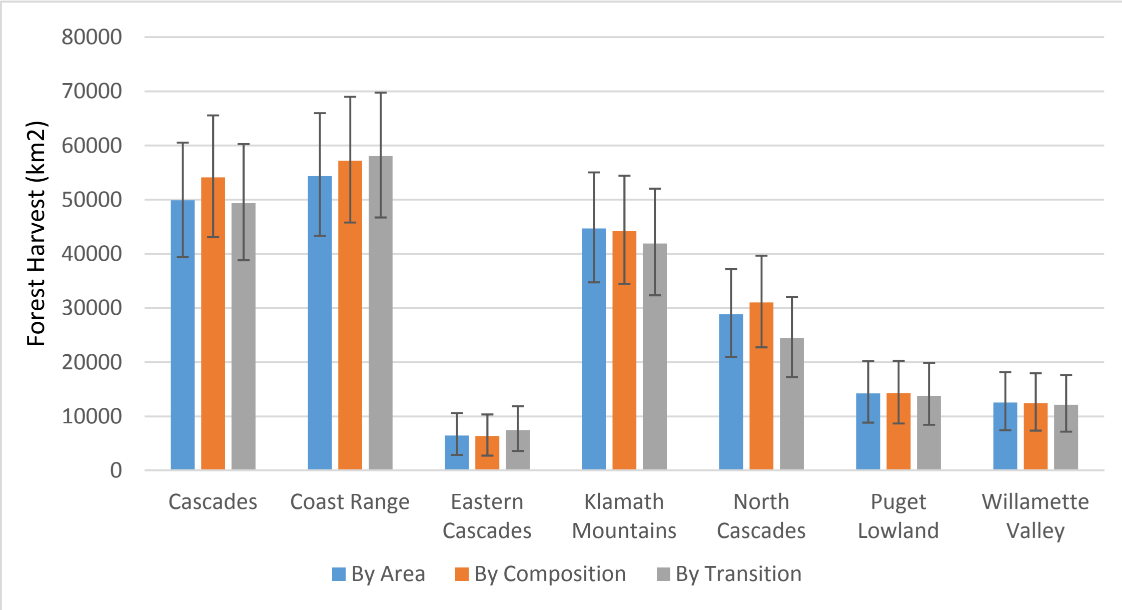


**Figure 11. Projected total forest harvest by ecoregion and downscaling scenario between 2005 and 2100 (average over 100 Monte Carlo replicates).** Error bars represent the 95th percentile of Monte Carlo simulations.

### 3.2.4 Grass/shrub change

Grass/Shrub area was projected to increase in all ecoregions with the exception of the Eastern Cascades and North Cascades (Figure 12). Only in the North Cascades and Willamette Valley between the Transition and Composition scenarios and in the Willamette Valley between Composition and Area scenarios were differences in projected grass/shrub seen.

While grass/shrub makes up a relatively small proportion of landcover within our study region, the Columbia Plateau, Northern Basin and Range and Blue Mountains ecoregions to the East of the study region are largely composed of grass/shrub (Figure 13A). However, looking closely at cells on the border of the Columbia Plateau and the Northern Cascades, actual grass/shrub boundaries are not as abrupt as ecoregion boundaries. In some places dense grass/shrub areas spill over into the Northern Cascades (Figure 13B).

