Appendix X

Impacts of Global Climate Change on California's Agricultural Water Demand

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Abstract

In this appendix, we bring the integrated interdisciplinary approach used to analyze the impacts of selected global climate change on California's agricultural industry to a conclusion. The knowledge base for the resulting physical and economic impacts on California agriculture draws from several sources. The change in water runoff resulting from climate change is one of the driving factors, as is the estimation of the changes in crop yield and evapotranspiration. Projections of changes in crop market demand and other sources of yield changes are also important in their ability to mask or reinforce climate change effects. Changes in the availability of agricultural land caused by increased urbanization are predicted by the Landis and Reilly model (see Appendix III), and the effect of changed runoff on the optimal operation of the California water system is calculated by the California Value Integrated Network (CALVIN, Appendix VII) model. The net effect of these trends on the agricultural resource base and relative crop profitability is combined in the postoptimality runs that use the Statewide Water and Agricultural Production (SWAP) Model to measure the different effects of the CALVIN water allocations on regional crop production and economic returns. SWAP is an economic optimization model that identifies demand for water for different regions in California, along with the resulting value of agricultural output.

In these runs, the SWAP model allows for three types of adjustments that farmers can make to mitigate the effects of water changes. The first level of change is in the total area of irrigated agriculture in any given region. This area is altered by the change in the demand for crops and by the supply of both irrigable land and water. In the second adjustment margin, farmers can modify the combination of the crops they grow. Again, both physical and economic factors influence the adjustments. Expansion of the demand for some crop types is a strong influence, especially on the area of the high-value crops grown. The availability of water and changes in yield also affect the relative crop proportions grown because some crops will have greater returns per unit of water than others. Finally, farmers can also adjust by substituting among the different inputs used to grow crops. Economists call this the "intensive margin." For example, when faced with water shortages, such as in past droughts, farmers have responded by investing in more efficient field-level water delivery systems. This investment enables them to reduce applied water, but not crop yield, because a more efficient system delivers a similar quantity of water to the growing plant.

The main finding of our postoptimality analysis is that the ability of California agriculture to adjust to water shortages resulting from climate change significantly reduces the economic impact of the water shortages. In Section 7 of this appendix, we summarize the net effects by comparing the projected agricultural production in 2100 (with optimal water allocation but no climate change) with the effects of the parallel climate model (PCM) climate change. We will see that even though aggregate water supply is cut by 24.3%, changes in crops and irrigation systems mean that irrigated area is reduced by only 14.5%. Because the cuts are concentrated in

the low-value crops, this area reduction results in a 8.3% reduction in gross income and a 6% reduction in net income. In short, our analysis concludes that California agriculture can and will adjust to even the more severe forms of climate change.

1. The Model Used: The SWAP Model

1.1 Brief Presentation of the Model[1]

The SWAP model is unique in its ability to identify specific agricultural water allocations that are consistent with observed water use and that match the willingness to pay by different agricultural water users for irrigation water supply.

By using a supply-demand approach, SWAP is indeed able to estimate the “shadow value” per unit of water, by region and month. This approach explicitly recognizes the effect of higher prices on water demand. The objective function used in SWAP maximizes each region’s total net returns from agricultural production, subject to the pertinent production and resource constraints on water and land. Production constraints are in the form of functional relationships that describe the productive trade-offs between land and water use efficiency, in conjunction with capital expenditures. The model distributes water supply based on each region’s annual water allocation, the local water costs, and the production opportunities facing the region. The model assumes a perfectly competitive market structure in that producers are unable to influence prices in either input or output markets. It follows that each producer is perceived as being relatively small in relation to the market. Furthermore, this model is calibrated against observed data and is consistent with microeconomic theory, which asserts that productive decisions are based on marginal conditions. Published data, on the other hand, are based on average conditions. The divergence between the average and marginal conditions, either in the context of costs or revenues, is attributed to additional information not contained in the collected data (such as variations in land quality). Because the farm operators know this information, it affects the cropping allocations and technologies used. These differences in marginal cost can be attributed to heterogeneous land and resource quality, on-farm productive capacity, and economies of scale, among other factors.

Although the model has spatial water constraints, which include physical limitations on annual water availability, the optimal solution allows for transfer of water between different months so that the marginal value of water by month and crop is equated. A shadow value represents the

1. This appendix is composed by some parts of Appendix A, “Statewide Water and Agricultural Production Model,” in the *Improving California Water Management: Optimizing Value and Flexibility* report. See http://cee.engr.ucdavis.edu/faculty/lund/CALVIN/.

