Appendix

Section 1. Land Use and Land-use Change Models

The land-use change component of the WW2100 model simulates decisions to change land between agricultural, forest, and urban uses as a function of economic returns to alternative uses. These economic returns are estimated on the basis of site characteristics, such as farm rents (annual net returns to farming), distance to cities, and population and income of nearby cities. Returns to land and land-use transitions also are influenced by urban growth boundaries (UGBs). The land-use component includes a mechanism by which UGBs expand over time (described under "Zoning and UGB expansion," page 67).

Changes between forest, agricultural, and urban land uses comprise the focus of the WW2100 land-use change model, since these are the major uses, and sources of land-use change, that occur within the Willamette River Basin (WRB) study area (USGS, 2012). In addition, the property value data used to parameterize the economic returns to different land uses are not readily available for more disaggregated land-use categories (e.g., specific crops or forest types). Differences within each of these broad land-use categories are controlled for by including separate sets of fine-scale land characteristics in each land value equation. Across the WW2100 study area, the initial land use on each Integrated Decision Unit (IDU) is determined by overlaying a set of spatial data layers, which include data from the National Land Cover Data (NLCD) data set and Cropland Data Layer (CDL).

The scope of the land-use transitions model is limited to privately owned lands, as the bulk of land-use change in our study area occurs as the result of decisions made by private actors. Wetland areas are not allowed to change uses, in accordance with local and federal planning rules and regulations that discourage wetland conversion. In addition, it is difficult to determine the market value of wetlands, since they do not easily fit into any one of the three categories we consider, and much of their value stems from recreation and nonmarket ecosystem service provision (e.g., water filtration). Bidirectional transitions are allowed between privately owned forest and agricultural land anywhere in the "lowland" portion of the study area. Land development, on the other hand, or the conversion of forest or agricultural land to an urban use, is restricted to occur within UGBs, which, as mentioned above, are allowed to expand over the course of the model simulations. Development is also considered to be irreversible for the purposes of the WW2100 model (i.e., transitions from urban to agriculture or forest are not allowed).

Economic returns to different land uses

Parcel-level data were collected from county assessors in four counties (Benton, Lane, Marion, and Washington) in the WRB. Data included the real market value (RMV) of developed, agricultural, and forest land; parcel size; and value of improvements on the property (e.g., structures). These four sample counties were selected to represent the major urban areas within the WRB (Corvallis, Eugene-Springfield, Salem, and Portland Metro), which have historically been the predominant drivers of land-use change in our study area (USGS, 2012), and to cover the geographic extent of the WRB (see Bigelow, 2015, for more details).

The parcels included from each county were stratified according to three broad land use categories: agriculture, forest, and residential development. County-specific random samples were then drawn from each category, with samples for Benton (430), Lane (1,134), Marion (1,576), and Washington (1,599) counties. The relative size of the county samples is proportional to the size of the urban areas they represent. Observations were obtained for the years 1973, 1980, 1986, 1992, and 2000, making it possible to use panel data methods to estimate a hedonic land value model for each of the three major land uses considered. The set of variables, definitions, and data sources are described in Table A1 (page 62).

Table A1. Variable descriptions and sources for hedonic land value models.

Variable	Description	Source
Constant	= constant, applies to all observations; includes effects of year 2000 dummy variable (the Marion County dummy variable or "fixed effect") and average lot size for developed sample parcels (0.39 acre)	County assessment offices (lot size)
UGB	= 1 located within UGB; 0 otherwise	Oregon Department of Land Conservation and Development
Population density	= population density of nearest UGB for a city with a population of greater than 20,000 (number of people per acre)	U.S. Census of Population
Household income	= natural log of household income in county where parcel is located (in $1,000s)	Woods and Poole
Improvement value	= value of improvements on parcel	County assessment offices
Dist. city center	= Euclidean distance to nearest city center (in miles; cities are defined as those with population > 20,000)	Google Maps (used for generating city centroid)
Dist. city center^2	= squared Euclidean distance to nearest city center	Google Maps (used for generating city centroid)
Benton County	= 1 if parcel located in Benton County group; 0 otherwise	County assessment offices
Lane County	= 1 if parcel located in Lane County group; 0 otherwise	County assessment offices
Washington County	= 1 if parcel located in Washington County group; 0 otherwise	County assessment offices
Acres	= acreage of parcel	County assessment offices
Slope	= average slope of parcel (degrees)	U.S. Geological Survey
Farm rent	= per-acre farmland rental value	WW2100 farmland rent model (see "Farmland rent," page 80)
Mean improvement value	= parcel average of improvement value over sample years	County assessment offices
Elevation	= average elevation of parcel	U.S. Geological Survey
River footage	= footage of rivers and streams running through parcel	U.S. Environmental Protection Agency
Pvt. non-industrial owner	= 1 if under private nonindustrial ownership; 0 otherwise	Oregon State Forestry Science Lab
Dist. UGB	= distance to nearest UGB boundary	Department of Land Conservation and Development

The model estimation is summarized in Table A2 (pages 63–64) for developed, agricultural, and forest land values. Developed land values were estimated using a Hausman-Taylor (1981) model, which allows for certain covariates in the model to be treated as endogenous and does not require the use of external instruments (see, e.g., Abbott and Klaiber, 2011). The time-invariant effect of a parcel being located within a UGB was treated as endogenous. The area covered by a given municipality's UGB is determined by city planners who, when setting the UGB, would likely target land parcels with characteristics that make them suitable for urban-oriented land uses. If unobserved factors influence both the decision to place a parcel within a UGB and the subsequent value of that land, the UGB effect will not be properly identified.

Table A2. WW2100 hedonic model coefficients.[1]

	Agriculture	Urban	Forest
Year1980	-0.260***	0.676***	0.119*
	(-5.750)	(16.90)	(1.872)
Year1986	-0.942***	0.569***	-0.438***
	(-15.91)	(13.61)	(-5.290)
Year1992	-1.066***	0.526***	-0.455***
	(-13.49)	(11.61)	(-4.421)
Year2000	0.516***	1.269***	0.0321
	(3.540)	(19.05)	(0.192)
Parcel acreage	-0.00768***	-0.518***	-0.000335
	(-6.286)	(-29.38)	(-1.383)
Benton County	-0.209*	0.0923**	-0.996***
	(-1.797)	(2.141)	(-8.949)
Lane County	-0.354***	-0.276***	-0.295***
	(-3.738)	(-7.972)	(-2.769)
Washington County	-0.786***	0.239***	-1.274***
	(-3.915)	(6.116)	(-7.157)
Dist. urban center	-0.0182	-0.0458***	-0.111***
	(-1.193)	(-8.354)	(-7.928)
Dist. urban center^2	0.000459	0.000765***	0.00187***
	(1.105)	(6.897)	(6.563)
Population density	0.179***	0.107***	0.137**
	(3.515)	(9.345)	(2.410)
Household income	0.0335***	0.627***	0.0590***
	(8.726)	(5.592)	(11.06)
Inverse Mill's ratio	-0.335**	0.130***	0.205
	(-2.460)	(4.104)	(1.533)
Improvement value	0.000975**	0.00106***	0.000333
	(2.551)	(13.20)	(1.416)
UGB*Year1980	—	0.0529	—
	—	(1.295)	—
UGB*Year1986	—	-0.147***	—
	—	(-3.647)	—
UGB*Year1992	—	-0.218***	—
	—	(-5.445)	—
UGB*Year2000	—	-0.322***	—
	—	(-7.953)	—
UGB	—	0.756***	—
	—	(12.84)	—
Slope	-0.0144	—	-0.0514***
	(-1.195)	—	(-8.536)

[1]Statistical significance is indicated as: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Continued on next page

Table A2. WW2100 hedonic model coefficients.[1] (*continued*)

	Agriculture	Urban	Forest
Farm rent	0.00264**	—	—
	(2.422)	—	—
Elevation	—	—	-0.00105***
	—	—	(-4.431)
River footage	—	—	-8.97e-05**
	—	—	(-2.328)
Pvt. non-industrial owner	—	—	0.252***
	—	—	(3.353)
Ag/Forest zoning	-0.345***	—	-0.672***
	(-3.419)	—	(-6.417)
UGB distance	-0.0312**	—	0.0393***
	(-1.988)	—	(3.197)
Mean pop. density	-0.115	—	—
	(-1.377)	—	—
Mean income	-0.0163	—	-0.0148**
	(-1.582)	—	(-1.982)
Mean IMR	1.027***	—	0.894***
	(2.757)	—	(2.997)
Mean imp. value	0.00204*	—	0.00588***
	(1.676)	—	(7.055)
Constant	6.994***	7.606***	5.849***
	(13.50)	(17.16)	(12.61)
Correction factor	1.167	1.035	1.226
Observations	4,392	8,640	3,753
Number of parcels	1,056	2,735	948

[1]Statistical significance is indicated as: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The following equation illustrates the general form of the hedonic models that were estimated:

$$ln\left(V_{it}^{j}\right) = \beta_{0it}^{j} + \sum_{k=1}^{K_j} \beta_{kit}^{j} X_{kit}^{j} + \mu_i^j + \varepsilon_{it}^{j}$$

where the dependent variable, $ln\left(V_{it}^{j}\right)$, denotes the natural log of the per-acre land value for parcel i in use j at time t. Additional terms denote the use-specific constant term (β_{0it}^{j}); use-specific covariates (X_{kit}^{j}) and their associated parameters (β_{kit}^{j}), where the number of covariates (K_j) varies by land use; a parcel-specific error component (μ_i^j); and a standard idiosyncratic error term (ε_{it}^{j}).

In modeling the land values for forest and agricultural uses, a general method was used to control for unobserved parcel heterogeneity that could influence land values. Specifically, the correlated random effects (CRE) (Mundlak, 1978) estimator was used. This approach entails including the parcel means of the time-varying explanatory factors in the model as additional regressors and provides a means to generate parameter estimates for time-invariant land characteristics, such as soil quality and topography, which are important in estimating the value of undeveloped land.

Initial estimates of agricultural and forest land values included several factors that convey a parcel's potential for development (e.g., population density, household income). For purposes of predicting land use transitions as a function of the relative economic returns to developed, agricultural, and forest uses, the values of forest and agricultural lands should not be confounded by the capitalization of expected future development rents. To accomplish this, the effects of population density and household income were set to zero prior to using the estimated forest and agricultural land value estimates. The UGB distance variable was also set to zero for predictions in the agricultural land value equation for similar reasons.

Additional adjustments were made prior to using the hedonic model estimates for prediction in the WW2100 simulations. Each model in Table A2 contains an inverse Mill's ratio variable (IMR) and, in the case of forest and agriculture equations, its mean. This variable is derived from a set of panel sample selection models, estimated with the approach given in Wooldridge (1996), which describe the attrition that is present in the land value panel. For the purposes of using the models for prediction in the WW2100 simulations, each of the use-specific IMR variables is set to one. Additionally, there is a large discrepancy between the developed land parcels used in the developed land hedonic equation and the size of the WW2100 simulation model IDUs. In order to assure that development decisions are made at the average lot size observed in the underlying hedonic model data, the average observed developed parcel size (0.39 acre) was used to compute developed land returns. Not doing so would substantially reduce the developed land values that drive land-use changes. Last, the estimated hedonic models also contain variables representing the value of improvements on each parcel. Since land improvements (e.g., houses and barns) are not accounted for in the WW2100 simulations, the average improvement value for each land use is set to its average value observed in the underlying hedonic model input data.

The dependent variable in each land value equation is the logged per-acre value of land. To obtain the unlogged predictions, the exponent of each predicted value is computed and multiplied by a correction factor listed at the bottom of Table A2. For example, the developed land value prediction is given by $1.035 \ e^{ln(V_{it}^{D})}$. This adjustment is required to remove any bias stemming from the standard assumption in linear regression models that the disturbances are normally distributed, which does not necessarily apply in our case due to the log-transformation on the hedonic dependent variables (Wooldridge, 2003).

The estimated hedonic model for each land use contains a set of county dummy variables to control for unobserved county-level heterogeneity. In using these models for prediction in the WW2100 simulation, the county dummy coefficients were applied to the four counties that comprised the samples used to estimate the hedonic models and to the other counties in the Basin, based on their proximity to the four original study counties. Predictions with the county dummy variables in non-sample counties were made as follows: the Washington County coefficient was applied to IDUs in Clackamas, Columbia, Multnomah, and Yamhill counties; the Lane County coefficient was applied to IDUs in Douglas County; the Marion County coefficient was applied to IDUs in Linn and Polk counties.

Land-use change model

In the WW2100 model, each IDU is described by a set of attributes, including land cover. The initial land use on each IDU is determined by overlaying a set of spatial data layers, which include data from the U.S. Geological Survey National Land Cover Data, or NLCD (http://landcover.usgs.gov/), and the USDA Cropland Data Layer, or CDC (https://nassgeodata.gmu.edu/). Starting from an initial land cover map for 2006, we model changes in land use as a function of the land values described above. This component of the model (as well as the components related to zoning and UGB expansions) is concerned only with privately owned land and considers land in only three uses: agriculture, forest, and developed. Land in public uses or in uses other than agriculture, forest, or developed is assumed to remain in the same use.

With three uses, there are a total of nine possible transitions (counting transitions in which land does not change use; e.g., forest-to-forest). This number is reduced to six because land that is in developed use can be assumed to remain in that use indefinitely. Thus, we are concerned with the six transitions shown in Table A3.

Table A3. Potential land conversions.

		Ending uses		
		Agriculture	Forest	Developed
Starting uses	Agriculture	P_{aa}	P_{af}	P_{ad}
	Forest	P_{fa}	P_{ff}	P_{fd}

In particular, we model the probability that each transition takes place, where P_{jk} in the above matrix indicates the probability that land moves from use j to use k (e.g., P_{af} is the probability that land moves from j = agriculture to k = forest). Because land must end up in one of the three categories, it follows that $P_{aa} + P_{af} + P_{ad} = 1$ and that $P_{ff} + P_{fa} + P_{fd} = 1$.

For those IDUs that begin 2006 in agriculture or forest and are categorized as privately owned, we define the six probabilities indicated above as logistic functions of economic returns to agriculture, forest, and development. Formulas given below are used to compute transition probabilities for a 5-year time period for each IDU. Calculation of these transition probabilities requires three steps. First, we use the equations described above, together with data on IDU characteristics, to calculate dev_val, ag_val, and for_val for each IDU. Note that some of the IDU attributes are fixed over time (e.g., slope), but others, such as population and income of the nearest city, change according to the procedure described under "Population and income projections," page 68. Second, the computed economic returns (dev_val, ag_val, and for_val) are scaled using formulas given in Table A4.

The scaling was necessary because the parameters in the transition probability formulas were obtained from another study (Lewis et al., 2011), which used different measures of economic returns from those used here.[1]

Thus, if an IDU begins in forest, the economic return to agriculture on that IDU is found by first computing ag_val, multiplying ag_val by 0.01, and then (if necessary) constraining the result to lie between 0 and 2,000. We refer to the scaled/constrained values of the economic returns as AR_a, FR_a, and DR_a when the starting use is agriculture, and AR_f, FR_f, and DR_f when the starting use is forest. Because $DR_f = DR_a$, we simply refer to this value as DR.

Once the values of AR_a, FR_a, and DR or AR_f, FR_f, and DR are determined for each IDU, the third step is to plug them into formulas that determine the 5-year transition probabilities. As mentioned above, the parameters of these functions were obtained from Lewis, et al. (2011). Specifically, for IDUs starting in agriculture, the 5-year transition probabilities are given by:

$$P_{aa} = \frac{e^{0.00489AR_a}}{e^{0.00489AR_a} + e^{-7.799 + 0.00242FR_a} + e^{-4.788 + 0.00013DR}}$$

$$P_{af} = \frac{e^{-7.799 + 0.00242FR_a}}{e^{0.00489AR_a} + e^{-7.799 + 0.00242FR_a} + e^{-4.788 + 0.00013DR}}$$

$$P_{ad} = 1 - P_{aa} - P_{af}$$

For parcels starting in forest, the 5-year transition probabilities are given by:

$$P_{ff} = \frac{e^{0.00489FR_f}}{e^{0.00489FR_f} + e^{-7.799 + 0.00242AR_f} + e^{-4.788 + 0.00013DR}}$$

$$P_{fa} = \frac{e^{-7.799 + 0.00242AR_f}}{e^{0.00489FR_f} + e^{-7.799 + 0.00242AR_f} + e^{-4.788 + 0.00013DR}}$$

$$P_{fd} = 1 - P_{ff} - P_{fa}$$

Table A4. Formulas for computing economic returns to various land uses.

		Economic return to:		
		Agriculture	Forest	Development
Starting use	Agriculture	Min(Max(0,ag_val • 0.05),200)	Min(Max(0,for_val • 1.6),2000)	Min(Max(0,dev_val),7500)
	Forest	Min(Max(0,ag_val • 0.01),2000)	Min(Max(0,for_val • 0.7),200)	Min(Max(0,dev_val),7500)

[1] Lewis, et al. (2011) estimated a model of land-use transitions for western Oregon and Washington using land-use data from the National Resources Inventory and measures of economic returns from Lubowski, et al. (2006).

With the WW2100 model, we wish to represent land-use change on an annual basis. To this end, the 5-year probabilities are converted to equivalent annual probabilities using the following formula: if P_{jk} is the 5-year transition probability, then the corresponding annual transition probability (AP_{jk}) is given by

$$AP_{jk} = 1 - (1 - P_{jk})^{0.2}$$

When the model is run, the annual probabilities are used for a 5-year period and then updated.