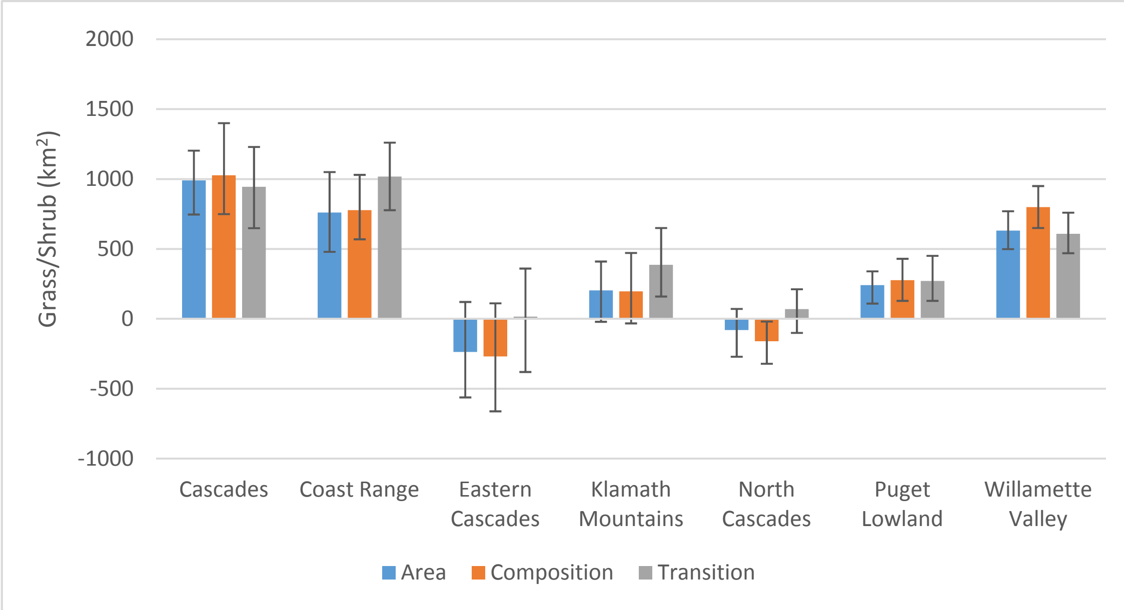


**Figure 12. Projected total grass/shrub area change by ecoregion and scenario between 2005–2100 (average over 100 Monte Carlo replicates).** Error bars represent the 95th percentile of Monte Carlo simulations.

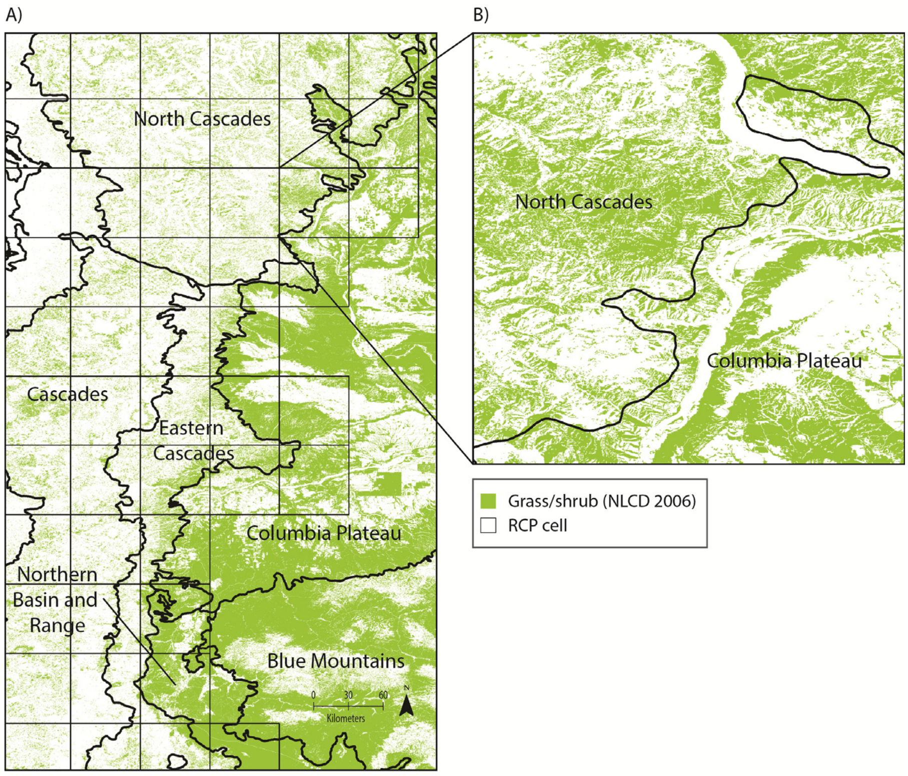


**Figure 13. A) The Northeast edge of the study site with grass/shrub area from NLCD 2006 and RCP cell boundaries. B) A close up of an RCP cell spanning the North Cascades and Columbia Plateau Ecoregions.**

For transitions out of grass/shrub, transition-based downscaling may underestimate the amount of transition that should be apportioned to ecoregions such as the Northern Cascades because Trends values are derived for ecoregions as a whole. Within ecoregion variation, not captured in the Trends transition value, may warrant higher rates of transition near ecoregion borders.