"true" value of an additional unit of water to a buyer in the region. Generally speaking, this additional unit of water would in turn produce additional agricultural output. The value of that output depends on the type of crop grown and the price that is specific to the region. The SWAP model explicitly recognizes each region's unique willingness to pay for water as a function of its productive opportunities and *adapts* to changing surface supply scenarios.

Production function specification

Each region has a different production function for each of the crops produced. Within a region, the production of different crops is connected by the restrictions on the total land and water inputs available. Crop production is modeled using a multi-input production model for each region and crop.

The quadratic form of the production function is one of the simplest functional forms that will allow for decreasing marginal returns to additional input and substitutability of inputs, as required by theory. Several different agricultural inputs have been aggregated and simplified to aggregate measures of land, water, and capital.

Because crop production is a function of land, water, and capital, substitutions among these inputs can take the form of stress irrigation or of substituting capital for applied water. The capital input is an amalgam of labor management and capital used to improve irrigation efficiency under different technologies.

The model, then, captures the three ways in which farmers can adjust crop production when faced with changes in the price or availability of water. The total amount of irrigated land in production can change with water availability and price. This reaction is particularly observed during California's periodic droughts, when the largest reduction in water use comes from a reduction in irrigated acres. The second avenue of adjustment, termed the extensive margin of substitution, changes the mix of crops produced so that the value produced by a unit of water is increased. The third approach, called the intensive margin of substitution, measures the changes in the intensity of input use on the crops that are grown. The production function is written in general as:

$$y = f(x_1, x_2, x_3) \tag{1}$$

The specific quadratic used in the SWAP model has the form:

$$y = \begin{bmatrix} \alpha_1 & , & \alpha_2, \alpha_3 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} - \begin{bmatrix} x_1 & x_2 & x_3 \end{bmatrix} \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} \\ \gamma_{31} & \gamma_{32} & \gamma_{33} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \tag{2}$$

where y is the total regional output of a given crop and x_i is the quantity of land, water, or capital allocated to regional crop production.

Defining the total annual quantities of irrigated land and water available in each region as X_1 and X_2. The total problem defined over G regions and i crops in each region for a single year is:

$$\begin{aligned} &\text{Max} \quad \Sigma_G \Sigma_i \quad p_i f_{Gi}(x_1, x_2, x_3) - \omega_1 x_1 - \omega_2 x_2 - \omega_3 x_3 \\ &\text{subject to} \quad \Sigma_G \, x_{1Gi} \le X_1 \qquad (\text{Land}) \\ &\qquad\qquad\quad \Sigma_G \, x_{2Gi} \le X_2 \qquad (\text{Water}) \end{aligned} \tag{3}$$

1.2 SWAP Regions

The model includes the original 21 regions that span the Central Valley of California and four regions in southern California. Figure 1 shows the regions and their designations.

1.3 Agricultural Crop Categories in SWAP

Because of the data available, the crop categories used in this version of the SWAP model differ between the northern California SWAP regions and the southern California SWAP regions (see Table 1). It would be more uniform, and therefore preferable, to use the same crop categories for all the regions, but the data are not reported consistently. Because optimization is done for each region, the differences in crop categories do not influence the conclusions that result from the SWAP runs.