Given sets of values of AP_{jk} for each IDU, the final step is to determine whether or not land-use changes occur on an IDU. For this, we will use a random number generator. Suppose that a given IDU is currently in agriculture and has an 80% probability of remaining in agriculture (i.e., $AP_{aa} = \mathbf{0.80}$), a 10% probability of switching to forest ($AP_{af} = \mathbf{0.10}$), and a 10% probability of switching to developed use ($AP_{ad} = \mathbf{0.10}$). We draw a random variable r from a uniform distribution defined on the unit interval. The IDU remains in agriculture if $0.8 > r \geq 0$, changes to forest if $0.9 > r \geq 0.8$, and changes to developed use if $1.0 \geq r \geq 0.9$. This procedure is repeated for each IDU using a newly drawn random variable. As the end of this process, a new land-use map is produced.

Zoning and UGB expansion

To account for zoning rules under Oregon's land-use planning system, we treat land inside and outside of UGBs differently. Land outside of UGBs can move between undeveloped uses (i.e., agriculture-to-forest and forest-to-agriculture transitions are allowed), but transitions to developed use are not allowed. To account for this restriction on development, the transition probabilities need to be adjusted. For IDUs outside of UGBs, the probability associated with the transition to developed use is added to the probability associated with the land remaining in the same use. Thus, if the initial use is agriculture, $P_{aa}(new) = P_{aa}(old) + P_{ad}$. If the initial use is forest, $P_{ff}(new) = P_{ff}(old) + P_{fd}$. These restrictions on development are also applied to areas zoned as rural residential (which are outside of UGBs), since only a small portion of the lot is allowed to be developed.

For IDUs inside of UGBs, all of the transitions are allowed, except for transitions out of developed land. Given the irreversibility of development, it follows that, over time, the share of developed land within each UGB will increase. To mimic the land-use planning process, we allow for UGBs to expand once the developed share becomes sufficiently large. The developed share is defined as the ratio of the area of private land within a UGB that is developed to the area of private land within a UGB that is developable. Developable land includes all private land that is in developed, agriculture, other vegetation, and forest categories. It excludes land in the barren, wetlands, and water/snow/ice categories. As long as the developed percentage of the UGB is below a specified threshold (in the reference scenario, the threshold is 80%),[2] the existing UGB remains as it is. However, once the threshold is exceeded, a UGB expansion is triggered. We assume that the need for a UGB expansion is evaluated every 5 years, coinciding with the updating of the 5-year transition probabilities.

A UGB expansion involves adding new IDUs to the existing UGB area until the specified threshold is no longer exceeded. Which IDUs to add is determined by the following criteria:

1. Select only IDUs that are adjacent to the existing (or expanded) UGB area.
2. Select only IDUs that are privately owned and developable (i.e., in developed, agriculture, other vegetation, or forest categories).
3. Do not select IDUs that are already inside another UGB.
4. Select IDUs in order of least equally weighted distance from: (a) the centroid of the IDU to the center of the UGB area, and (b) the centroid of the IDU to the nearest major road.
5. Do not select IDUs that are zoned for exclusive farm use (EFU) or forest conservation (FC), unless there are no other IDUs that satisfy criteria 1–3 and the developed percentage is still higher than the prescribed threshold. Once the non-EFU and non-FC IDUs that satisfy criteria 1–3 are exhausted, continue selecting IDUs that are zoned as EFU or FC using criteria 4 until the developed

[2] In the reference scenario, the developed threshold for Eugene-Springfield is 70%. This change was made in recognition of the ongoing UGB expansion process during our model's development (2010–2015).

land percentage is again below the prescribed threshold.

These criteria do not apply to expansions in the Portland Metro UGB. In this case, the regional planning authority (Metro) has designated areas called urban reserves that indicate where future expansions will take place until 2060. For expansions in the Portland Metro UGB prior to the year 2060, the criteria are as follows:

1. Select only IDUs that are adjacent to the existing (or expanded) UGB area.
2. Select only areas within designated urban reserves.
3. Select IDUs in order of least equally weighted distance from: (a) the centroid of the IDU to the center of the UGB area, and (b) the centroid of the IDU to the nearest major road.

After 2060, the Portland Metro UGB is treated like all other UGBs in the WW2100 study area, and expansions take place in accordance with criteria 1–5 listed above.

Population and income projections

The developed land value equation includes variables for the population density and household income of the nearest city. As the WW2100 model progresses through time, we allow population and income to increase. Future population and income are assumed to be exogenous and, as such, are external drivers in the same way as climate. County-level population projections to 2050 and real (2005 dollars) mean household total personal income projections to 2040 are taken from the Oregon Office of Economic Analysis and Woods and Poole, respectively. Linear extrapolation is used to obtain projections to 2100. Actual, forecasted, and extrapolated population and income by county for the period 1970–2100 are reported in Tables A5 and A6 (page 69), respectively. For the 10 WRB counties, population increases at an average annual rate of 2.1% over the 1970–2100 period. The rate of increase is 1.2% over the period 2010–2050 and 0.8% over the period 2050–2100. For the 10 counties, mean household total personal income increased at an annual rate of 1.9% over the period 1970–2010 and is projected to increase at a rate of 1.7% over the period 2010–2040 and 1.4% over the period 2040–2100.

As the WW2100 model runs, population is allocated on a 5-year basis to UGBs and areas zoned for rural residential (RR) use. No population is allocated to areas outside UGBs and RR areas. For a given increase in a county's population, we use the following procedure to determine the allocation of population to the UGB and RR areas within the county. We begin with the Census block data for 2010 from the U.S. Bureau of the Census. These data provide a population count for each block, allowing us to mine the initial spatial distribution of population within each county. The block-level estimates are aggregated into a single population count for each UGB and RR area within each county.[3] Weights are then determined for each UGB and RR area within a county according to their respective share of the 2010 population, disregarding the residual population outside of UGB and RR areas. As the model runs, the increase in a county's population is allocated to the UGB and RR areas according to these weights.

In allocating population to RR areas, we impose a maximum density of one household for every 2 acres of land to remain consistent with the existing rules governing rural land development. When an RR area as a whole meets this prescribed density threshold, it is shut off from future population growth and its population weight is reallocated proportionally to UGBs and other RR areas that are still eligible to receive population. We allow household size to vary through time using county-level forecasts in the Woods and Poole data for 2010–2040 and linear extrapolation to 2100.

[3] Note that a UGB may span several counties. For example, the Salem-Keizer UGB includes land in both Marion and Polk counties. In such cases, we treat a county's portion of a UGB as a separate area for the purpose of allocating population.

Table A5. Population by county, 1970–2010, with projections to 2100.

County	1970	1980	1990	2000	2010	2020	2030	2040	2050	2060	2070	2080	2090	2100
Benton	54,002	68,493	71,059	78,334	85,735	91,379	98,516	105,050	111,666	117,965	124,654	131,324	138,046	144,747
Clackamas	167,440	242,981	280,862	339,299	376,780	422,576	485,054	537,753	583,814	632,743	683,634	733,473	784,317	835,025
Columbia	28,894	35,744	37,809	43,698	49,430	54,517	61,273	66,683	71,406	76,602	81,893	87,075	92,382	97,665
Lane	216,476	275,828	284,261	323,663	352,010	378,335	410,247	437,345	464,839	484,993	510,123	535,347	561,186	586,691
Linn	72,635	89,716	91,690	103,394	116,840	128,454	143,673	156,505	168,189	182,975	196,074	208,984	222,121	235,208
Marion	152,298	205,599	229,938	285,572	315,900	355,189	406,612	453,557	498,624	546,985	594,121	640,937	688,158	735,286
Multnomah	554,765	563,632	586,617	662,290	736,785	807,198	879,987	936,729	982,504	1,043,468	1,099,046	1,153,091	1,208,765	1,264,178
Polk	35,651	45,362	49,924	62,679	75,495	88,081	105,274	121,044	135,877	151,482	167,094	182,557	198,156	213,739
Washington	159,382	247,848	315,469	447,298	531,070	622,368	731,125	830,100	915,979	1,029,672	1,129,306	1,227,089	1,326,142	1,425,214
Yamhill	40,610	55,660	65,999	85,325	99,405	113,611	133,907	151,564	167,300	185,049	202,225	219,098	236,251	253,371

Table A6. Mean household total personal income by county, 1970–2010, with projections to 2100 (constant 2005 dollars).

County	1970	1980	1990	2000	2010	2020	2030	2040	2050	2060	2070	2080	2090	2100
Benton	40,018	49,921	58,694	80,515	81,135	90,837	111,158	138,697	159,685	183,327	207,001	230,198	253,719	277,111
Clackamas	55,204	69,002	76,640	108,420	106,818	115,168	135,842	164,259	185,514	209,709	233,902	257,593	281,633	305,531
Columbia	46,503	56,170	60,470	79,186	80,447	87,493	100,768	118,270	131,802	146,987	162,141	177,027	192,106	207,105
Lane	45,340	51,818	56,841	70,178	73,652	78,525	92,866	112,348	126,928	143,555	160,150	176,421	192,924	209,330
Linn	43,158	48,911	54,758	66,222	70,689	76,486	89,999	107,938	121,658	137,143	152,595	167,768	183,141	198,431
Marion	45,848	54,543	61,104	75,736	83,378	89,362	105,957	128,319	145,205	164,373	183,508	202,279	221,311	240,233
Multnomah	52,205	57,608	67,783	87,620	86,976	94,535	112,009	134,985	152,595	172,482	192,297	211,771	231,498	251,115
Polk	43,040	50,893	56,491	73,201	75,922	78,801	90,878	107,493	119,668	133,724	147,728	161,453	175,383	189,224
Washington	58,883	68,995	75,212	98,631	96,366	96,077	109,461	130,367	144,147	160,894	177,606	193,837	210,410	226,841
Yamhill	45,758	56,573	61,994	76,535	83,544	89,774	105,060	125,919	141,576	159,383	177,173	194,605	212,289	229,870

Section 2. Urban Water Use Models

The urban water demand component developed for WW2100 consists of models of residential and nonresidential urban water demand for the Portland metropolitan area, Salem-Keizer, Corvallis, and Eugene-Springfield, as well as a separate model for smaller urban areas. These models were developed to predict water consumption for urban areas in the WRB. The variables included in these models were selected on the basis of a review of the economics literature on urban water demand. An additional consideration was the need to use variables that could be forecasted over the entire study period, either as exogenous drivers (such as income and population growth) or as variables generated by other models within the Envision framework (such as population density).

Data and methods

The economics literature that focuses on estimation of water demand suggests that a water demand function must include marginal price of water, pricing structure, and income, and must control for seasons and weather (Olmstead et al., 2007; Olmstead, 2009; Olmstead, 2010; Bell and Griffin, 2011; Mansur and Olmstead, 2012). Given the specific forecasting needs of the urban water component for WW2100, we also included population and population density in the model.

Despite anecdotal evidence of the effect of non-price water demand management policies (e.g., installing low-flow appliances), there is very little empirical evidence in the economics literature of the impact of such measures on water demand. A literature review yielded only one peer-reviewed paper that systematically measured the effect of non-price management policies on water demand; this paper was based on data from 1989–1996 (Renwick and Green, 2000). Furthermore, the water demand literature emphasizes the fact that, while the demand reductions attainable from non-price management options are clear from a technical perspective, once consumer behavior is taken into account the net effects are not well understood. For example, there is anecdotal evidence of "double-flushing" low-flow toilets, of consumers altering low-flow devices to function like traditional fixtures (see Timmins, 2003, and references cited therein), and of households increasing the frequency of clothes washing when using more efficient front-loading clothes washers (a "rebound effect" from increased efficiency) (see Olmstead, 2010, and sources cited therein).

The magnitude of these effects, and hence the net impact of conservation policies to promote adoption of more efficient appliances, has not been sufficiently studied in the economics literature and hence is not as well understood and quantified as the effect of price and income. Because of this lack of reliably measured impacts, and given the difficulty of projecting conservation attitudes or development of new technologies over the study period (up to the year 2100), we opted to omit the non-price management effect from the water demand model. To the extent that this component would be expected to have a negative impact on demand (assuming rebound effects are smaller than direct impacts), we are being conservative by slightly over-predicting residential demand for water.

The model of residential demand therefore predicts total daily water used by residential customers in hundreds of cubic feet (ccf) as a function of price ($/ccf), pricing structure (increasing block rate (IBR) or flat rate),[4] city population, median household income, and population density (persons/square mile). The model of nonresidential water demand predicts total daily water used by nonresidential customers (in ccf) as a function of price, total city industrial (manufacturing) income, total city commercial income, and population.

The values of the response parameters for these variables were obtained from the economics literature:

- Price: Long-term price elasticity of demand = -0.6 (Olmstead, 2010)
- Income: Income elasticity = 0.13 for flat rate pricing, 0.18 for increasing block rate pricing (Olmstead et al., 2007)

[4] An increasing block rate pricing structure charges different prices for incremental volumes consumed each month. One price is set for a given base volume, and a higher rate applies for quantities above that volume. In some cases, another threshold triggers a third "block rate."

- Population: 1.0 (Portland Water Bureau Water Management and Conservation Plan, 2010)
- Population density: -0.048 (Gaudin, 2006)
- Industrial (manufacturing) income: 0.11 (Bell and Griffin, 2011)
- Commercial income: 0.04 (Bell and Griffin, 2011)

We collected the most current information available (at the time the project was started) on each of these variables for Portland, Salem-Keizer, Corvallis, Eugene, and Springfield. Information on water rates, price structure, and water use was obtained from Water Management and Conservation Plans for Portland (2010), Salem-Keizer (2009), Corvallis (2005), and Eugene (2012), and through personal communication for Springfield (2012). Information on personal, manufacturing, and commercial income comes from the Bureau of Economic Analysis. Population and population density information is from the U.S. Census.

We used the coefficients specified above and the averages of water quantity, price, income, population, and density for the five cities to calibrate a log-linear model and calculate the intercept term corresponding to the baseline averages. Because the intercept varies with the pricing structure, we calculated two intercepts, using the corresponding averages for cities with flat rate and IBR. Then we calculated the necessary coefficient for the IBR indicator variable to give the correct intercept when IBR is set to 0 or 1. Finally, the demand models are adjusted to reflect seasonal variations in demand. Thus, note that the model is not intended to predict water use for any particular city in the WRB. Rather, its purpose is to generate predictions for the Basin's urban areas in general on the basis of a limited number of variables that are forecasted to the year 2100 as part of the WW2100 project.

The specific models for the four main cities (Portland Metro, Salem-Keizer, Corvallis, Eugene-Springfield) are as follows:

Residential demand *(ccf/day):*

$$\ln(Q^R_{Avg}) = -(3.0159618 + 0.47698 \bullet IBR) - (0.6 \bullet \ln(p)) + \ln(Pop) + (0.13 + 0.05 \bullet IBR) \bullet (\ln(I)) - (0.048 \bullet \ln(D))$$

$$Q^R_t = \exp(\ln(Q^R_{Avg}))$$

Nonresidential demand *(ccf/day):*

$$\ln(Q^{NR}_{Avg}) = -2.727616 - (0.6 \bullet \ln(p)) + (0.11 \bullet \ln(Ind.\ I)) + (0.04 \bullet \ln(Comm.\ I)) + (0.85 \bullet \ln(Pop))$$

$$Q^R_t = \exp(\ln(Q^{NR}_{Avg}))$$

where

Q^R and Q^{NR} = sum of the total daily water use for the entire city in hundreds of cubic feet (ccf)

p = price (\$/ccf)

Pop = city population

D = population density (persons/square mile)

I = median household income

IBR = 1 if city has an increasing block rate pricing structure; = 0 otherwise

$Ind.\ I$ = total city industrial (manufacturing) income (\$1,000s)

$Comm.\ I$ = total city commercial income (\$1,000s)

We adjust residential demand for seasonality by decomposing daily water use into outdoor and indoor use components, based on 24 years of daily data from the Portland Water Bureau. Total predicted yearly water demand is divided by 365 to obtain daily use, and then multiplied by indoor and outdoor fractions to reflect seasonality.

Baseline prices for the four main cities are as follows:

Residential:

Portland (all of metro area): $2.44/ccf
Salem-Keizer: $2.04/ccf
Corvallis: $1.93/ccf
Eugene-Springfield: $2.00/ccf

Nonresidential:

Portland (all of metro area): $2.44/ccf
Salem-Keizer: $1.50/ccf
Corvallis: $2.11/ccf
Eugene-Springfield: $2.00/ccf

IBR = 1 for Corvallis, Eugene-Springfield; IBR = 0 for Portland, Salem. Use IBR = 0 for other urban areas.

Baseline (initial) manufacturing income ($1,000s):

Portland: 9,851,720
Salem-Keizer: 651,857
Corvallis: 461,476
Eugene-Springfield: 723,165

Baseline (initial) commercial income ($1,000s):

Portland: 58,292,148
Salem-Keizer: 7,350,692
Corvallis: 1,598,343
Eugene-Springfield: 6,565,399

Price adjustments

Urban water utilities set prices to achieve multiple goals. These include generating revenues so that the water utility can cover its costs. Providing a sufficient and stable source of revenues is important, but rate structures should not be overly complex. Water providers want to achieve a fair allocation of costs, and they may have a goal of allocating costs among different types of uses and users. They wish to fully allocate private and social costs, and at the same time provide incentives for conservation to customers, and do so in a way that is efficient and transparent to customers. Because urban water delivery systems are highly capital intensive, with a need to make large capital investments for infrastructure building, maintenance, or replacement on an intermittent basis (sometimes decades apart), in a typical year these capital costs are not in ratepayers' minds, so it is frequently difficult to set prices in such a way that long-term average or marginal costs are covered, as opposed to short-run (current-year) average costs. This situation is endemic to urban water supply systems and is well established and widely recognized in economics research.