The composition-based downscaling approach may be beneficial in this case because the NLCD map can indicate where gradual change between LULC occurs (Figure 13B). The impact of this type of spill over is not always clear, however, since historical drivers of LULC change such as management practices may be more important than land-cover in determining how LULC change should be reapportioned between ecoregions.

## 4. Discussion

Of our three downscaling approaches, the area-based approach is the simplest to implement because it requires no additional datasets. This method may be entirely sufficient when splitting transitions across a homogenous landscape and would also be suitable if land-use history data or a land-use composition data was not available or reliable. However, area-based downscaling has several key disadvantages. In some cases, regions have distinct differences in the amount of expected LULC transition. Area-based downscaling fails to incorporate the regional heterogeneity of the landscape in the downscaling method. As demonstrated above, this can lead to large differences in land-use projections and reduced confidence in the scenario itself. Results from area-based downscaling may be especially questionable when a large proportion of RCP cells fall on the edge of two or more regions of interest. Such is the case with most of the ecoregions within our study site. The Willamette Valley, for example is made up of only edge cells.

Differences between the Area and Composition scenarios were mostly within each other's range of variability, indicating that they were not large enough to be important. One main benefit of composition-based downscaling is that it accounts for regional heterogeneity between LULC. However, the composition-based downscaling assumes LULC composition is a suitable proxy for LULC change. This may prove inaccurate for transitions where land management practices are more important drivers of change than landcover presence [38]. Furthermore, since composition-based downscaling is determined only by the relative zone composition of the "from" class for each transition, transitions can be apportioned to ecoregions where the LULC of the "to" class is not historically present. LULC composition datasets, such as the NLCD, are available for the conterminous United States, and coarser datasets such as the Global Landcover 2000 dataset are available globally [39]. Datasets like the MODIS dataset have been effective in downscaling scenario data and may be applicable in this case as well [13].

The transition-based downscaling method has the inherent advantage of using the same data type as the original data to downscale. Differences between the Transition scenario and the Area and Composition scenarios were found for most LULC classes, and were especially pronounced for projections of developed land. Historical transition data can be used to guide future patterns of transitions not evident in land-cover composition data. Land-use management and ownership patterns are inherently represented in historical transition datasets, providing an added benefit over area and composition-based downscaling methods. However, one potential problem with transition-based downscaling is the process inherently assumes regional patterns and distribution of land-use change will continue on a similar trajectory into the future. In reality LULC change is driven by a host of processes, both physical and anthropogenic, with interactions varying across space and time [40]. In addition, land-use transition datasets are less likely to be available at desired regional scales. The most important advantages and shortcomings of each of the three downscaling methods are outlined in Table 6.

**Table 6. Summary of advantages and disadvantages of area-based, composition-based, and transition-based downscaling approaches.**

| | Downscaling Method | | |
|---|---|---|---|
| | Area | Composition | Transition |
| Advantages | 1. No additional data needed.<br>2. May be applicable when region boundaries do not follow LULC patterns. | 1. Easy to find composition dataset like "NLCD".<br>2. Does a better job than Area based downscaling at accounting for transition differences between regions. | 1. Using transition history data to downscale incorporates historical management and ownership patterns.<br>2. Historical transition data takes into account both the "from" and "to" class of transition. |
| Shortcomings | 1. Reapportions transition data without regard to regional land use pattern or history.<br>2. Simplistic approach, can lead to large discrepancies. | 1. Since only the "from" class of the transition is considered, in some cases, may not accurately reapportion transition data.<br>2. The presence of a land-cover is not necessarily indicative of future change. | 1. Low availability on large scale or globally. |