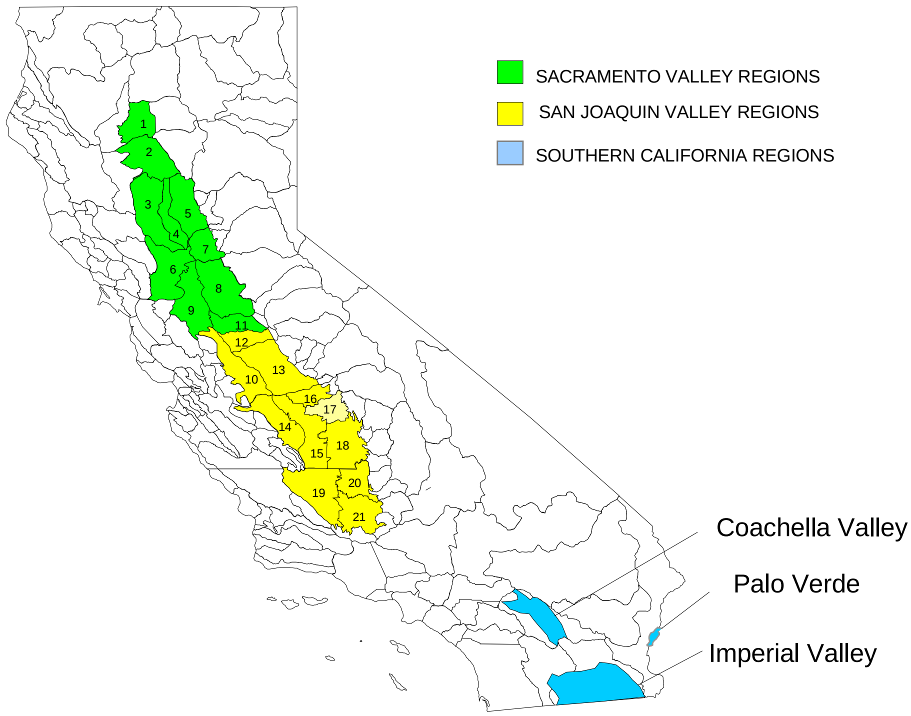


Figure 1. California map with southern and northern SWAP regions

2. Parameters Changed in the Model for this Project

Two different sets of parameter changes had to be made in the initial SWAP model specification to accommodate this project's very long forecast horizon and the required climate change scenarios. Figure 2 shows the parameters that were changed and their relationships to other parts of the overall study. We changed the parameters for 2020 and 2100.

3. Scenarios Tested to Study the Effect of Climate Change on Irrigation Water Demand

The SWAP model was run under three different scenarios for 2100 (see Table 2). The scenarios differed by the assumptions about the level of California's population in 2100. The "high" scenario, designated as "H," is for a population of 93 million in 2100. The "low" scenario ("L") assumes a population of 69 million. Other parameters that affect the SWAP projections are the rate of exogenous technological progress, the temperature and precipitation changes resulting from climate change, and the effect of increased carbon dioxide (CO_2).

Table 1. Crop categories used in SWAP

Northern California SWAP crop categories		Southern California SWAP crop categories	
Cotton	Cotton	Cotton	
Field crops	Field corn	Grain and field crops	Field corn, miscellaneous field crops, and wheat
Fodder	Alfalfa hay, pasture, and miscellaneous grasses	Market crops	Tomatoes and truck crops
Grain crops	Wheat	Low-value crops	Pasture, alfalfa hay, and miscellaneous grasses
Grapes	Table, raisin, and wine grapes	Fruit and nut crops	Orchard and nut crops
Orchard	Almonds, walnuts, prunes, and peaches		
Pasture	Irrigated pasture		
Tomatoes	Fresh market and those for processing		
Rice	Rice		
Sugar beets	Sugar beets		
Subtropical	Olives, figs, and pomegranates		
Truck	Melons, onions, potatoes, and miscellaneous vegetables		