As a result of these characteristics of urban water systems, water prices tend to be somewhat lower than long-run average or marginal costs, leading to financial deficits and delays in infrastructure investments, repairs, and replacements. It is common that when the severity of financial needs leads water providers to raise prices, the result may be a worsening financial situation, as price increases discourage consumption and thus reduce the anticipated increase in revenues.

These phenomena are well documented in historical data, surveys, and engineering analyses. U.S. Environmental Protection Agency (EPA) survey data, for example, indicate that average water prices are frequently more than 20% below long-run average cost (EPA, 2009). In a separate survey, the EPA has documented the resulting backlog of infrastructure needs for drinking water systems nationwide (EPA, 2013). The nationwide total "20-year need" reported to EPA in 2011 was $376 billion, which amounts to more than $1,200 per capita.

The gap between average price and average cost has fluctuated over time and across cities and states for a variety of reasons. Nationwide, we have observed rising (inflation-adjusted) urban water prices since about the mid-1980s. Prior to that time, there was an extended period of declining urban water prices. The backlog of infrastructure needs, as estimated from EPA surveys, has also fluctuated, but has been rising nationwide, from $843/person in 1995 to $1,205/person in 2011. The backlog of infrastructure needs in Oregon has generally been higher than the national average, rising from $1,108/person in 1995 to $1,442/person in 2011. The exception was in 2007, when Oregon's per-capita need was only $845, compared to the national average of $1,220. The reduced backlog of infrastructure needs in Oregon between 2003 and 2007 came following a 53% increase in average prices in Portland between 1999 and 2007, which likely contributed to financing significant infrastructure improvements.

For our modeling purposes, we want to project future price trends that recognize the relatively large backlog of infrastructure needs in Oregon in the most recent EPA survey, as compared to national levels and historic levels in Oregon. Since most urban populations in Oregon live in the WRB, we use Oregon-wide data as a reasonable indicator of the situation in our study area. In order to finance infrastructure needs over the next 20 years, additional increases in water prices will be needed. To reduce the level of these system needs over the next 20 years from the 2011 Oregon estimate ($1,442/person) to the national average observed since 1995 ($1,050/person) would require additional revenues of $40/person/year—more than a 25% increase in average per-capita water payments. To recognize the unusually high level of infrastructure needs currently estimated for Oregon, our model includes an increase in average water prices of 1.5% per year for the first 15 years of the modeled scenario, resulting in a cumulative rise in price of 25%. After that point, prices are held constant in real terms for a given population served.

Further changes in price beyond 2025 occur as a function of average current cost, which is a function of population served. These relationships were estimated based on national data (EPA, 2009). The average cost is estimated as

$$AC_t = 0.748 \bullet \exp\left\{9.93 - 0.355 \bullet \ln(Pop(t)) + 0.030 \bullet (\ln(Pop(t)))^2 - 0.001 \bullet (\ln Pop(t))^3\right\}$$

We assume that prices will increase at the same rate as average cost:

$$\frac{P_t - P_{t=0}}{P_{t=0}} = \frac{AC_t - AC_{t=0}}{AC_{t=0}},$$ which implies that

$$P_t = \frac{AC_t}{AC_{t=0}} \bullet P_{t=0}$$

For other cities, demand is also a function of population, income, and price ($/ccf). Other cities do not have separate nonresidential demand functions, nor do they use IBR pricing.

Prices are based on the water delivery average cost. Demand is based on assuming price equals *AC* from the relationship above, so that

$$\text{Ln } Q_t = -2.16432007 - (0.6 \bullet \ln(p_t)) + \ln(Pop_t) + (0.13 \bullet \ln(I_t)) - (0.048 \bullet \ln(D_t))$$

and $p_t = AC_t$. Demand is adjusted for seasonality as described above.

Rural residential demand is

$$\ln(Q_{RR}) = -3.55 - (0.6 \bullet \ln(PC)) + \ln(Pop) + (0.13 \bullet \ln(I)) - (0.048 \bullet \ln(D))$$

where PC = "price" for water ($/ccf) (cost of pumping, $0.30/ccf)

Pop = the population of the rural residential IDU

I = income per household ($/household), average for relevant county

D = population density (people per square mile) (assumed to be 768 per square mile in rural areas, or 2 acres per household)

Demand (Q_{RR}) is in ccf/day

The model that determines price and demand also tracks the evolution of estimated long-run average cost (LRAC) ($/ccf) as a function of changing population (but holding other variables constant). Long-run average cost, including capital costs, is estimated with national data (EPA, 2009) as follows:

$$LRAC = (0.748/1{,}000) \bullet \exp\left\{13.39 - 1.246 \bullet (\ln Pop) + 0.117 \bullet (\ln Pop)^2 - 0.004 \bullet (\ln Pop)^3\right\}$$

Validation

Table A7 (page 74) shows the predicted residential and total per-capita water consumption calculated from output generated by the WW2100 model (April, 2015) for the first forecast year (2010) for the four major urban areas. For reference, Table A7 also shows values reported by the corresponding city utilities.

Table A7. Estimated and reported water use for major municipalities in the Willamette Basin.

Urban area	Envision-predicted water use, 2011 (gal/person/day)[1]	Reported water use (gal/person/day) and year of reporting
Portland Metro	108	111 (2011)[2]
Corvallis	124	129 (2009)[3]
Salem-Keizer	122	124 (2007)[4]
Eugene-Springfield	118	Eugene: 144 (2009)[5] Springfield: 129 (2010)[6]
Average	112	124

[1]Generated April 23, 2015
[2]Source: Portland Water Bureau Conservation Rate Structure Review (June, 2013)
[3]Source: Corvallis Water Management and Conservation Plan (November, 2012)
[4]Note: Salem only. Source: Salem Water Management and Conservation Plan Final Report (March, 2009)
[5]Source: Eugene Water Management and Conservation Plan (January, 2012)
[6]Source: Calculated from data provided by Springfield Utility Board

Table A8. Portland water use—actual and predicted.

Year	Prediction (gal/person/day)	PWB Data (gal/person/day)[1]
1995	126.88	150.40
1996	127.00	143.70
1997	128.30	142.90
1998	129.74	143.50
1999	128.59	139.60
2000	107.37	141.70
2001	107.66	134.00
2002	109.23	134.30
2003	105.58	135.10
2004	102.04	132.60
2005	102.72	124.00
2006	102.83	128.60
2007	106.20	129.80
2008	106.45	124.99
2009	100.23	122.59
2010	91.85	118.99
2011	87.04	110.57

[1]The Portland Water Bureau (PWB) Water Management and Conservation Plan has demand per capita up to 2006. The PWB Conservation Rate Structure Review has demand per capita for 2006–2011, but the 2006 numbers do not coincide. We apply the growth rates from the Conservation Rate Structure Review to the data from the Management and Conservation Plan.

Table A7 suggests that the model predicts per-capita water use for 2011 reasonably well, both on average and for individual urban areas. The model estimate for per-capita consumption for 2011 is somewhat lower than observed levels. This reflects in part the rising prices and declining trend in per-capita consumption observed during this period.

As an additional validation exercise, we used the urban water demand model and data on water prices and water consumption for Portland from 1995 to 2011 (from Portland Water Bureau) to generate a "precast" of water consumption in Portland during that period. The objective is to compare water consumption predicted by the model with observed data. As shown in Figure A1 (page 75), prices increased (in real terms) during this period. The average yearly increase was 5.3%.

Table A8 and Figure A2 (page 76) show the water use predicted for Portland by the model, along with observed consumption amounts.

Per-capita water use decreased by 39.83 gallons per day (26%) between 1994 and 2012. For that period, our model predicts a total decrease of 39.84 gallons per day (31%).

Hence, this "precasting" exercise suggests the urban water model is capable of replicating the trend in per-capita water consumption in response to changes in water price fairly well.[5]

[5] Note that the model is not intended to predict water consumption in Portland specifically, as it is calibrated using data for the five major urban areas in the Basin.

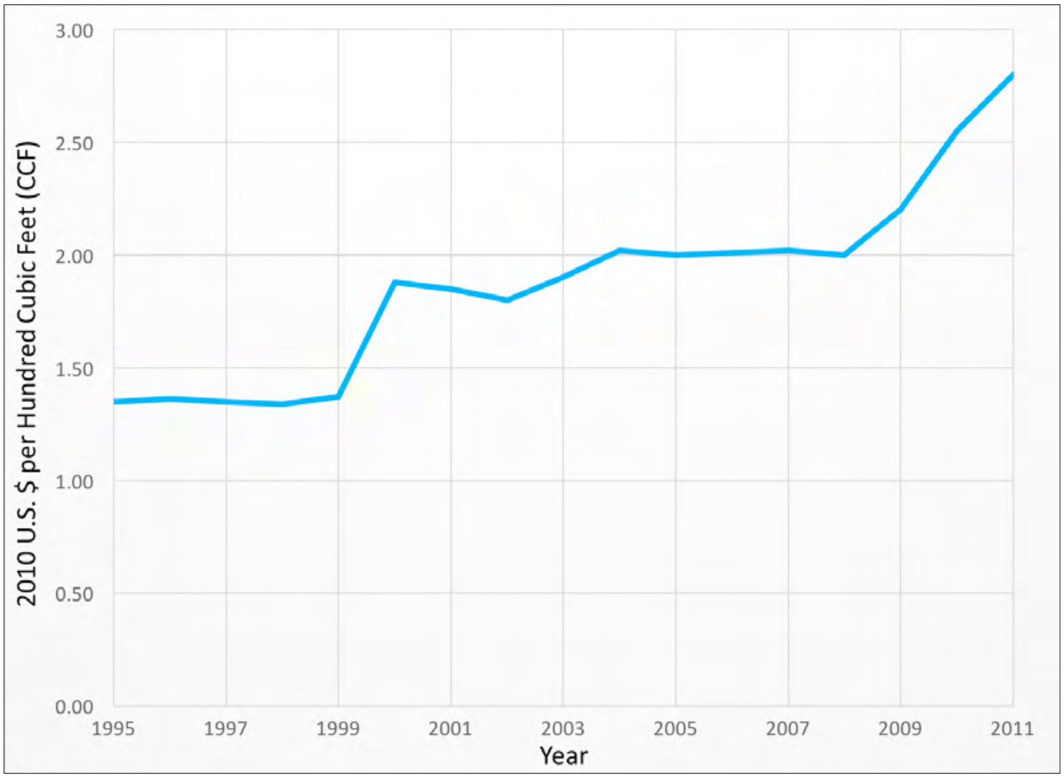

Figure A1. Portland water prices, 1995–2012.

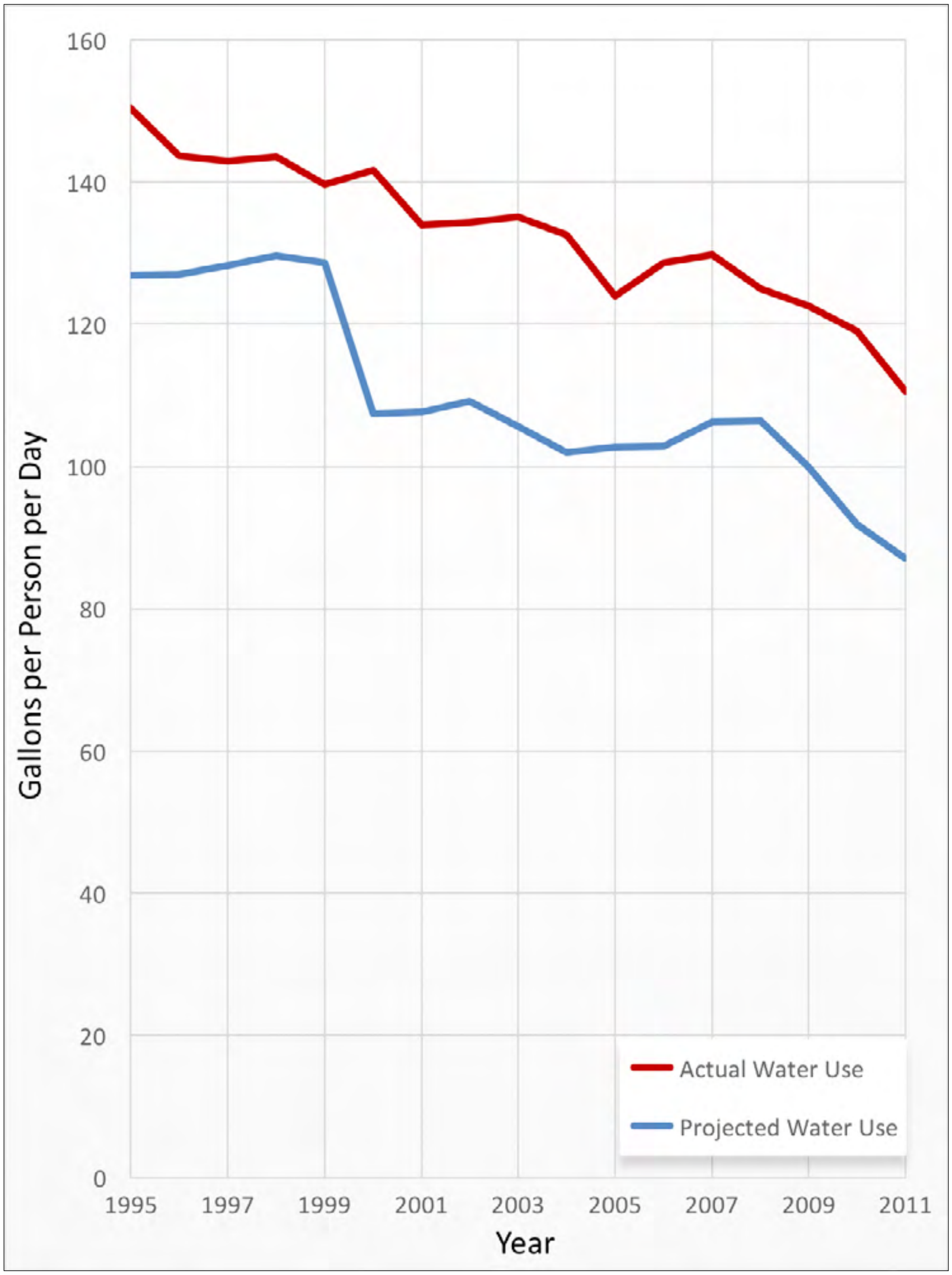

Figure A2. Portland water use, actual and projected, 1990–2015.

*Water use for 2006 through 2011 is estimated based on per-capita water-use figures in the Portland Water Board Conservation Structure Review (2013).

Section 3. Agricultural Crop Choice and Irrigation

In each year that an IDU is assigned to agricultural land use, farmer decisions are modeled to simulate crop choices and irrigation decisions. Irrigation is possible only on IDUs with existing irrigation water rights. These initial decisions are then followed by daily decisions related to planting and harvesting, and (possibly) applying irrigation water. The availability of irrigation water is also subject to regulatory shutoffs in accordance with the prior appropriations seniority system under state law (described under Section 6). These combinations of decisions, choices, actions, and responses to exogenous factors produce a unique pattern of crop water use, irrigation diversions, soil moisture and groundwater contributions, and net farm income (annual land rent) at the IDU level. To the extent that irrigation water is shut off by regulators, short-run annual land rent is reduced, as is long-run (expected) land rent.

Crop water use in agriculture is estimated on a daily basis reflecting the crop or vegetative cover of each IDU and ET as a function of meteorological factors, crop type, and growth stage. The model also estimates crop planting and harvest dates.

Crop choice

The crop choice model estimates the probability of growing each of seven crop types or groups for the modeled year. The empirical model is estimated at the parcel level based on observed cropping patterns in recent years. The model estimates the crop observed as a function of IDU characteristics, including soil quality (land capability class), elevation, and the presence of an irrigation water right, as well as variable attributes, including crop prices and expected water availability (for those IDUs with irrigation water rights). Given the estimated probabilities for each IDU, the simulation models determine the crop for each IDU in each year with a random draw reflecting these estimated probabilities. No evidence of crop choices being correlated across years (i.e., a crop rotation schedule) was found in the data or in interviews with farmers or agricultural Extension personnel.

The crop choice model is estimated as a hedonic relationship based on parcel-level GIS data for 100,555 parcels over a 6-year period. Crops were identified using USDA CropScape agricultural land cover data. Parcel data included land characteristics (land capability class (LCC), elevation, slope, field size, and water rights), climatic characteristics (average precipitation and minimum growing season temperature), and crop prices.

The model was estimated using ordinary least-squares as follows:

$$P_j = \beta_0 + \sum_{i=1}^{14} \beta_i$$

for crops j = 1 to 8, where 8 is "other crops,"

where P_j is the probability of planting crop j in a given year, and independent variables 1–14 are as follows (see Kalinin, 2013):

LCC_1 to LCC_7	= the dominant soil type (land capability class) in the IDU
EL	= elevation (in meters, demeaned, where $\overline{EL}$ = 97.2)
SL	= slope (percent, demeaned, where $\overline{SL}$ = 3.704)
PR	= precipitation, April–October (inches, demeaned, where $\overline{PR}$ = 13.63)
MT	= minimum temperature, April–October (degrees C, demeaned, where $\overline{MT}$ = 8.556)
PG	= price of grass seed (average over period = $64/ton)
PW	= price of wheat (average over period = $5/bushel)
IR	= existence of irrigation water right (1 if a water right exists; otherwise 0)

The estimated coefficients are indicated in Table A9 (page 78).