Several other factors impact the outcome of the downscaling method for reapportioning RCP values. Total region size determines the relative influence of edge cells since reapportioned edge cells have relatively less impact when aggregating to larger regions. Also, the shape of the region, specifically the ratio between area and perimeter of the region will impact the proportional contribution of edge cells to the total transition amount within the ecoregion (e.g. Willamette Valley). Ecoregions do a very good job of spatially organizing LULC change, but do not perform well when using an area-based downscaling approach. If spatial strata or regions are a) sufficiently coarse, b) represent large homogenous regions, or c) based on administrative boundaries or some other non-ecological framework, area-based downscaling might be a more suitable approach.

Since our STSM was driven solely by RCP transition probabilities and available land-use for transition, model outputs closely reflect RCP projections. It should be noted that an initial inventory of RCP transition totals at the ecoregion level suggests that a validation process is needed to ensure values are within reasonable bounds.

## 5. Conclusion

Here we present the results of three downscaling methods used to downscale RCP transition values to scales relevant for analysis in an STSM model. While all three methods may be sufficient in certain circumstances, downscaling using a historical LULC transition data such as the Trends dataset has some distinct advantages. Most importantly using a historical transition dataset to downscale RCP transition values accounts for regional patterns in both the "from" and "to" class of the RCP transition. Historical LULC change data also often captures LULC change information related to land ownership and management. When historical transition data is not available it may be necessary to apply an area or composition downscaling approach instead.

To our knowledge this is the first attempt to use global RCP LULC transition data to drive a region level STSM of LULC change. This paves the way for more sophisticated STSM analysis of LULC change using the latest global climate data. One such refinement will be to run the model in a spatially explicit manner as was done by Wilson et al. [21]. In this case a raster of LULC was used to initialize the model spatially. Also, spatial multipliers were included to further spatially constrain allowable transition areas. The use of downscaled RCP data in an STSM allows modelers to incorporate climate change scenarios at the regional scale. It will also enable comparisons between study areas, scales, and land cover types within a larger framework.

Our approach was developed specifically for reapportioning RCP transition values to region level scales, but it may be applicable to several other global gridded LULC change products. Our reapportioning techniques are immediately applicable to the HYDE dataset which provides global gridded LULC change data for the past 12,000 years [41]. Downscaling historic and future data projections will provide a consistent and continuous set of LULC change data that can be used within a STSM.

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**Conflict of Interest**

The authors declare no conflict of interest.

**Disclaimer**

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**References**

1. Zaehle S, Bondeau A, Carter TR, et al. (2007) Projected changes in terrestrial carbon storage in Europe under climate and land-use change, 1990–2100. *Ecosystems* 10: 380-401.