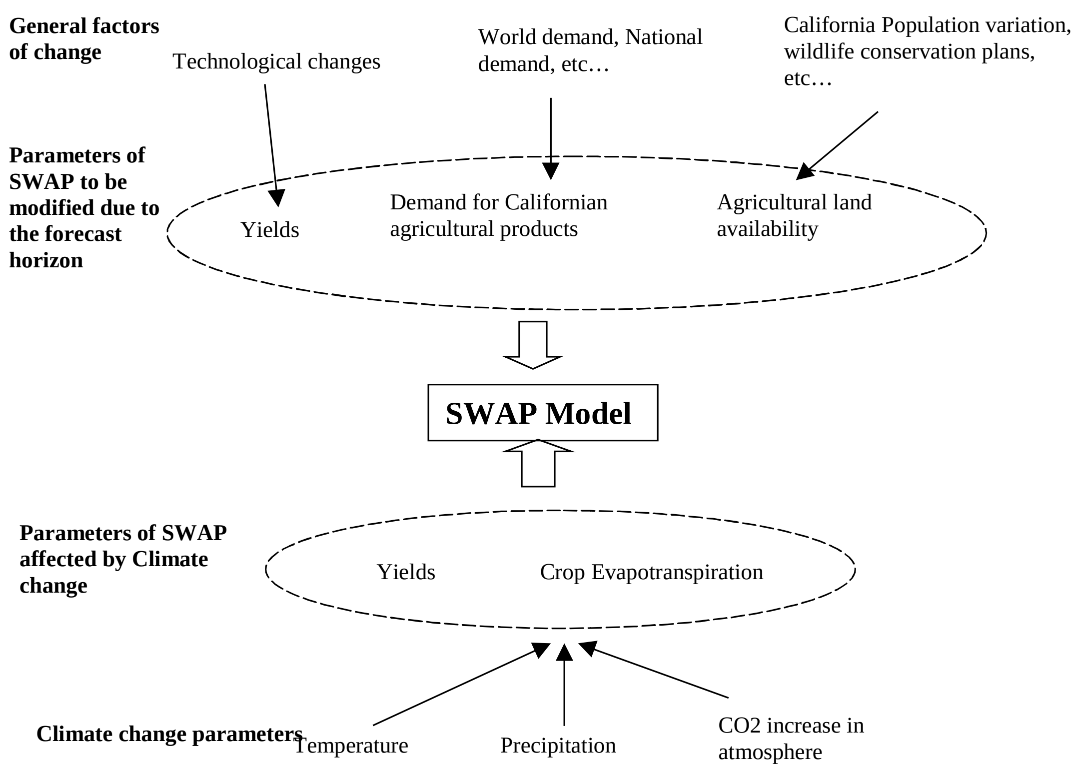


Figure 2. Parameters changed in the initial SWAP model

Table 2. Characteristics of different scenarios tested in terms of parameters

SWAP runs/ result sets	Population scenario/land use effects on land availability for agriculture 2100 H (93 million) 2100 L (69 million)	Technology effects on yield (0.25% or 1% per year)	Temperature + precipitation effects on yield and irrigation water	CO_2 effects on yield and irrigation water
A	2100 H (93 million)	0.25%/year	+3°C +18% precipitation = Scenario 2 in Oregon file	Yes
B	2100 L (69 million)	0.25%/year	+3°C +18% precipitation = Scenario 2 in Oregon file	Yes
C	2100 H (93 million)	0.25%/year	HadCM2 climate change scenario	Yes
D	2100 H (93 million)	0.25%/year	PCM climate change scenario	Yes

4. Parameter Changes

4.1 Agricultural Land Availability and Irrigated Acreage

It is important to take into account the modification in agricultural land availability that may occur as a result of external factors. A change in agricultural land availability will influence the cropping pattern and therefore water demand and consumption, which are the parameters that we want to forecast.

The main external factors that drive the modification in the availability of agricultural land are population growth and urbanization. For this reason, other factors that influence land retirement, such as drainage problems, were neglected. To calculate the increase in urbanized land and the decrease in agricultural land, we used the population forecasts and resulting forecasted land use estimates based on the projections by Landis and Reilly in Appendix III of this report.

Urbanization may eliminate irrigated acreage in one area, but may shift agricultural development to lands that are not currently irrigated. In the model projections, only the first phenomenon is taken into account. Indeed, the second change in agricultural land can be considered a marginal factor of minor importance. Moreover, it would be very difficult to quantify.

Because two scenarios were forecasted for population growth until 2100, we also used two scenarios for the agricultural land availability in 2100. Most of the results reported are for the high-population scenario.

Decrease in agricultural land in northern regions and specific assumptions

Note that we assumed an equal (homogeneous) distribution of the loss of land within a given county. We also assumed that the distribution of the agricultural land in the county is homogeneous. These assumptions were required because land use data are limited to (1) the percentage of land in each county in each SWAP region, and (2) the increase in urbanized land in each county.

Although this assumption may initially appear to be quite significant, the results for the SWAP regions make sense and show that this assumption is acceptable (see Figure 3). The northern region decrease in agricultural land availability from 2020 to 2100 is 3.37% with the high-population scenario (93 million people in California in 2100) and 1.58% with the low-population scenario (63 million people).

These predictions can be improved by urbanization projections on a more detailed basis. More precise data may or may not result in a larger decrease in agricultural land for each SWAP region. However, the loss of land will no longer be uniformly distributed in the county and we can estimate the distribution of land change more precisely.

Decrease in agricultural land in the southern regions and specific assumptions

Because the distribution of the crop acreage among counties in the new southern SWAP regions is not recorded, we chose a “representative county” for each SWAP region. In other words, we had to assume that each southern SWAP region was contained in a given county. The percentage of the county constituted by the SWAP region was calculated by (SWAP region acreage/representative county acreage).

As a result, the decrease in land is assumed to be uniformly distributed within the county. We then calculated the decrease in acres that affects the SWAP regions, as shown in Figure 4.

The decrease in agricultural land is small in the Imperial region and in Coachella Valley. The decrease is more important for Palo Verde, and even more important for the San Diego SWAP region.

These trends show that the decrease in agricultural land is expected to be less important in percentage terms in the southern area than in the northern regions. Because the agricultural land area in the south is small compared to the total acreage of the counties, the increase in urban acreage may have less effect.