Table A9. Crop choice model estimation.[1]

	Grass seed	Pasture	Wheat	Fallow	Corn	Clover	Hay
β_0	0.2220***	0.3702***	0.0126	0.066***	-0.0041	0.0154***	0.0616***
β_1	0.1656***	-0.1870***	0.0655***	-0.0340***	0.0076	-0.0031	-0.0613***
β_2	0.1545***	-0.1793***	0.0535***	-0.0309***	0.0147	0.0079	-0.0576***
β_3	0.1453***	-0.1237***	0.0294*	-0.0315***	0.0183	0.0024	-0.0411***
β_4	0.2361***	-0.0546	0.0135	-0.0349***	0.0045	-0.0036	-0.0528***
β_5	-0.2460***	-0.2004***	-0.0054	-0.0191	0.1213***	-0.0044	-0.0369*
β_6	0.1030**	-0.0503	0.0111	-0.0127	0.0123	-0.0103	-0.0472***
β_7	-0.2976***	-0.1071	0.0511	0.0419	0.0541**	-0.0110	-0.0329*
β_8	-0.0006***	0.0007***	-0.0001**	0.0005***	-0.0002***	0.000002***	-0.0001***
β_9	-0.0169***	0.0071***	-0.0002	0.0033***	-0.0010***	-0.0002	0.0007***
β_{10}	-0.0133***	0.0218***	-0.0067***	0.0054***	0.0027***	-0.0035***	-0.0001
β_{11}	-0.0500***	-0.0358***	0.0042**	-0.0084***	-0.0059	0.0088***	-0.0001***
β_{12}	0.0092***	-0.0160***	-0.0026***	0.0080***	0.0003***	-0.0002***	0.0004***
β_{13}	-0.0147***	0.0745***	0.0020**	-0.0125***	-0.0041***	-0.0024***	-0.0170***
β_{14}	-0.0591***	-0.0262***	-0.0047***	0.0010	0.0185***	-0.0078***	-0.0016**

[1]Statistical significance is indicated as: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The resulting modeled values are interpreted as the probabilities for each crop to be grown. The model is implemented as a "random draw" to determine which crop is grown each year at a given IDU location. The effect of the existence of an irrigation water right on crop choice will be moderated to the extent that a water right shutoff is anticipated in a given year. To represent this circumstance, the implemented crop choice model included an additional term, ***IR•SE***, the interaction of ***IR*** as defined above with ***SE*** (Expected Snow), where (a) ***SE* = 1** if the model estimate of April 1 snowpack[6] is greater than or equal to the average April 1 snowpack in the previous 10 years, or (b) ***SE* = (1 – *SH*)** if the April 1 snowpack measure is less than the average snowpack in the previous 10 years, and where ***SH*** is the frequency in the previous 10 years that the water right experienced a regulatory shutoff (**0** < ***SH*** < **1**, and its initial value is 0 for all IDUs).

For perennial crops (orchards, vineyards, and tree crops), a fixed set of IDUs is permanently assigned. These areas represent a relatively small proportion of farmland in the Basin. These crops are relatively stable in area and location, and changes would be difficult to predict.

Irrigation decisions

Farmers in the WRB typically own and cultivate multiple fields and each year make decisions about which crops to grow on each field, whether to irrigate those fields with irrigation water rights, what equipment to use on which fields, etc. We model these decisions at the parcel (or IDU) level as representative of farm-level decisions. A survey was conducted in the fall of 2012 to collect data from farmers about their irrigation and crop choice decisions for a sample of parcels and over the previous 6 years for those individual fields. The survey had a unique design in that farmers were asked to identify their irrigated fields on a map, so that their responses could be matched to land quality and climate data. Integration of survey responses with spatial data allowed for development of an irrigation decision model that could explain why a large percentage of existing water rights are not used in a given year.

A sample of 530 farmers was surveyed, and data were collected on up to three fields for each farmer over a 6-year period (see Kalinin, 2013, for more details). A discrete choice irrigation decision model was estimated based on these data (see also Kalinin,

[6] Snowpack is estimated in the model on a daily basis at the IDU level, based on the interactions of precipitation, temperature, and other factors. Data on snowpack for calibration purposes come from the Natural Resources Conservation Service's data collection service, SNOWTEL (http://www.wcc.nrcs.usda.gov/). See also Nolin (2012).

2013). The logit model estimated takes a form such that the probability P_{IRR} of irrigating a given field is estimated. Using a panel of 4,409 observations, the following relationship was estimated:

$$ln\left(\frac{P_{IRR}}{(1-P_{IRR})}\right) = \beta_0 + \sum_{I=1}^{17} \beta_i x_i$$

where the variables and their estimated coefficients are as indicated in Table A10.

The spatial data sources include PRISM data for monthly precipitation from April to August (2007–2012), as well as for 30-year monthly averages (1980–2010). The soils gridded data (10 meters) and elevation data came from USDA GeoSpatial Gateway. Groundwater data was provided by Roy Haggerty, Oregon State University. Water rights were from the Oregon Water Resources Department (OWRD). Distances to major cities and to the Willamette River were computed using Oregon GIS clearinghouse data on streams and city boundaries. Soil water-holding capacity comes from the Arc GIS SSURGO layer.

Irrigation efficiency is assumed to be 0.8 for all irrigation in the Basin (meaning that 1.25 acre-feet must be applied to make 1 acre-foot available to plants). This is a midrange assumption for sprinkler irrigation, which is by far the dominant technique used in the Willamette Valley. Efficiency losses are assumed to include conveyance losses.

Crop choice and irrigation decisions are interdependent. Farmers may make crop choices and irrigation decisions simultaneously or, if sequentially, in either order. In the WRB, most major crops are sometimes grown nonirrigated and sometimes irrigated. The correlations in these decisions are reflected in the crop cover data, irrigation survey data, and crop choice probabilities. In addition, farmland rent reflects profits from farming and irrigation decisions. In general, farmers will not plant or irrigate land that is expected to generate no profit or rent. Reflecting this, the following rules were introduced in the simulations:

- If farmland rent < \$1, crop choice is fallow and probability of irrigating = 0.
- If the irrigation decision is "yes," the probability of fallow is zero.
- If the irrigation decision is "yes," the probability of wheat is zero.
- If the irrigation decision is "no," the probability of corn is zero.

As a result of these adjustments for fallow, wheat, and corn, the probability of "other crops" ($j = 8$) is adjusted for consistency so that

$$P_8 = 1 - \sum_{j=1}^{7} P_j$$

Irrigation can increase profits through higher yields and by expanding the range of crops that can be grown. However, it is also costly in time, energy costs, and capital costs. Since farmers are heterogeneous in their production skills and in the attributes of their land, the additional benefits will justify irrigation for some farmers but not for others, and in some years but not in others.

Table A10. Irrigation decision regression model results.[1]

Variables	Coefficient	*P*-value
June precipitation (deviation)	-0.0943*	0.065
July precipitation (deviation)	-0.4134**	0.005
August precipitation (deviation)	-0.1584	0.188
Elevation	-0.0098***	0.000
Elevation * (April–June precipitation)	0.0008***	0.000
EFU (Exclusive Farm Use) zoning	0.4307***	0.000
Field size	-0.0038***	0.000
Groundwater right	0.3311***	0.000
Poorly drained soils (%)	-0.0084***	0.000
Groundwater right * depth	-0.0094***	0.000
Water-holding capacity	-0.2190***	0.000
Willamette River distance	-0.0261***	0.000
Distance to large city	-0.0087**	0.037
Soil LCC1	0.8397***	0.002
Soil LCC2	1.0799***	0.000
Soil LCC3	0.8206***	0.001
Soil LCC4	1.4981***	0.000
β_0	2.42***	0.000

[1]Statistical significance is indicated as: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Farmland rent

The economic rent or annual profit from farming a given piece of land can play an important role in farm decisions to plant a crop, irrigate, or transition out of farming. Our estimation of farmland rent takes a Ricardian approach that is common in models of the economic returns to agriculture (Mendelsohn et al., 1994). Land value is assumed to equal the net present value of future rents from putting the land to its highest value use; as a result, we expect to see variation in land values and annual rents due to characteristics of the land that would influence agricultural productivity, such as soil quality and precipitation or irrigation water rights. Similar to the hedonic model of crop choice, here we decompose the farmland rent associated with factors affecting agricultural productivity (see Kalinin, 2013, for more detail).

The source data on farmland values and rents originate from data collected by county assessors, a process required in Oregon to monitor levels and trends in both real market land values and assessed values. Drawing on land sales, land rentals, surveys, and expert analysis, county assessors produce estimates of average farmland rents within a county by soil type (LCC) and zone for parcels with and without irrigation water rights (Table A11, page 81). In the absence of an adequate sample of data on individual farmland sales, these semiaggregated data reflected sufficient variation across zones and soils that hedonic analysis could be used to infer the contribution of other covariates such as elevation, precipitation, growing season minimum temperature, etc. The first step was to assign a rent to each parcel across zones, soils, and water right assignments, according to the county-estimated real market value for those locations and characteristics. These became the dependent variables for a hedonic model estimation that included two variables that determined the assigned rent level (LCC and existence of irrigation water rights), as well as other characteristics of the parcels (elevation, temperature, precipitation, etc.). By regressing these variables on the farmland rent estimate, we are able to recover, for example, the marginal value of higher summer temperature or lower elevation, independent of soil class.

Table A11. Agricultural land rents (net returns), 2011.

			Land capability class ($/acre/year)							
County	**Zone**	**Irrigation**	**Special**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Benton	Zone 1	Irrigated	—	120	112	109	116	—	—	—
Benton	Zone 1	Nonirrigated	—	84	81	70	70	70	70	—
Benton	Zone 2	Irrigated	—	117	145	—	—	—	—	—
Benton	Zone 2	Nonirrigated	—	—	63	55	55	—	12	—
Clackamas	Valley	Irrigated	452	270	225	160	—	—	—	—
Clackamas	Valley	Nonirrigated	142	155	130	122	—	—	—	—
Clackamas	Hill	Irrigated	—	230	215	—	—	—	—	—
Clackamas	Hill	Nonirrigated	—	190	125	125	—	69	55	16
Lane	Zone 1	Irrigated	—	123	117	99	93	76	—	—
Lane	Zone 1	Nonirrigated	—	—	—	—	—	22	19	8
Lane	Zone 2	Nonirrigated	—	68	55	52	49	12	6	5
Lane	Zone 3	Nonirrigated	—	55	48	40	25	10	6	5
Linn	Zone 1	Irrigated	—	110	100	90	70	—	—	—
Linn	Zone 1	Nonirrigated	—	95	85	80	70	15	10	5
Linn	Zone 2	Irrigated	—	95	90	90	70	—	—	—
Linn	Zone 2	Nonirrigated	—	85	75	75	55	15	10	5
Linn	Zone 3	Irrigated	—	90	85	70	50	—	—	—
Linn	Zone 3	Nonirrigated	—	80	70	60	40	10	10	5
Marion	North bench	Irrigated	—	—	150	—	130	—	—	—
Marion	North bench	Nonirrigated	—	—	125	—	105	—	40	—
Marion	South bench	Irrigated	—	—	115	—	100	—	—	—
Marion	South bench	Nonirrigated	—	—	100	—	85	—	40	—
Multnomah		Irrigated	—	—	—	—	—	—	—	—
Multnomah		Nonirrigated	—	—	—	—	—	—	—	—
Polk	East bottom	Irrigated	—	140	128	110	80	—	—	—
Polk	East bottom	Nonirrigated	—	120	108	90	60	31	18	12
Polk	East bench	Irrigated	—	140	122	104	80	—	—	—
Polk	East bench	Nonirrigated	—	120	102	84	60	31	18	12
Polk	East hill	Irrigated	—	134	116	92	68	—	—	—
Polk	East hill	Nonirrigated	—	114	96	72	48	31	18	12
Polk	West bottom	Irrigated	—	97	89	78	57	—	—	—
Polk	West bottom	Nonirrigated	—	77	69	58	37	18	11	7
Polk	West bench	Irrigated	—	97	82	71	57	—	—	—
Polk	West bench	Nonirrigated	—	77	62	51	37	18	11	7
Polk	West hill	Irrigated	—	92	81	66	52	—	—	—
Polk	West hill	Nonirrigated	—	72	61	46	32	18	11	7
Washington	Bottom	Irrigated	—	130	102	84	48	35	—	—
Washington	Bottom	Nonirrigated	—	90	65	72	35	18	18	18
Washington	Hill	Nonirrigated	—	—	65	55	35	—	—	—
Yamhill		Irrigated	—	185	155	115	80	—	—	—
Yamhill		Nonirrigated	—	145	115	75	40	9	9	9
Mean values:		Irrigated	—	146	134	103	84	56	—	—
		Nonirrigated	—	102	86	72	53	25	21	9
		Difference:	—	45	48	31	31	31	—	—

To compile a data set of agricultural tax lots spanning the extent of the Willamette Valley, cadastral and zoning tax lot data were collected from all counties, identifying the tax lots zoned for agricultural use. Small tax lots of fewer than 10 acres were excluded. See Kalinin (2013) for additional detail. The hedonic estimation includes the following variables: soil classes LCC 1–4, 6, and 7 independently and, in the case of LCC 1–4, interacted with a dummy variable for existence of an irrigation water right (*IRR*);[7] IDU elevation; historical average growing season precipitation (demeaned using the basinwide mean); and historical average growing season minimum temperature (demeaned using the basinwide mean). In addition, parcel size in acres was interacted with each of the variables elevation, precipitation, and temperature. For the IDU values of farmland rent, mean parcel size was assumed.

Table A12. Farmland rent model—estimated parameters.[1]

Variables	Coefficient	P-value
Soil LCC1 (unirrigable)	104.7***	0.000
Soil LCC2 (unirrigable)	95.6***	0.000
Soil LCC3 (unirrigable)	69.9***	0.000
Soil LCC4 (unirrigable)	66.6***	0.000
Soil LCC6 (unirrigable)	20.5***	0.000
Soil LCC7 (unirrigable)	19.9***	0.000
Soil LCC1 (irrigable)	143.6***	0.000
Soil LCC2 (irrigable)	134.7***	0.000
Soil LCC3 (irrigable)	87.7***	0.000
Soil LCC4 (irrigable)	88.7***	0.000
Elevation (demeaned)	-1.06***	0.007
Precipitation (demeaned)	98.5***	0.000
Temperature min (demeaned)	351.6***	0.000
Elevation * Acres	-0.02***	0.000
Precipitation * Acres	-0.44***	0.000
Temperature * Acres	20.1***	0.000
Constant	65.5***	0.000

[1]Statistical significance is indicated as: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Using these data, the rent for each parcel was estimated with the following form:

$$R = \beta_0 + \sum_1^{16} \beta_j X_j + \varepsilon$$

where R is the parcel rent (per acre per year), β_0 is the intercept, X_j represents the variables in Table A12, and β_j is the coefficient on X_j.

Expected (long-run) farmland rent

The long-term farmland rent denotes the expected rents, $E(R)$, in future years based on recent observed rents, including the potential risk associated with shutoffs of irrigation water rights. With the short-term economic rent estimations above, and the updated modeled values for shutoffs, the value of $E(R)$ is estimated annually by interacting the four irrigable LCC variables with a measure of the risk of an irrigation shutoff (SH), where SH in year t equals the frequency in the previous 10 years that the IDU's water right was shut off ($0 < SH < 1$; initial value $SH = 0$).

The farmland rent data, as well as farmland sales data, indicate a relatively low value for irrigation water rights ($17/acre-foot) compared to other irrigated areas in the western U.S. These lower values for irrigation water reflect the less arid conditions in the Willamette Valley, at least in the spring and early summer in most years. There is sufficient rainfall leading up to and over the course of the growing season, so that irrigation is not essential for many crops, to the extent that a large share of existing water rights in the Valley are not used every year. As a result, the acres of land irrigated in a given year (based on the USDA Census of Agriculture) represent only two-thirds the number of acres with irrigation water rights (Kalinin, 2013).

Validation: Crops, irrigation, land use, and farmland values

The combination of model results for crop choice, irrigation decisions, and farm rents are compared here with data from the USDA Census of Agriculture, 2012. The main crop categories among harvested cropland acreage in the USDA data are grass seed (53%), hay (15%), orchards (5.6%), vegetables (included in Table A13, page 83, as "other") (5.4%), field crops (4.5%), and nursery crops (4%),

[7]There were insufficient observations of LCC5 land in the data to estimate a coefficient. As a result, we are assuming LCC5 lands are treated as if they have the same value as LCC6 lands.

also included as "other." This pattern has been relatively stable for many years for the major crops; grass seed has been the dominant crop by acreage for more than 50 years.

Harvested cropland has averaged about 900,000 acres over the past decade, declining from a high of about 1 million acres in the 1980s. About 267,000 of these acres, or about 30%, are irrigated in any given year (USDA Census of Agriculture data, 1997–2012). Of these, just over half (about 140,000 acres, or 52%) are irrigated with surface-water rights. The breakdown between surface and groundwater irrigation is based on our own farm survey (discussed under "Irrigation decisions," page 78).

The acreage of irrigated farmland in the Basin has remained relatively stable since the mid-1990s. Prior to that time, irrigated acres rose gradually, reflecting the acquisition of new irrigation water rights. Since the available live flow water rights were fully allocated as of the 1990s, no new irrigation water rights have been approved by the OWRD.

Data on existing irrigation water rights indicate about 462,000 acres with irrigation water rights from surface, groundwater, or stored water (federally contracted) sources. Given the annual irrigated acreage of 267,000 acres, this indicates a rate of utilization of irrigation water rights of 55 to 60%. The estimated frequency of utilization of irrigation water rights from our farm survey (and the basis for the modeled acreages irrigated) was 62%.