2. Kim J, Choi J, Choi C, et al. (2013) Impacts of changes in climate and land use/land cover under IPCC RCP scenarios on streamflow in the Hoeya River Basin, Korea. *Sci Total Environ* 452: 181-195.
3. Sleeter BM, Sohl TL, Loveland TR, et al. (2013) Land-cover change in the conterminous United States from 1973 to 2000. *Global Environ Chang* 23: 733-748.
4. Hurtt G, Chini LP, Frolking S, et al. (2011) Harmonization of land-use scenarios for the period 1500–2100: 600 years of global gridded annual land-use transitions, wood harvest, and resulting secondary lands. *Climatic Change* 109: 117-161.
5. Pitcher HM (2009) The future of scenarios: issues in developing new climate change scenarios. *Environ Res Lett* 4: 1-7.
6. Nakicenovic N, Swart R (2000) Special report on emission scenarios. Edited by Nakicenovic N, Swart R, pp. 612. ISBN 0521804930. Cambridge, UK: Cambridge University Press.
7. Lambin EF, Turner BL, Geist HJ, et al. (2001) The causes of land-use and land-cover change: moving beyond the myths. *Global Environ Chang* 11: 261-269.
8. Moss RH, Edmonds JA, Hibbard KA, et al. (2010) The next generation of scenarios for climate change research and assessment. *Nature* 463: 747-756.
9. Van Vuuren D, Edmonds J, Kainuma M, et al. (2011) The representative concentration pathways: an overview. *Climatic Change* 109: 5-31.
10. Van Vuuren DP, Smith SJ, Riahi K (2010) Downscaling socioeconomic and emissions scenarios for global environmental change research: a review. *Wiley Interdiscip Rev Clim Change* 1: 393-404.
11. Van Vuuren DP, Lucas PL, Hilderink H (2007) Downscaling drivers of global environmental change: Enabling use of global SRES scenarios at the national and grid levels. *Global Environ Chang* 17: 114-130.
12. Dendoncker N, Bogaert P, Rounsevell M (2006) A statistical method to downscale aggregated land use data and scenarios. *J Land Use Sci* 1: 63-82.
13. West T, Le Page Y, Huang M, et al. (2014) Downscaling global land cover projections from an integrated assessment model for use in regional analyses: results and evaluation for the US from 2005 to 2095. *Environ Res Lett* 9: 064004.
14. Rounsevell M, Ewert F, Reginster I, et al. (2005) Future scenarios of European agricultural land use: II. Projecting changes in cropland and grassland. *Agr Ecosyst Environ* 107: 117-135.
15. Abildtrup J, Audsley E, Fekete-Farkas M, et al. (2006) Socio-economic scenario development for the assessment of climate change impacts on agricultural land use: a pairwise comparison approach. *Environ Sci Policy* 9: 101-115.
16. Sleeter BM, Sohl TL, Bouchard MA, et al. (2012) Scenarios of land use and land cover change in the conterminous United States: utilizing the special report on emission scenarios at ecoregional scales. *Global Environ Chang* 22: 896-914.
17. Sohl TL, Sleeter BM, Zhu Z, et al. (2012) A land-use and land-cover modeling strategy to support a national assessment of carbon stocks and fluxes. *Appl Geogr* 34: 111-124.
18. IPCC (2013) Working Group I Contribution to the IPCC Fifth Assessment Report (AR5), Climate Change 2013: The Physical Science Basis. Intergovernmental Panel on Climate Change, Geneva, Switzerland.
19. Omernik JM (1987) Ecoregions of the conterminous United States. *Ann Assoc Am Geogr* 77: 118-125.