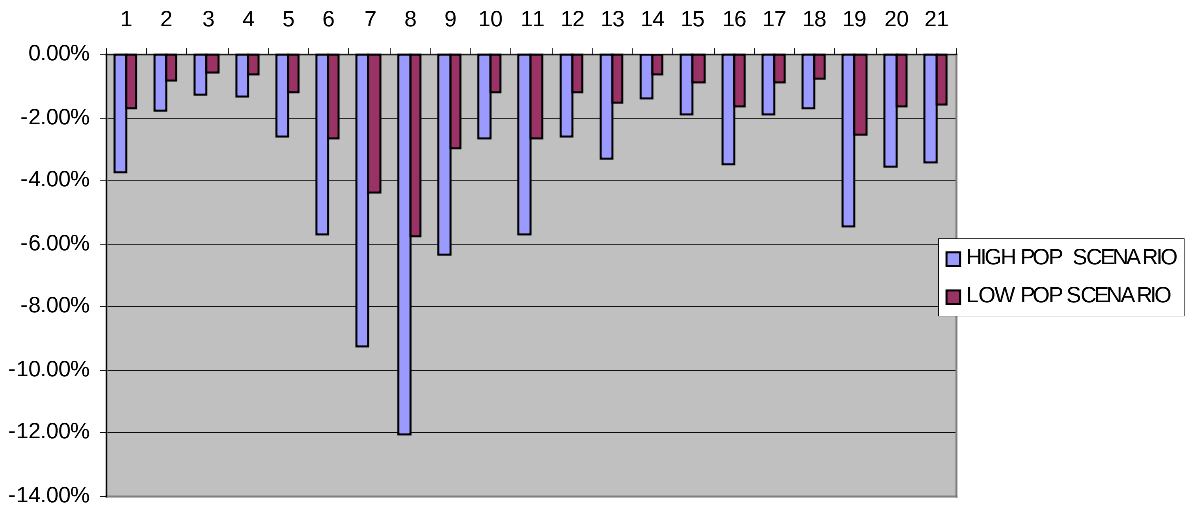


Figure 3. Decrease in agricultural land availability from 2020 to 2100 in the northern SWAP regions

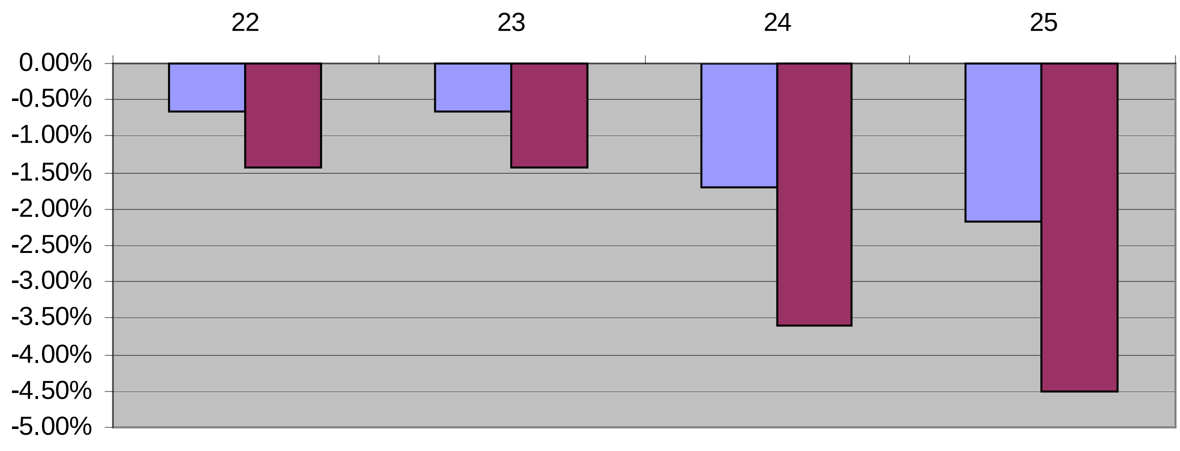


Figure 4. Decrease in agricultural land availability from 2020 to 2100 in the southern SWAP regions

4.2 Endogenous Prices and Shift in the Crop Demand Faced by California

Why is a change likely, and what are the consequences?

The prices for goods sold by farmers are assumed to remain constant for individual farms: whatever the amount of output produced by the farmer, they will allocate inputs as if the output price remained the same. However, this assumption does not hold when the analysis is performed on a regional or statewide basis. Given the importance that California crops have for national and export markets, the statewide output level will affect the price that the farmers receive. To incorporate this phenomenon, we modify the model to make statewide crop prices endogenous, using a demand function for each crop produced in California.