An exact count of irrigation water rights is complicated by several factors: (a) Water rights can sometimes have multiple uses (irrigation, domestic, and livestock); (b) A small fraction of irrigation water rights in the WRB are "supplemental water rights" rather than primary, and thus cannot be used unless the primary right is exhausted or unavailable (supplemental water rights were not included in this model); (c) The Oregon water rights database contains measurement errors, GIS errors, and other imperfections; and (d) Some water rights may have been abandoned or are not known to the landowner.

The farmland rent model described above is used to estimate farm income, farmland values, and the incentive to keep land in agriculture or transition to other land uses. The farmland rent estimates, as described above, are based on county-level market transaction information, land rental information, and farmer surveys undertaken annually by WRB county assessors. Using the variation in these estimates across counties and zones, the per-acre rents by soil class and for irrigated and nonirrigated lands were used to estimate a relationship for expected farm rents as a function of soil class (LCC), presence of irrigation water rights, average precipitation, elevation, etc. These annual rents can be converted to land prices based on a standard capitalization formula. Using a (real) discount rate of 4%, our farmland rent estimates are comparable to the land prices in Table A14, intended to reflect market prices

Table A13. Comparison of model results and USDA Census of Agriculture, 2007.

Model results, reference scenario (2010–2015)			USDA Census of Agriculture (2012)	
Crop category	**Harvested acres**	**Irrigated acres**	**Crop category**	**Harvested acres**
Grass and clover seed	350,067	101,870	Grass, clover, and other field seed crops	389,000
Hay and pasture	184,571	36,506	Hay, forage, silage	149,784
Orchards, vineyards, and tree farms	36,101	7,444	Orchards, vineyards, and tree farms	74,893
Corn	13,468	8,304	Corn	38,765
Wheat	31,416	—	Wheat	97,700
Other crops	309,224	110,536	Other crops	161,641
Total acres	924,847			911,783
Total irrigated		264,600		267,000[1]

[1]Total irrigated acres is an average for Census of Agriculture, 1997, 2002, 2007, 2012.

in 2010. A real discount rate of 4%, given inflation of about 2% per year, is approximately equivalent to a market interest rate of 6%.

These values are similar to data reported by the USDA Land Values 2012 Summary (August 2012) (http://www.nass.usda.gov/Publications/Todays_Reports/reports/land0812.pdf). That report estimates the average farmland value to be $2,290/acre in Oregon overall; average values for irrigated lands are $3,650/acre, for nonirrigated lands $1,800/acre, and for pasture lands $670/acre. For irrigated lands, the USDA Oregon average is higher than for all but the best soil class in the WRB. Indeed, comparisons with data from other parts of Oregon where irrigation is prevalent suggest that the value of irrigable land in the WRB is somewhat lower than that of irrigated lands in the Deschutes, Klamath, or other basins in Oregon. In general, the estimated farmland values are very close to the averages reported by the USDA. Looking at farmland prices in years after 2010 (e.g., 2016), modeled prices would be expected to diverge from those observed. The reason is that the model assumes prices to be inflation-adjusted so that a stable real (inflation-adjusted) price is constant in the model. Inflation has been about 3% per year; farmland prices in the WRB have risen faster than that during the 2010–2015 period.

Table A14. Farmland values in WW2100 model.

	Farmland market price ($/acre)[1]	
LCC	Nonirrigable	Irrigable
1	2,648	3,620
2	2,420	3,398
3	1,778	2,223
4	1,695	2,248
5	543	—
6	543	—
7	528	—

[1]Computed based on capitalization rate of 4%

The implicit farmland prices in our model, if adjusted to reflect inflation from 2010 to 2016, would range from $2,500 to $4,000 for irrigated land, and from $600 to $3,000 for nonirrigated land. Indeed, farmland sales reported as of June 2016 in several WRB counties average $3,100/acre, with a high of $4,800/acre. Lands with buildings and infrastructure, for example to support nursery production, have significantly higher market values due to these capital improvements. Sales prices will be higher for lands where there is an expectation that land development will be possible in the near future, for example where changes in land-use regulations and/or UGBs are anticipated.

Section 4. Conveyance Cost Estimation

Agricultural lands in the Willamette Basin that currently do not have irrigation water rights may benefit from opportunities to acquire new water rights under federal contracts for stored water at one of the U.S. Army Corps of Engineers (USACE) reservoirs. The profitability of a new contract for stored water will depend on a comparison of the irrigation benefits (higher yields and a wider range of crop choices) and the additional costs (capital investments in infrastructure, labor, and energy costs). For farmlands with existing irrigation water rights, these costs and benefits are already incorporated into the WW2100 estimates of farmland rent (annual profits) by soil class.

For new contract water rights, we would expect the irrigation premium to be the same as for existing irrigation water rights if the costs of irrigating are similar to the average costs for existing surface and groundwater rights. In the case of new water rights from stored water, we expect the costs to be somewhat higher due to (a) the fee paid to the U.S. Bureau of Reclamation (USBR) for the water contract, (b) the extra cost for mainline conveyance to bring the water from a below-reservoir tributary to the field, and (c) the extra lift required. Whether or not a new irrigation water right will be attractive to a farmer will depend on whether farming is more profitable with irrigation than without.

The extra costs are estimated here. There are two components to these costs: (a) the infrastructure and installation capital costs, and (b) the additional energy costs. For both of these costs, we estimate average values for a representative irrigation operation of 120 acres (which could involve combining multiple fields via cooperation or land sales).

Capital costs for mainline conveyance infrastructure

Capital costs for mainline conveyance systems include the pipe and below-ground installation costs. The size of the pipe is tied to the flow rate needed to serve the irrigable area; larger pipes are more costly, but increase capacity and reduce friction losses. For a range of pipe diameters, the costs, capacity, friction losses, and irrigable areas are shown in Table A15 (page 86). Our analysis is based on use of an 8-inch pipe to serve a 120-acre farm. The annualized capital costs are estimated to be \$0.59/year/100 feet of mainline (assuming 120 acres, or an average rate of 6.5 gpm). For a mainline of 1,000 feet, this would mean an added cost of \$5.90/acre/year. In addition, the charge from the USBR averages about \$9/acre.

Variable cost: Per-acre energy costs

The additional energy costs for irrigation from stored water contracts will reflect the additional distance and lift along the mainline to bring water from the point of diversion to the irrigated field. The added cost is estimated as a function of the mainline length and the lift (Fipps, 1995; English, 2015).

The energy cost, ***c***, can be expressed as

$$c = p \bullet E \tag{1}$$

where ***p*** is the price of electricity (\$/kwh), and ***E*** is the energy consumed in kwh. We have

$$E = t \bullet (\mathit{Output\ power}) \tag{2}$$

where ***t*** is time (hours), and *output power* is the power per unit time. The rate of energy use is

$$\mathit{output\ power} = \frac{q \cdot TDH}{3{,}960} \tag{3}$$

where ***q*** is the pumping rate per hour, and ***TDH*** is the total dynamic head, or the sum of the lift, head losses, friction losses, and the pressure at the pump (in psi multiplied by 2.306 to get horsepower).

To convert output power from horsepower to kilowatts, we multiply by 0.746. To adjust for the overall pumping plant efficiency, E_{plant}, the expression is divided by this value, which can range from 0.7 to 0.8. A midrange value for pumping plant efficiency is 0.75, meaning that input power must be one-third higher than output power.

The hours of pumping, ***t***, necessary to apply the required irrigation water (acre-inches), ***d***, is computed as

$$t = \frac{(d \cdot 27{,}154)}{(q \cdot 60)} \tag{4}$$

Combining the relationships in (2), (3), and (4) above and simplifying (e.g., 27,154/(60•3,960) = 0.114285), we can write this as

$$c = p\left[\frac{d \cdot TDH \cdot 0.114285 \cdot 0.746}{E_{plant}}\right] \tag{5}$$

Table A15. Estimated mainline capital costs for new irrigation conveyance piping, for a range of representative systems.[1]

Pipe diameter (inches)	Cost ($/foot)	Capacity (gal/min)	Friction loss (psi)	Distance (feet)	Friction loss per 1,000 feet (psi)	Irrigable area (acres)		Cost per acre for 100 feet ($/acre)		Annualized cost (per 100 feet) ($/acre)[2]		Annualized cost (per 100 meters) ($/acre)[2]	
						7 gpm	6 gpm	7 gpm	6 gpm	7 gpm	6 gpm	7 gpm	6 gpm
10	17	1,225	9.0	3,000	3.0	175	204	9.7	8.3	0.71	0.61	2.34	2.01
8	9.5	780	9.6	2,500	3.8	111	130	8.5	7.3	0.63	0.54	2.06	1.76
6	6.9	450	9.0	1,600	5.6	64	75	10.7	9.2	0.79	0.68	2.59	2.22
5	5.8	305	9.3	1,400	6.6	44	51	13.3	11.4	0.98	0.84	3.21	2.75
4	4.5	195	9.5	1,100	8.6	28	33	16.2	13.8	1.19	1.02	3.90	3.34
3	4	110	9.1	750	12.1	16	18	25.5	21.8	1.87	1.61	6.14	5.27

[1]Source for cost per foot, friction losses, and irrigable areas: Anthony Knox, CID, Pacific Ag Systems, Inc.
[2]20-year amortization at 4%

For our benchmark assumptions, we use $p = 0.06$, d = 16 inches/acre, and $E_{plant} = 0.75$.

To estimate the incremental energy costs for the length and lift of additional mainline systems, we need to compute the additional *TDH* due to the additional mainline length and lift.

The Hazen-Williams formula for head loss in a pipe is

$$H_f = K \bullet \left(\frac{\left(\frac{Q}{C}\right)^{1.852}}{D^{4.87}} \right) \bullet (Length) \tag{6}$$

where H_f is friction head loss (feet/foot), Q is flow rate (gpm), D is the inside diameter of the pipe (inches), K_f is a constant (1,046), length is the length of the pipe (feet), and C is a "roughness factor."

To provide an indication of the likely pumping costs, and how those costs will vary by distance and lift, the estimates are applied to a representative system in the WRB as follows. We will assume $C = 140$ (for PVC pipe), $Q = 672$ gpm (5.6 gpm for 120 acres), and $D = 8$ inches. With these assumptions, we can estimate H_f as a function of the length of the pipe. To this we add the required lift (in feet) to get the portion of *TDH* attributable to the extra mainline conveyance. With these parameters, the additional cost for mainline conveyance is estimated to be $0.069/acre for every 100 feet of mainline, and about $0.091/acre for every 10 feet of lift (Figure A3). The figure suggests a cost of $80/acre/year for a pumping distance of 1,000 feet, but no lift. With a 200-foot lift, a distance of 700 feet would have the same cost as a distance of 1,000 feet with no lift.

Total additional costs with stored water contracts

Combining these fixed and variable cost estimates on an annualized, per-acre basis, we get the following costs per 100 feet of mainline: $9 (contract price), plus $0.59 (capital cost), plus $8.35 (energy cost). To this add $0.11 per foot of lift. For a parcel that is 300 feet from the below-reservoir stream, and 20 feet above the stream, the extra conveyance cost would be $36.80/acre/year.

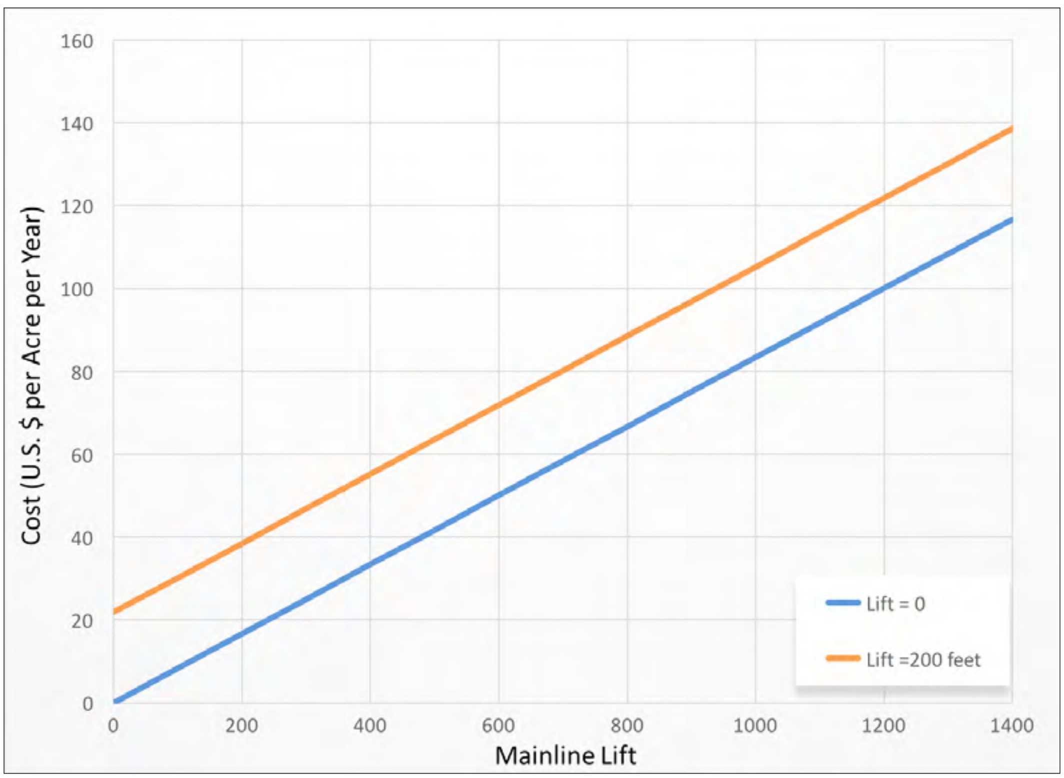

Figure A3. Per-acre mainline annual energy cost (120 total acres) by distance and lift.

Computations were undertaken with input from Marshall English (Oregon State University), Steve Amosson (Texas A&M University), and consultation with Anthony Knox, Pacific Ag Systems, Junction City, OR.

Section 5. Reservoir Recreation: Visitation and Economic Value Estimation

This model draws on analysis conducted by Moore (2015). The number of recreational visits per day at each reservoir is a function of the reservoir, the day/month, the fill level relative to full pool, and the population in a given year.

$$V_{r,d,t} = V_{rd} I_t \left(1 - 0.003 \cdot \left(E_{rf} - E_{rd}\right)\right)$$

where $V_{r,d,t}$ is visits at reservoir r, on day d, in year t for Julian days ranging from 153 to 244. E_{rf} is the full pool elevation for reservoir r, and E_{rd} is the elevation on day d. The base number of visitors (V_{rd}) estimated for year 2010 differs by reservoir and month as follows: June (day 153–182), July (183–213), and August (day 214–244), as shown in Table A16. The index (I_t) scales the base number of visitors for each year t according to the expected growth in population since 2010.

Table A16. Estimated daily visits at full pool, 2010.

Reservoir	June	July	August
Detroit	6,738	9,144	8,181
Fern Ridge	4,170	5,658	5,064
Foster	2,673	3,630	3,246
Green Peter	1,326	1,800	1,611
Dorena	825	1,119	999
Fall Creek	435	591	528
Cottage Grove	525	711	636
Blue River	495	672	600
Hills Creek	261	354	315
Lookout Point	117	162	144
Cougar	15	18	18

Based on 11 years of visitor count data, the statistical model estimated indicates that on average for every foot drop in water elevation below full pool, the total number of reservoir visitors (V^{TOT}) declines by 0.3%:

$$V_{rt}^{TOT} = \sum_{d=153}^{244} V_{rd} I_t \left(1 - 0.003 \cdot \left(E_{rf} - E_{rd}\right)\right)$$

That is, for each foot decline in the water elevation of the reservoir, on average, the number of visitors declines by 0.3% from the estimated base levels (for a given reservoir, in a given month).

Welfare losses ($) from foregone recreation due to a decline in visits, valued at $55/visit (see Moore, 2015, and Loomis, 2005), in year t are estimated as:

$$W_{rt}^{REC} = \sum_r \sum_{d=153}^{244} -0.165 \cdot V_{rd} I_t \left(E_{rf} - E_{rd}\right)$$

The coefficient -0.165 equals the average value per visit ($55) times the visitor response to declining water levels (-0.003).The scarcity or marginal value of water ($/acre-foot) for recreation at reservoir r, on day d, in year t, also reflects how water elevation changes with fill volume (Q) at each reservoir:

$$\frac{dW_{rt}}{dQ_d} = -0.165 \cdot V_{rd} I_t h(E_{rd}) \quad for \quad E_{rd} < E_{rf}$$

$$\frac{dW_{rt}}{dQ_d} = 0 \quad for \quad E_{rd} = E_{rf}$$

The water level–volume relationship, $h(E_{rd})$ in feet/acre-foot, is computed each day, d = 153–244, at each reservoir based on a quadratic estimation of the inverse function of the storage volume, $S = f(E)$, taking the derivative, and inverting the marginal value (slope) to get dE/dS, as shown in Table A17. (For Fern Ridge, the estimation is based on a second-order polynomial).

Table A17. Water level–volume relationship by reservoir.