20. Gallant AL, Loveland TR, Sohl TL, et al. (2004) Using an ecoregion framework to analyze land-cover and land-use dynamics. *Environ Manage* 34: 89-110.
21. Wilson TS, Sleeter BM, Sleeter RR, et al. (2014) Land-use threats and protected areas: A scenario-based, landscape level approach. *Land* 3: 362-389.
22. Masui T, Matsumoto K, Hijioka Y, et al. (2011) An emission pathway for stabilization at 6 Wm−2 radiative forcing. *Climatic Change* 109: 59-76.
23. Sleeter BM, Wilson TS, Acevedo W, Status and trends of land change in the Western United States—1973 to 2000. U.S. Geological Survey, 2012. Available from: http://pubs.usgs.gov/pp/1794/a/
24. Hurtt GC, Chini LP, Frolking S, et al. (2009) Harmonization of global land-use scenarios for the period 1500-2100 for IPCC-AR5. *ILEAPS Newslett* 7: 6-8.
25. Soulard CE, Acevedo W, Auch RF, et al., Land Cover Trends Dataset, 1973–2000. U.S. Geological Survey, 2014. Available from: http://dx.doi.org/10.3133/ds844
26. Fry JA, Xian G, Jin S, et al. (2011) Completion of the 2006 national land cover database for the conterminous United States. *Photogramm Eng Rem S* 77: 858-864.
27. Loveland T, Sohl T, Stehman S, et al. (2002) A Strategy for Estimating the Rates of Recent United States Land-Cover Changes. *Photogramm Eng Rem S* 68: 1091-1099.
28. Blankenship K, Smith J, Swaty R, et al. (2012) Modeling on the Grand Scale: LANDFIRE Lessons Learned. In: Kerns, BK, Shlisky, AJ, Daniel, CJ, editors. *Proceedings of the First Landscape State-and-Transition Simulation Modeling Conference, June 14–16, 2011*. Gen Tech Rep PNW-GTR-869. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station: 43-56.
29. Creutzburg MK, Halofsky JS, Hemstrom MA (2012) Using state-and-transition models to project cheatgrass and juniper invasion in Southeastern Oregon sagebrush steppe. In: Kerns, BK, Shlisky, AJ, Daniel, CJ, editors. *Proceedings of the First Landscape State-and-Transition Simulation Modeling Conference, June 14–16, 2011*. Gen Tech Rep PNW-GTR-869. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station: 73-84.
30. Duncan JA, Burcsu T (2012) Landscape development and mule deer habitat in Central Oregon. In: Kerns, BK, Shlisky, AJ, Daniel, CJ, editors. *Proceedings of the First Landscape State-and-Transition Simulation Modeling Conference, June 14–16, 2011*. Gen Tech Rep PNW-GTR-869. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station: 85-102.
31. Daniel CJ, Frid L (2012) Predicting landscape vegetation dynamics using state-and-transition simulation models. In: Kerns, BK, Shlisky, AJ, Daniel, CJ, editors. *Proceedings of the First Landscape State-and-Transition Simulation Modeling Conference, June 14–16, 2011*. Gen Tech Rep PNW-GTR-869. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station: 5-22.
32. Shlisky AJ, Vandendriesche D (2012) Use of state-and-transition simulation modeling in National Forest planning in the Pacific Northwest, U.S.A. In: Kerns, BK, Shlisky, AJ, Daniel, CJ, editors. *Proceedings of the First Landscape State-and-Transition Simulation Modeling Conference, June 14–16, 2011*. Gen Tech Rep PNW-GTR-869. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station: 23-42.

33. Kerns BK, Hemstrom MA, Conklin D, et al. (2012) Approaches to incorporating climate change effects in state and transition simulation models of vegetation. In: Kerns, BK, Shlisky, AJ, Daniel, CJ, editors. *Proceedings of the First Landscape State-and-Transition Simulation Modeling Conference, June 14–16, 2011*. Gen Tech Rep PNW-GTR-869. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station: 161-172.
34. Hemstrom MA, Halofsky JE, Conklin DR, et al. (2014) Chapter 7: Developing climate-informed state-and-transition models. In: Halofsky JE, Creutzburg MK, Hemstrom MA, editors. *Integrating social, economic, and ecological values across large landscapes*. Gen Tech Rep PNW-GTR-896. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station: 175-202.
35. Apex Resource Management Solutions Ltd., ST-Sim: State-and-Transition Simulation Model Framework. 2014. Available from: http://www.apexrms.com/.
36. Sleeter RR, Acevedo C, Soulard CE, et al. (2015) Methods used to parameterize the spatially-explicit components of a state-and-transition simulation model. *AIMS Environ Sci* [accepted].
38. Huang B, Zhang L, Wu B (2009) Spatiotemporal analysis of rural–urban land conversion. *Int J Geogr Inf Sci* 23: 379-398.
38. Jin S, Sader SA (2006) Effects of forest ownership and change on forest harvest rates, types and trends in northern Maine. *Forest Ecol Manag* 228: 177-186.
39. Giri C, Zhu Z, Reed B (2005) A comparative analysis of the Global Land Cover 2000 and MODIS land cover data sets. *Remote Sens Environ* 94: 123-132.
40. Lambin EF, Turner BL, Geist HJ, et al. (2001) The causes of land-use and land-cover change: moving beyond the myths. *Global Environ Chang* 11: 261-269.
41. Goldewijk KK (2001) Estimating global land use change over the past 300 years: the HYDE database. *Global Biogeochem Cy* 15: 417-433.