To briefly review the meaning of integrating endogenous prices, we mention the following basic ideas. If the amount of crop produced in California is higher than for the base year, the price that the farmers receive will go down. And if the amount of crop produced in California is lower than for the base year, the price the farmers can command will go up. The critical factor is the elasticity of demand for the crops. An inelastic demand will result in large price shifts for relatively small changes in the quantity sold, and the reverse is true for inelastic demands. California's valuable fruit, nut, and vegetable crops generally have inelastic demands.

For empirical reasons, we break the forecast horizons from 2000 into those until 2020 and then 2100. We first need to forecast the crop demands that California would face in 2020 and 2100 at current real prices. The crop demands in 2020 and in 2100 will be influenced by several heterogeneous factors. Factors such as the competition with emerging or developing countries, NAFTA agreement modification, or WTO agreements will certainly strongly influence the demand for Californian crops. We did not include these factors, however, because it would have required much additional work that might prove to be unnecessary. Indeed, given the uncertainty related to these factors and their effects, including these factors would have required several additional scenarios. Finally, taking these factors into account would have created too much "noise" in the results. In other words, the effects of factors that we are interested in (the effect of climate change) would certainly become unobservable because the shifts in demand would mask global climate effects.

To forecast these demands, we used two different techniques based on the forecast horizon:

- For the short-term forecast (2020), we used time-series analysis techniques. Basically, these techniques assume that what happened in the past indicates a plausible trend of what will happen in the future.

- For the long-term run, we used some income elasticities for commodities, which represent the change in consumption of a commodity — a crop — when the income of the average consumer is modified. Based on the forecasted income growth in the United States, we generated trends in the crop demands in 2100.

Crop demands used for 2100

Figure 5 shows that the shifts in demand are clearly important for high-value crops such as tomatoes, market crops, and truck crops. These crops see increases in demand of 100% or more for 2020 and 2100. The increase in demand for orchard crops, grapes, fruits, and nuts is also important, around 50% (or more) in 2020 and 2100. The forecasted demand is unchanged for the low-value crop, pasture, and field crop SWAP categories. The decrease in the demand is important for the cotton and grain crop categories, and also for the "grain and field" SWAP category in the southern regions.

4.3 Parameter Changes Resulting from Climate Change

The changes in precipitation and temperature resulting from climate change will obviously trigger some changes in the yields, as well as in the amount of irrigation water needed to meet crop requirements. The change of the CO_2 level in the atmosphere will also trigger changes in yields because it will produce a fertilizer effect. Therefore, two "agronomic" parameters in the SWAP model, yields and the amount of irrigation water use, were modified to integrate the climate change scenarios.