Blue River	*dE/dS* = 1/(-6.2474 + 0.005292843 * *E*)
Cottage Grove	*dE/dS* = 1/(-15.3072 + 0.020808375 * *E*)
Cougar	*dE/dS* = 1/(-6.1086 + 0.004329286 * *E*)
Detroit	*dE/dS* = 1/(-20.8111 + 0.015445427 * *E*)
Dorena	*dE/dS* = 1/(-15.9301 + 0.021178034 * *E*)
Fall Creek	*dE/dS* = 1/(-9.3633 + 0.01335917 * *E*)
Fern Ridge	*dE/dS* = 1/(1054.169439 – 6.186737126 * E + 0.009075152 * (*E*^2))
Foster	*dE/dS* = 1/(-6.5225 + 0.012090552 * *E*)
Green Peter	*dE/dS* = 1/(-13.9199 + 0.017353763 * *E*)
Hills Creek	*dE/dS* = 1/(-15.1254 + 0.011520661 * *E*)
Lookout Point	*dE/dS* = 1/(-15.8657 + 0.021801233 * *E*)

Section 6. Water Rights Model

Under Oregon law, all water is publicly owned. A permit from OWRD is required for irrigation, municipal water use, and other uses. The water allocation module in WW2100 simulates the seniority system for water allocation that is used in Oregon and other western states. This system allocates water according to water right priority date (first date of use historically); it is based on western water law known as the prior appropriation doctrine—"first in time, first in right." Under Oregon law, surface or groundwater must be put to a "beneficial purpose without waste." Final certificates of water rights define the timing of use, the maximum rate of diversion, and the annual volume (duty) allowed under the water right. When conflicts arise due to shortage, the more senior water right is given priority, and more junior water rights are required to curtail their water use if it conflicts with the appropriation of water by a senior water right holder. Water rights may be transferred between points of use under Oregon law when transactions are arranged by parties and approved by the OWRD.

In cases of regional shortage, when available water supplies are insufficient to meet all needs (such as during drought), Oregon's statutes give priorities for domestic uses. In this situation, preference is given in the following order: human consumption, livestock consumption, and all other beneficial purposes. Oregon water law also provides protections for minimum perennial streamflows for the environment.

Water rights model

Water is allocated in our model with a water rights and allocation model (AltWaterMaster) that simulates an approximation of the process that occurs in reality. The model takes account of the demand or request for water at a given point of diversion on a given day (from a farm, city, rural residential water user, or in-stream flow water right). It evaluates the availability of water from the relevant streams and groundwater source and, if sufficient water is available, it withdraws water to satisfy the demand. If there is insufficient water to meet the needs of an existing water right, the algorithm will determine whether a junior water right in the same river reach or any upstream reach could be curtailed in order to make water available to satisfy the senior water right.

In the case of an IDU with an irrigation water right, there are three steps: (1) crop choice, (2) irrigation decision, and (3) biophysical water requirements. Depending on the irrigation decision and crop choice outcomes, soil moisture and crop ET are estimated for each day from planting to harvest. If soil moisture falls below a level adequate to meet the needs of the crop at a particular stage of growth, there will be an "irrigation request" for an amount of water needed to satisfy crop growth requirements. The computation of the amount of water requested, therefore, depends on human decisions, crop development, temperature, precipitation, and soil moisture. In the case of urban water rights, urban water demand is estimated as described in Section 2.

In the case of an in-stream water right, the amount of water "requested" is the amount provided for as minimum flow for the in-stream water right. Under Oregon water law, in-stream flows are counted as a beneficial use so that in-stream water rights are protected from competing uses in the same way that out-of-stream beneficial uses are protected. State-sponsored studies in the early 1960s recommended in-stream flow levels needed to support native fishes in major streams, based on a series of Basin-specific reports. These reports recommended specific in-stream flows, month by month, needed to support anadromous salmonid species. These recommendations were then used by the OWRD to set minimum perennial streamflows throughout Oregon by administrative rule (ODFW, 1997). Figure A4 (page 90) shows the sum of both existing and unconverted in-stream water rights at the outlets of the WRB tributaries (all of which flow into the Willamette mainstem). Figures A5–A8 (pages 90–92) show these water rights individually for each tributary.

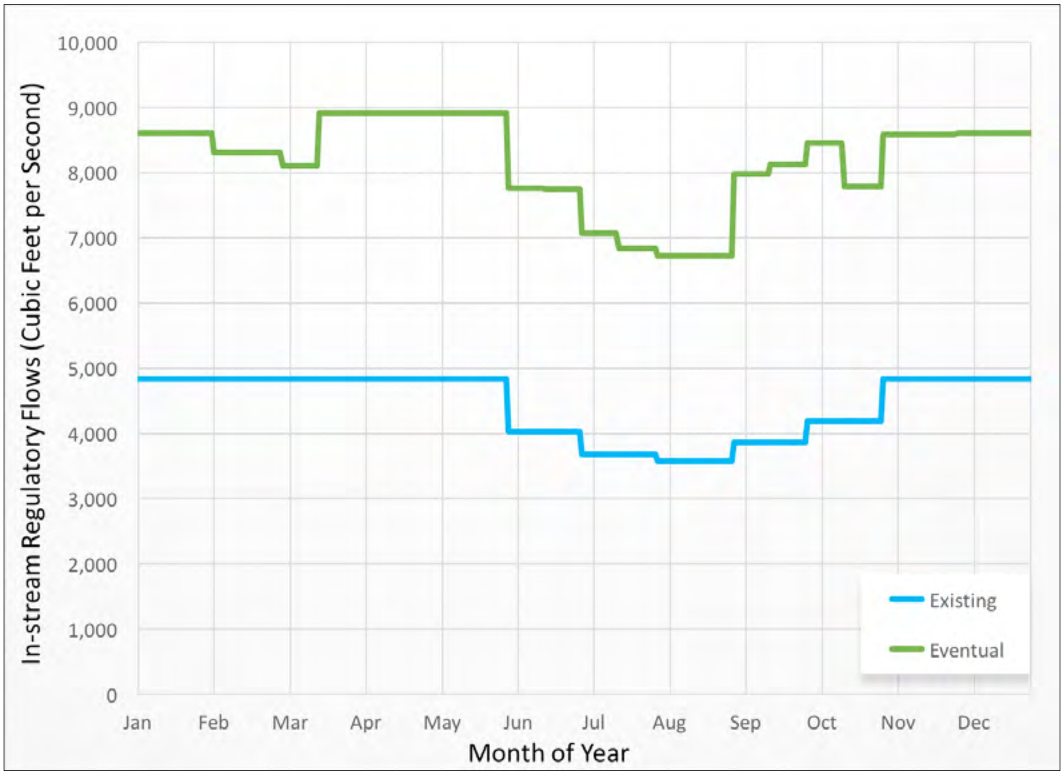

Figure A4. In-stream water rights at subbasin tributary outlets, existing and eventual.

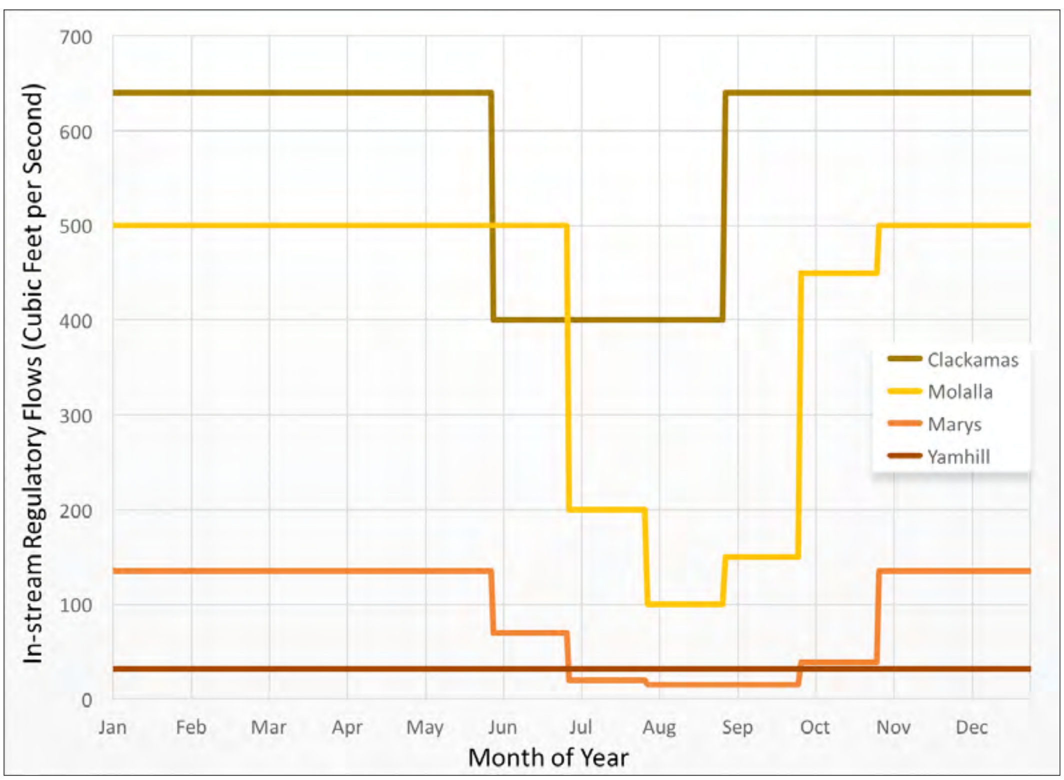

Figure A5. Existing regulatory flows at major Willamette tributary outlets.

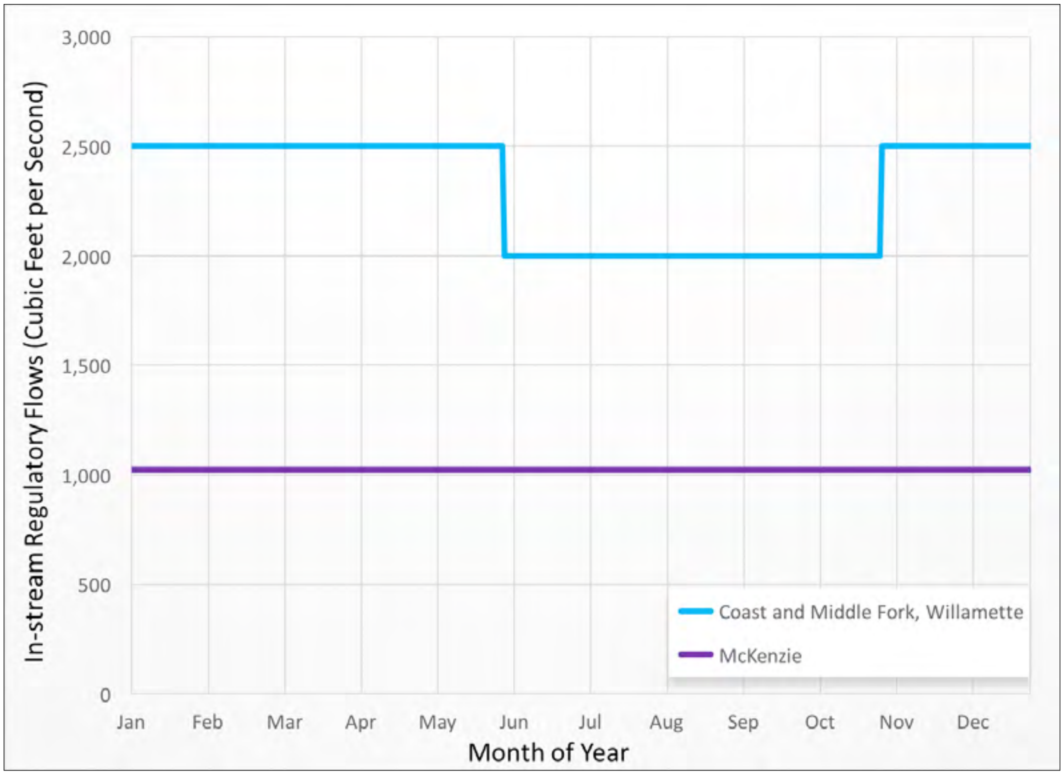

Figure A6. Existing regulatory flows at major Willamette tributary outlets.

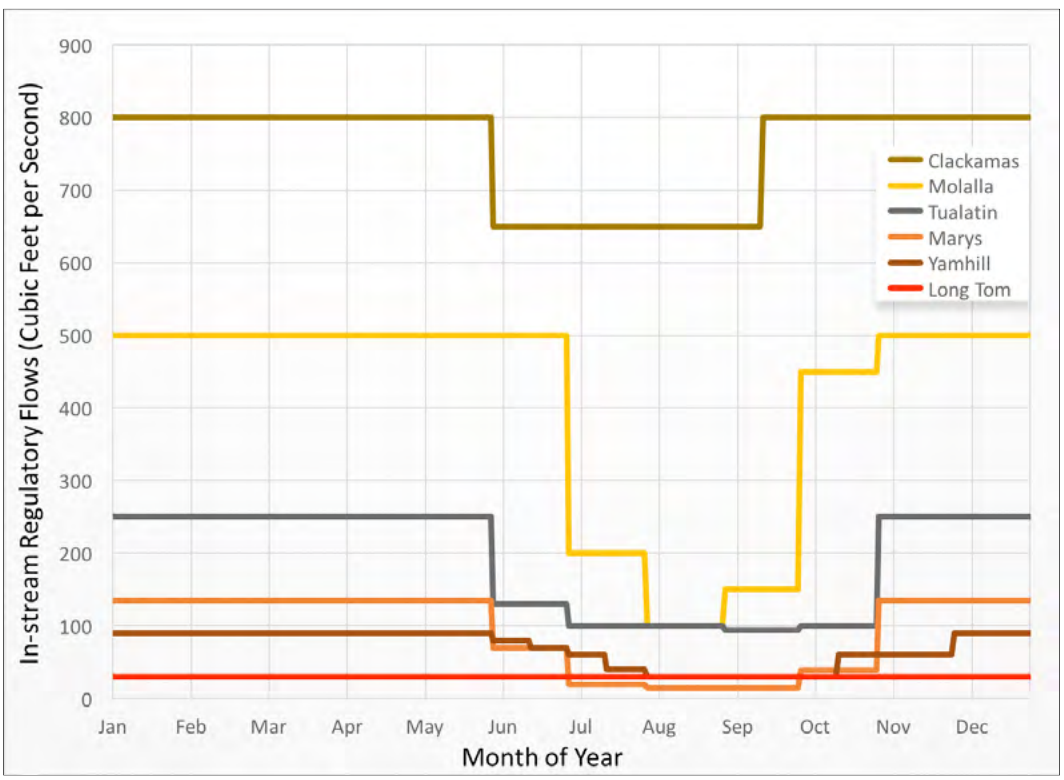

Figure A7. Anticipated future regulatory flows at major Willamette tributary outlets.

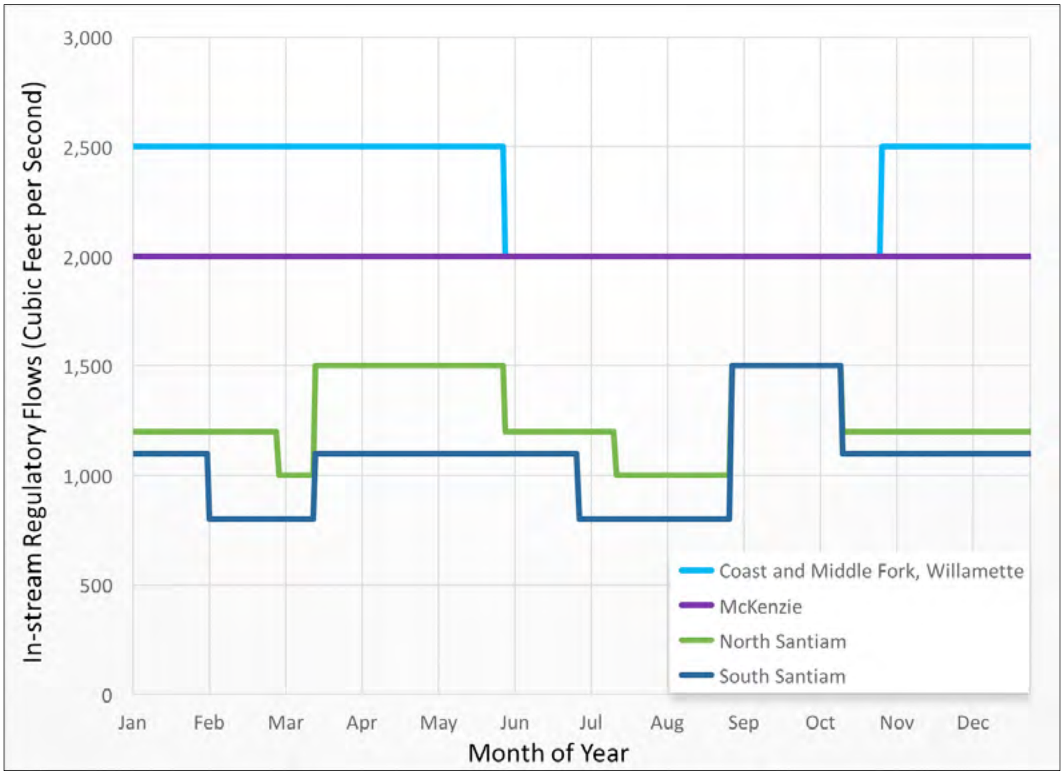

Figure A8. Anticipated future regulatory flows at major Willamette tributary outlets.

Many of the flows adopted were set at levels well below those recommended, especially during summer months. In 1987, the Oregon Legislature supplemented the perennial flow law with SB 140 (the Instream Water Right Act). Legislators sought to maintain water levels that support public uses within natural streams or lakes; these in-stream water rights are held by the state in trust to support public uses such as recreation, pollution abatement, navigation, and maintenance and enhancement of fish and wildlife and their habitats. Under Oregon law, water rights such as irrigation water rights may be temporarily leased or permanently transferred to in-stream use on a voluntary basis.

In-stream flows in the WRB are maintained at prescribed levels in two main ways (see Amos, 2014). State law, as described here, is one way (https://www.oregonlaws.org/ors/537.346). The other mechanism comes from Biological Opinions for threatened or endangered species of anadromous fish under the Endangered Species Act. In the WRB, there are several such species, and minimum flows to support their habitat are the basis for flow requirements on the mainstem and major tributaries (NOAA, 2008a). The BiOp flow requirements are tied to downstream control points. The control points at Salem are represented in Figure A9 (page 94). Figures A10–A12 (pages 94–95) show required flows below each reservoir.

In general, these flows are maintained by way of dam operations above the control points; reservoir management rules require the release of water to satisfy these BiOps.

Irrigation and in-stream rights are satisfied in order of priority date for the whole Basin, with the senior appropriated rights satisfied first. If water cannot be diverted from the stream reach without dropping the water level below the minimum in-stream flow for the reach, and if this occurs for 7 consecutive days, then the right is shut off for the remainder of the season. In the case of urban water rights, the prioritization for large cities occurs based on a range of factors other than the priority date of the water right.

The USBR has authority to enter into contracts with irrigators in the Basin to supply water from storage in the federal USACE reservoirs. Any contract for stored water must also be accompanied by an Oregon water right indicating the corresponding point of diversion, place of use, use, maximum rate, and duty. Currently USBR is authorized to offer water contracts only to agricultural users.

The total amount of stored water in years when the reservoirs are filled is approximately 1.6 million acre-feet. However, current ESA-related requirements for April–October minimum flows have resulted in a cap on the stored water contracts allowed from federal dams at 95,000 acre-feet of the total 1.6 million acre-feet (NOAA, 2008b). This level was increased in 2003 from 85,000 acre-feet. Currently, approximately 80,000 acre-feet are allocated under service contracts for irrigation in the Basin.

Initially, Congress authorized USBR to issue contracts for stored water for agricultural uses only. However, the Flood Control Act of 1950 expanded the authority of the USACE to (potentially) include municipal and industrial water supply as an intended and authorized project purpose. Currently the USACE has not issued any contracts to municipal or industrial users, but reallocation of stored water to these uses is currently under review as part of a multiyear process to assess the existing restrictions (see https://www.oregon.gov/owrd/Pages/mgmt_res_study.aspx).

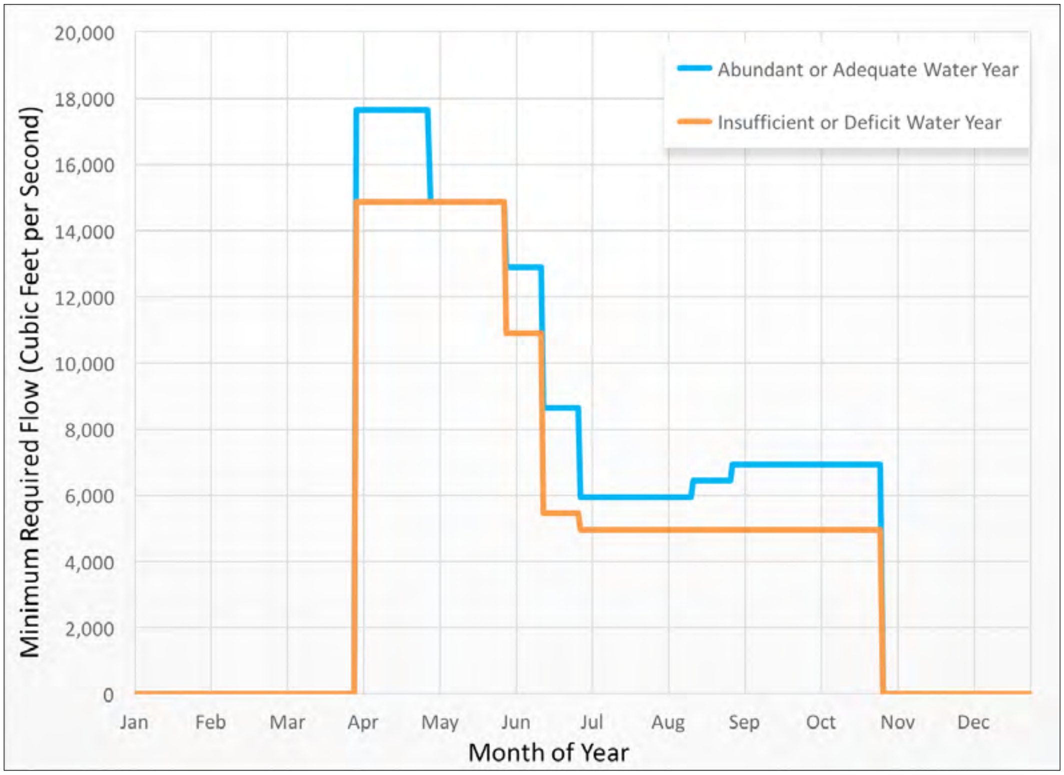

Figure A9. Federal BiOp minimum flow requirements for the mainstem Willamette at Salem by water year type.

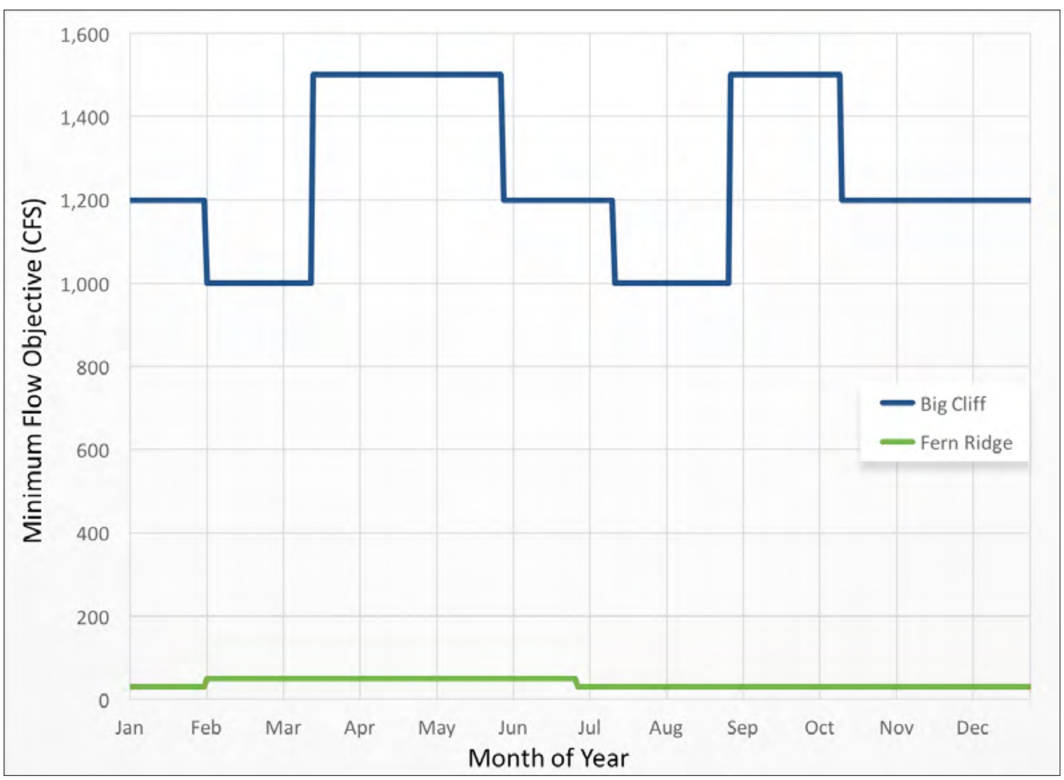

Figure A10. Federal BiOp minimum flow objectives below Willamette Project reservoirs.

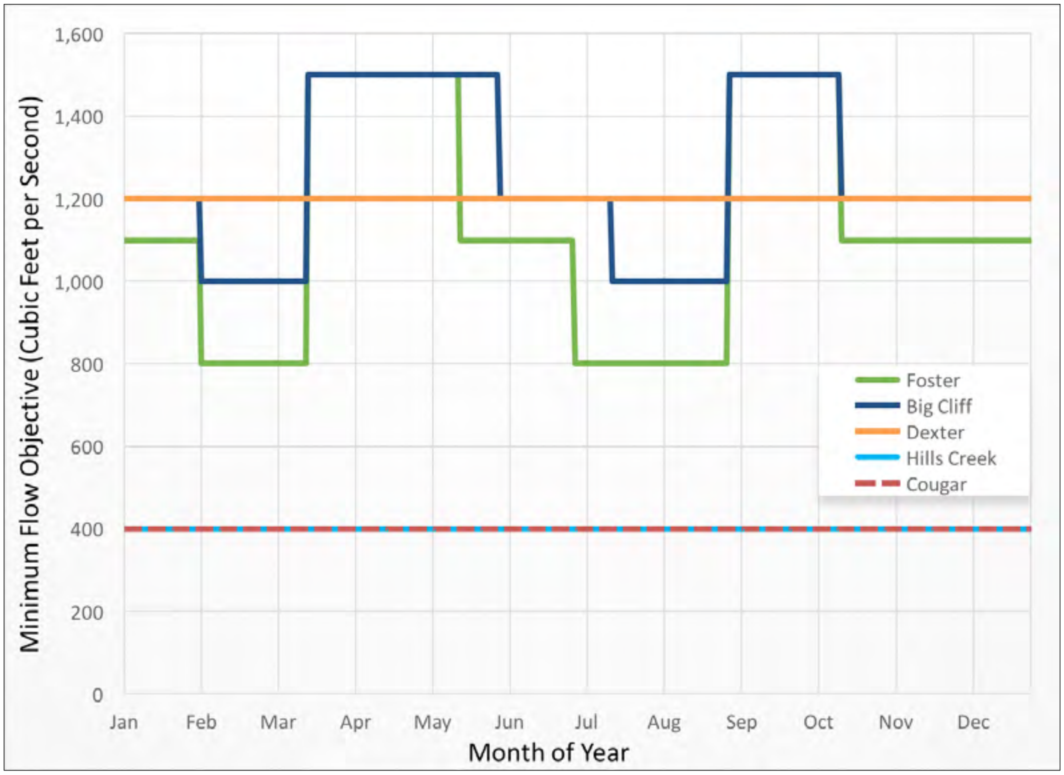

Figure A11. Federal BiOp minimum flow objectives below Willamette Project reservoirs.

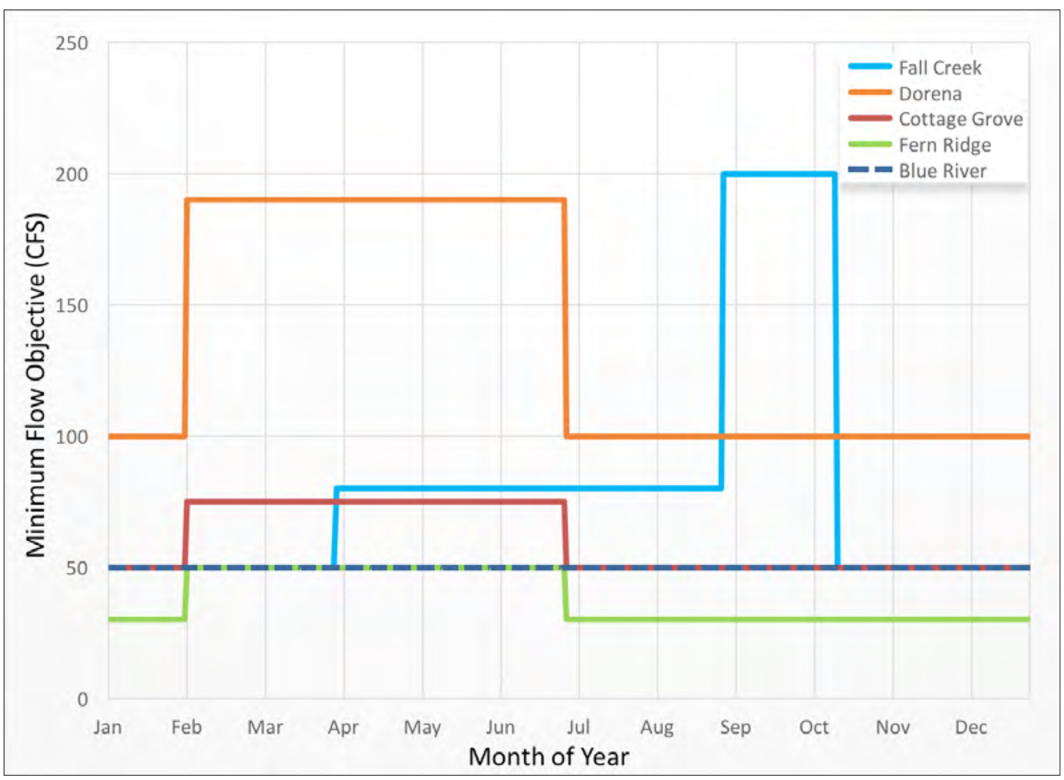

Figure A12. Federal BiOp minimum flow objectives below Willamette Project reservoirs.

Water rights input data

The water rights model requires a detailed input data set to represent the irrigation, municipal, and in-stream water rights in the Basin, with specific details about the locations (point of use and point of diversion), allowed use, priority date, maximum rates, and duties. The input data for the model were based on OWRD GIS files for points of use (POUs), points of diversion (PODs), and tabular data. These data were intersected with the model's IDU parcels and stream layer. Overlaps between POUs and PODs were not exact, but were approximated to achieve a high correspondence between the modeled and the actual existing water rights in terms of size, location, and other characteristics. The input data set includes 15,413 irrigation water rights, 1,024 municipal water rights, and 93 in-stream water rights. Of the irrigation water rights, 8,678 are surface water (232,720 acres), and 6,735 are groundwater (228,800 acres). A parcel of farmland cannot have more than one "primary" irrigation water right, which can be used if sufficient water is available. In some cases, farmers have a "supplemental" water right, usually a groundwater right, which can be used only if the primary water right is unavailable. Given the relatively small number of supplemental water rights in the WRB, these water rights are not included in our model. We also omitted some minor and nonconsumptive water right types such as hydropower and fluming.

Because the vast majority of irrigation water rights in the WRB have identical start dates (March 1), end dates (October 31), maximum rates ($1/80$ cfs/acre), and duties (2.5 acre-feet/acre), these values were applied uniformly in the model. For municipal and in-stream water rights, specific rates (maximum or minimum) were applied to each water right.

In the case of municipal water rights, most large cities have multiple water rights, including surface-water and groundwater rights, utilizing more than one point of diversion. Use of these water rights is prioritized based on a variety of considerations, including costs, water quality, seasonal availability, etc. It is therefore impossible to predict which water right will be used, or used first, based on the water right priority date. To simulate the sources preferred by the large cities in the Basin, water use reports for recent years were used to apportion the urban water demand to the water rights that have been used the most by each city. See Table A18 (pages 97–98).

The water right sources, types of storage, and forms of conveyance for municipal water supply represent a complex capital-intensive supply system that would be very difficult to accurately model and predict in terms of specifics decades into the future. For example, neighboring cities often buy and sell water from each other. Portland's main water supply is an out-of-basin source at Bull Run. Portland currently sells about one-third of Bull Run diverted water to other municipalities within the Metro area. Our model reflects an assumption that cities will buy and sell water as needed within the Metro area and will continue to rely on the major surface-water sources used currently. As demand grows, the model allows for additional water to be made available by utilizing Willamette mainstem sources of water, which is in fact what is currently being developed by the Tualatin Valley Water District as the largest new water supply in the Basin.

Table A18. Municipal water rights included in Willamette Water 2100 for main cities.

City	Company name	Facility name	snp-ID	Average use, 2008–2014 (acre-ft/yr)	Source[1]	Priority date	Max POD (point of diversion) rate (cfs)	Priority use ranking in model (by city)
Metro	City of Portland	Bull Run[2]	145069	117,735	S	8/6/1886	636.0	1
Metro	City of Hillsboro	Spring Hill intake	173101	32,798	S	6/9/88	75.0	2
Metro	Clackamas Water District	Clackamas River	133611	7,844	S	5/20/68	25.0	3
Metro	City of Lake Oswego	Facility "50"	135322	5,849	S	3/14/67	25.0	4
Metro	City of Forest Grove	Roaring Creek	65860	1,032	S	4/16/35	1.0	5
Metro	City of Hillsboro	Haines Falls intake	120228	937	S	8/15/30	9.0	6
Metro	City of Hillsboro	Barney (and Scoggins) Reservoirs [2,3]	142164	472	S	6/26/58	65.0	7
Metro	City of Forest Grove	Clear Creek	65860	820	S	4/16/35	1.0	8
Metro	City of Milwaukie	Well 7 (CLAC 315)	108806	700	G	6/28/82	2.7	9
Metro	City of Troutdale	Well 5	165351	576	G	5/1/80	2.2	10
Salem	City of Salem	Middle intake, Geren Island	175543	48,135	S	12/31/1856	62.0	1
Salem	City of Salem	IG @ GI (LINN 2676)	28159	2,609	G	12/31/36	12.4	—
Salem	City of Salem	Well and GI	19325	2,205	G	1/2/58	30.0	—
Salem	City of Salem	ASR 4	175371	29	G	6/16/58	2.0	—
Eugene-Springfield	Eugene Water and Electric	Hayden Bridge	43309	10,995	S	6/14/61	183.0	1
Eugene-Springfield	Springfield Utility Board	Thurston well 1	94482	964	G	4/21/66	1.7	—
Eugene-Springfield	Springfield Utility Board	Middle Fork Willamette River	42176	666	S	3/18/53	20.0	—
Eugene-Springfield	Springfield Utility Board	Willamette 11	88048	658	G	11/1/65	3.3	—
Eugene-Springfield	Springfield Utility Board	Thurston well 3	94485	535	G	2/10/72	1.1	—
Corvallis	City of Corvallis	Taylor intake	158859	5,422	S	8/21/70	46.7	1
Corvallis	City of Corvallis	South Fork Rock Creek	102583	1,202	S	9/30/07	1.9	2
Corvallis	City of Corvallis	North Fork Rock Creek	85734	1,192	S	8/27/59	4.7	3
Corvallis	City of Corvallis	G.C.	54716	614	S	12/10/12	1.5	—
Albany	City of Albany	A/M WTP to Albany	147761	6,191	S	7/12/79	29.0	—
Albany	City of Albany	Parks/Cox Creek	151694	2,119	S	6/9/70	5.0	1
Albany	City of Albany	ALS Canal	147761	858	S	7/12/79	29.0	2
Lebanon	City of Lebanon	Santiam Canal	47462	2,302	S	7/12/79	18.0	3
Cottage Grove	City of Cottage Grove	Row River WTP POD	156056	584	S	4/28/25	4.0	1

[1]S = surface water; G = groundwater

[2]Out-of-basin source of water

[3]Use is allowed from June 15 to November 15.