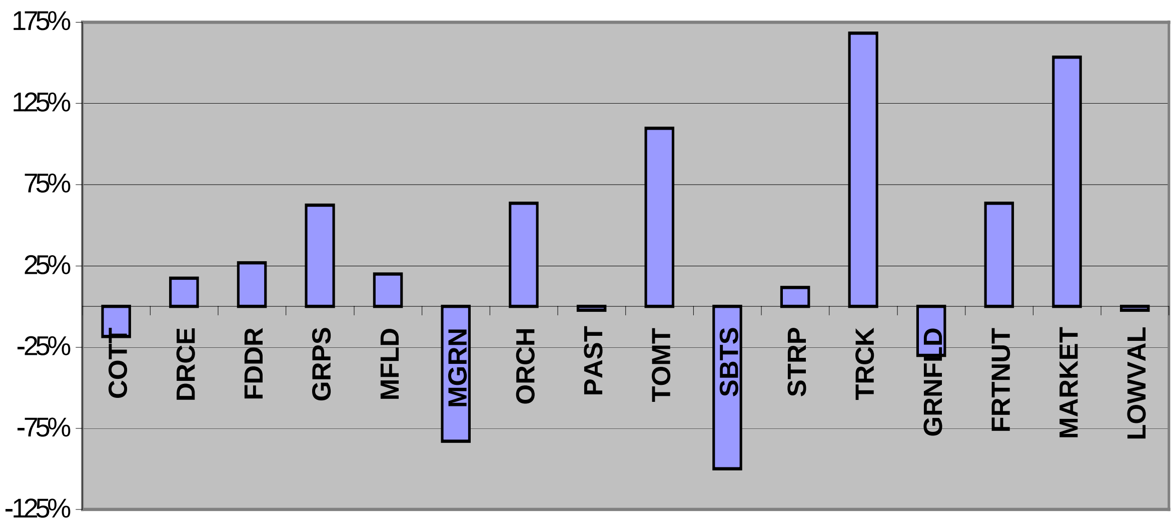


Figure 5. Shift in the crop demand in California in 2100

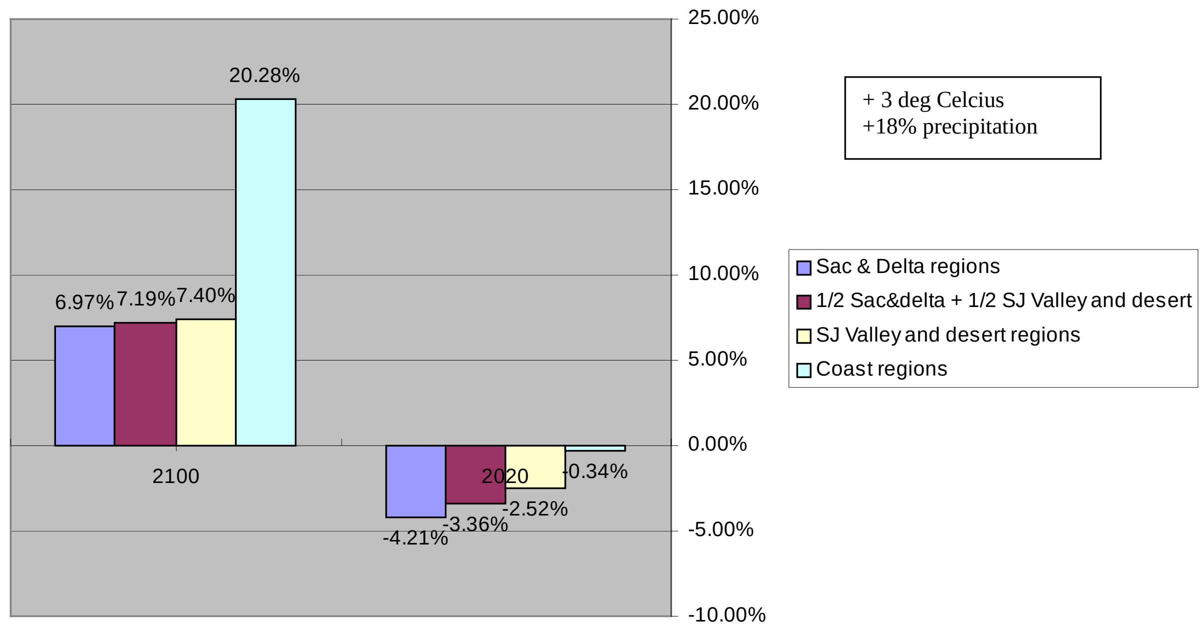


Figure 6. Percent change in water requirements in 2100 and 2020 under the +3°C, +18% precipitation scenario

Because the same climate change scenario will not produce the same consequences in all regions and for all crops, we differentiated the effects on yield and irrigation water use by region and by crop. We also took into account the forecast horizon because the importance of the climate change phenomenon will differ greatly between 2020 and 2100. Figure 6 shows this effect by plotting regional water use changes in 2020 and 2100.

It is important to note that the same climate change trend (scenario A with +3°C, +18% precipitation + an increase in the CO_2 concentration) results in opposite effects in irrigation water requirements. In comparison to the base year, the irrigation water needed by the crops decreases in 2020 and increases in 2100.

Figure 7 shows that the HadCM2 scenario water use changes represent significant increases over scenario A, especially in the Sacramento and Coastal regions.

The relationships between regional yields and the climate change and technological parameters were developed by Adams et al. and are reported in Appendix IX of this report. Scenario A was used for the set of yield changes.