Continued on next page

Table A18. Municipal water rights included in Willamette Water 2100 for main cities. *(continued)*

City	Company name	Facility name	snp-ID	Average use, 2008–2014 (acre-ft/yr)	Source[1]	Priority date	Max POD (point of diversion) rate (cfs)	Priority use ranking in model (by city)
Cottage Grove	City of Cottage Grove	Row River WTP POD	156057	584	S	6/18/28	4.0	2
Sweet Home	City of Sweet Home	Old diversion point	66130	1,316	S	7/14/38	0.6	1
Sweet Home	City of Sweet Home	Water treatment plant	176061	1,202	S	4/8/86	3.5	2
Creswell	City of Creswell	Water treatment plant	165272	836	S	8/10/89	3.0	—
Estacada	City of Estacada	—	78862	519	S	5/10/55	2.0	1
Estacada	City of Estacada	—	102967	519	S	1/19/73	2.0	2
Amity	City of Amity	South Yamhill River	45984	122	S	5/16/73	1.0	1
Amity	City of Amity	Briedwell Water Plant	114352	115	S	1/24/39	0.5	2
Adair Village	City of Adair Village	Water treatment plant	45110	287	S	7/7/71	82.0	—
Yamhill	City of Yamhill	Turner Creek Diversion	169379	373	S	3/27/40	1.3	—

[1]S = surface water; G = groundwater

[2]Out-of-basin source of water

[3]Use is allowed from June 15 to November 15.

Section 7. Modeling of Scenarios

This section describes some of the rationale for the set of scenarios developed for WW2100. Research studies such as WW2100 often use simulation models that compare a base case or "reference scenario" to a set of alternative scenarios (see Figure A13, page 102; and Table 19, page 103).

One of the most common uses of this kind of approach is for policy analysis, which is described as asking "What if?" questions (e.g., what if policy X were implemented?). By comparing a reference, or "business-as-usual," scenario to an alternative scenario in which a policy change has been introduced into the simulation, the impact of the policy change can be evaluated in a way that is impossible to do in the real world (comparing the outcomes in a world "with" the policy change to what the world would have been like "without" the policy change). Simulations of this kind represent one of the most widely used operations research methods, one that is widely applied for public policy analysis (Fischer and Miller, 2006, p. 364). The rationales for other scenarios described below include an effort to address the uncertainty surrounding some of the assumptions by running scenarios to do "sensitivity analysis."

Modeling challenges

Systems linking people and nature, often referred to as social-ecological systems, are recognized to be complex, adaptive systems with feedbacks, strategic interactions, variation across space, and varying time scales. Such systems pose substantial challenges for modeling. The features and dimensions of these kinds of systems must be studied and understood in an integrated way, because we cannot know in advance which features will be important for the outcome of a given policy question or potential management intervention (Levin et al., 2013).

Various kinds of models are used to represent complex social-ecological systems at the regional or global scale. These models are often referred to as "integrated assessment" models (IA). Integrated assessment has been defined by the Intergovernmental Panel on Climate Change (IPCC) as "an interdisciplinary process that combines, interprets, and communicates knowledge from diverse scientific disciplines from the natural and social sciences to investigate and understand causal relationships within and between complicated systems" (IPCC, 2001). Integrated assessment studies using spatial-temporal simulation models like the one developed in this project are an important tool to meet the needs of decision makers faced with policy and management questions. Given the complex nature of social-natural systems, the broad objective of these kinds of integrated models is to understand the direction and magnitudes of change in relation to specific management interventions so as to be able to differentiate between associated outcome sets (Jakeman and Letcher, 2003).

Key elements of multidisciplinary, integrated frameworks of this kind include an interdisciplinary and participatory process of combining, interpreting, and communicating knowledge from diverse scientific disciplines to achieve a better understanding of a system and its future trajectory (Rotmans and Van Asselt, 1996). Best practices include making assumptions transparent in both natural and social science components, and also including decision makers and other stakeholders in the model development process (Turner, 2000).

Reference case or "baseline" scenario

Model scenarios should contain as many of the elements that shape a society as possible and should aim to be a coherent, internally consistent, and plausible description of likely future states. Such a model can be used to predict future trends and inform policy makers of potential decisions and their consequences. With limited knowledge of processes determining both social change and biophysical change, multiple scenarios are needed to represent a plausible range of alternative outcomes. This kind of sensitivity analysis explicitly acknowledges the inherent uncertainty in a model and its projections (Holman et al., 2005). One category of scenarios described below represents sensitivity analysis.

The most common application of integrated models is as a tool to aid policy makers and public sector agency managers. The first step is to choose a "reference scenario," also called a "business-as-usual," or baseline, scenario. The idea is to include in this scenario what is believed to be the most likely future trajectory in the system under study, in the absence of any unexpected intervention. This base case then becomes a reference point against which alternative scenarios can be modeled and compared to the reference case.

The reference scenario, by including as many relevant elements of the social-ecological system as possible, makes it possible to project a trajectory of future change that provides evidence of changes in resource supply and demand, scarcity, and value. The economic components of the model not only project how people will use resources, but also how they will respond to changes in resource availability. These feedbacks in the human components of the model are critical to understanding how people will respond to changes in scarcity. Importantly, where these models include economic indicators and metrics, the trajectory in the reference scenario (especially when compared to alternative scenarios) generates output that allows policy makers and stakeholders to explicitly see evidence of costs, consequences, and tradeoffs involved in different courses of action. A strength of the WW2100 model is the ability to estimate the empirical magnitude of key tradeoffs so that decision makers are better informed about the true costs and benefits of alternative policies.

The reference scenario addresses the first two of the three objectives of the project: (1) to identify and quantify the linkages and feedbacks among human, hydrologic, and ecologic dimensions of the water system, and (2) to make projections about where and when human activities and climate change will impact future water scarcities and to evaluate how biophysical and human system uncertainties affect those projections. The third objective of the project is addressed with the alternative scenarios described below and compared to the reference scenario: (3) to create "alternative scenarios" in which one or more policy levers or other interventions have been introduced into the model and to evaluate how these interventions affect future water scarcities (relative to the reference scenario).

Alternative scenarios

In this study, we include five types of alternative scenarios for different purposes. First, we have scenarios that represent "sensitivity analysis." These scenarios are intended to evaluate how sensitive the model projections are to assumptions about specific parameters or assumptions. Specifically, we have varied our assumptions about "external drivers"—those aspects of the system that are essentially beyond the control of individuals or policy makers in the region. We include here our assumptions about how climate, population, and income will change in the future.

Second, we have a range of policy analysis scenarios. These scenarios are intended, as described above, to understand the direction and magnitude of change in relation to specific management interventions so as to be able to differentiate between associated outcome sets and their costs and consequences. Changes in water prices, water law, and reservoir management rules would come under this category of alternative scenario. These scenarios are integrative because a change in one part of the model has linkages and feedback effects elsewhere in the model. For example, a change in rules for UGB expansion will have implications for both municipal and agricultural land use in specific areas, which in turn will affect in-stream flows and reservoir management decisions. One advantage of running a policy scenario with one change or intervention relative to the reference scenario is that it allows us to attribute changes in outcomes to that individual change in policy or other model modification. Often policy analysis combines policy interventions in the same scenario. In some cases, this strategy is intended to evaluate whether a second intervention can offset the adverse side effects of the first intervention—ones that were identified when the first intervention was evaluated individually in a prior alternative scenario.

Two of the alternative scenarios included here involve changes to water rights: one for new irrigation water rights tied to stored reservoir water and one for in-stream water rights created in the 1960s but currently "unconverted" (see page 89).

Third, we have several scenarios described as "counterfactual" scenarios. The term "counterfactual" refers to the idea that these scenarios intentionally model a situation that will not occur, i.e., that is counter to the facts. These scenarios can help us measure the impact of changes in the model that have occurred, or will occur, by comparing one scenario intended to represent what we expect to happen (i.e., the reference scenario) with a scenario that omits one source of change, for example. We have included one scenario of this kind, in which climate does not change (but population grows), and one scenario in which there is no change in population or personal income (but where climate change does occur). Comparing these counterfactual scenarios to the reference scenario provides insights into the magnitude of the effects on future water scarcity due to one of these elements versus the other. In one other case, we have modeled a scenario with no agricultural production (all fallow). This is clearly counter to the facts; however, a comparison of this scenario to the reference scenario or other alternative scenarios will provide evidence of the impact of agriculture on water use and streamflows.

Fourth, we have modeled historical scenarios. Two scenarios covering a 60-year time span from the past (1950–2010) are used to compare modeled historical conditions with modeled future conditions.

Fifth, additional scenarios, referred to as "integrated scenarios," combine changes in multiple scenario elements and provide a way to evaluate the combined effect of multiple, simultaneous changes to the regional system. These scenarios were developed in collaboration with a group of interested stakeholders, the Technical Advisory Group (TAG), a group with diverse expertise in WRB land and water use and management. One scenario developed by the TAG was dubbed the "Extreme scenario" because it combines high change climate with high population growth and other model settings designed to maximize resource use and water demand for cities and agriculture. One other integrated scenario developed by the economics researchers was the "Worst case" scenario. This scenario combined mid-range climate change with high population growth, increased fire suppression, high utilization of irrigation, and the certification of all in-stream water rights. It also allowed for new irrigation at half the costs estimated in the New Irrigation scenario.

Not all scenario results are reported here. Additional information about the WW2100 project can be found at http://inr.oregonstate.edu/ww2100/about/project-overview.

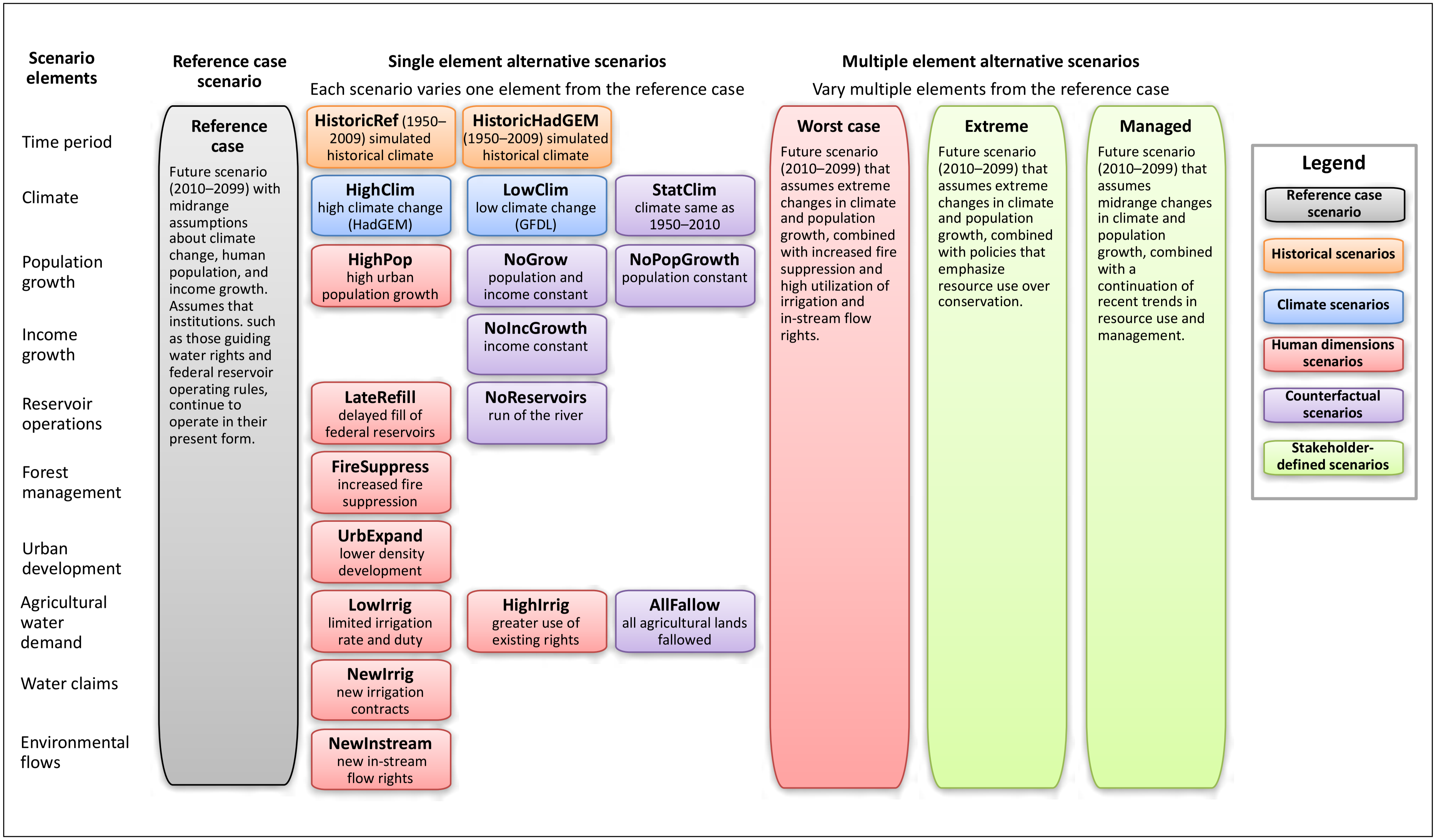

Figure A13. Summary description of reference scenario and alternative scenarios, WW2100.
*See also Table A19, page 103.

Table A19. Descriptions of selected reference case and alternative scenario components.

Model component	Model component descriptions
Climate	**Reference case:** Climate inputs are from the regionally downscaled projections from the MIROC5 global climate model with the RCP 8.5 emissions scenario. Projections are in the middle of the range of possible changes predicted by a suite of global climate models that perform well for the Pacific Northwest. Annual mean temperature in the Willamette River Basin (WRB) increases about 4°C (7.5°F) over the century.
	Alternative scenario: Low Climate Change—GFDL Model (LowClim). Projections are from the GFDL-ESM2M model, RCP 4.5. WRB annual mean temperature increases about 1°C (2°F) over the century.
	Alternative scenario: High Climate Change— HadGEM Model (HighClim). Projections are from the HadGEM2–ES model, RCP 8.5. WRB annual mean temperature increases about 6°C (10.5°F) over the century.
Population and income growth	**Alternative scenario:** High Population Growth (HighPop). Population growth rates within UGBs are doubled relative to the Reference Case. Basinwide population in 2100 = 8.25 million; population in Portland UGB in 2100 = 4.89 million.
	Alternative scenario: Zero Population Growth (NoPopGrowth). Population remains at 2011 levels throughout the century; income rises as in the Reference Case.
	Alternative scenario: Zero Income Growth (NoIncGrowth). Income remains at 2011 levels throughout the century; population rises as in the Reference Case.
	Alternative scenario: Zero Population & Income Growth (NoGrow). Population and household income remain at 2011 levels throughout the century.
Forest management	**Reference case:** The level of wildfire suppression is held at historical rates throughout the simulation. However, because of changing climate and forest conditions, the area of forest burned per year rises over the simulation from 0.2%/year in 2010 to 0.6%/year in 2100. Harvest by clear-cut is maintained at historical rates (8,000 acres/year on public lands + 29,000 acres/year on private lands). There is no harvest of protected areas. Harvest occurs only in stands older than 40 years on private lands, and between 40 and 80 years old on public lands.
	Alternative scenario: Upland Wildfire Suppression (FireSuppress). Fire suppression efforts are increased to hold the area burned annually to historical rates.
Urban Development	**Alternative scenario:** Relaxed Urban Expansion (UrbExpand). UGBs expand when 70% of the land within the UGB is developed; no urban reserves.
Agricultural water demand	**Alternative scenario:** Limited Irrigation Rates & Duties (LowIrrig). The legal maximum irrigation rate is reduced from 1⁄80 cfs/acre to 1⁄100 cfs/acre. The duty is reduced from 2.5 to 2.0 acre-feet/acre.
	Alternative scenario: Higher Irrigation Usage (HighIrrig). The average fraction of irrigation rights utilized in a given year is increased from two-thirds (Reference Case) to five-sixths.
	Alternative scenario: All Fallow (AllFallow). Crop choice is set to "fallow" for all agricultural lands (including trees and orchards); no irrigation.
Water rights	**Alternative scenario:** New Irrigation Rights (NewIrrig). New irrigation contracts for stored water in the Willamette Project and related rights are introduced 2015–2044. The probability of adopting irrigation depends on the profitability of irrigating, given increased revenue and increased costs for irrigation infrastructure and pumping, as well as contract fees (about $9/acre).
	Alternative scenario: New Instream Water Rights (NewInstream). New water rights are introduced in the model in 2010 (with priority dates for 1960s), reflecting recommended minimum flows established by the state (see https://www.oregonlaws.org/ors/537.346 and Amos, 2014).

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