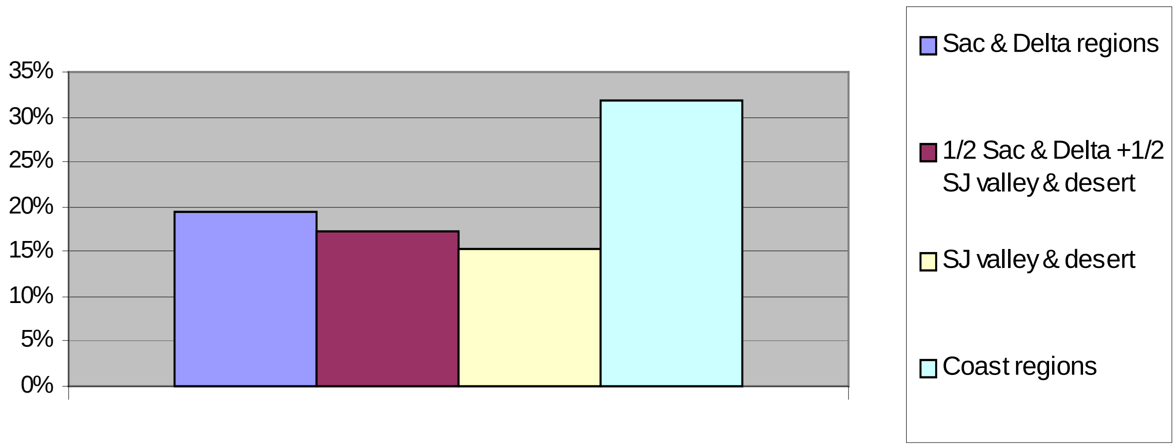


Figure 7. Percent regional changes in water requirements in 2100 under the HadCM2 scenario

The crop yields were also adjusted to account for exogenous technical change. After substantial discussion among the research team members and university agronomists, this additional yield increase was set at 0.25% per year. We purposely chose a technological effect that was smaller than the recent historical record, as the very long forecast horizon magnifies any small discrepancy in annual technological change. Assuming a larger technological change might have masked the effect of the global warming on yields and led to crop yield projections that cannot be justified under projections of current technology.

Even choosing a very low exogenous technological effect, the resulting increases in yields are extremely important. Over the horizon, the 0.25% compound technological change, coupled with the climatic effects, resulted in significant yield increases. Some upper limits for the yields, which are defined on the basis of agronomic potential and differentiated by crop categories, were used to bound the total yield increase and to more conservatively reflect the biological potentialities of the different crops.

Figure 8 presents the effect of climatic and technical change parameters on the change in yields for different crops in the northern region of the Central Valley. As we can see in the figure, yields change quite differently under different climate change and technology assumptions. The three sources of yield change are temperature and precipitation, CO_2 concentration, and exogenous technical change (which has been very conservatively set at a compound rate of 0.25% of past technical change levels).

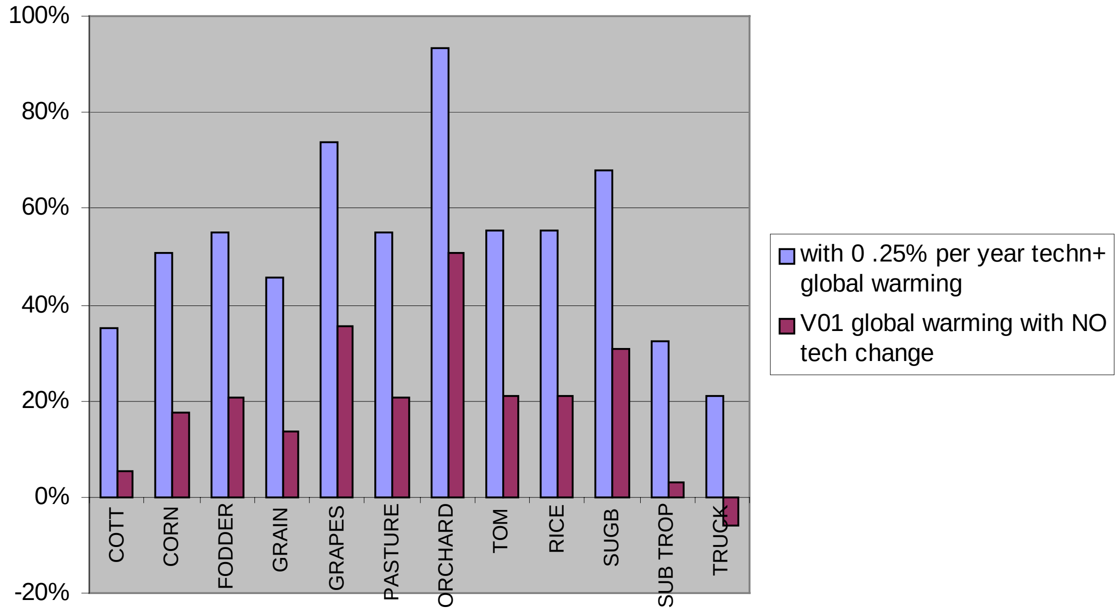


Figure 8. The basis of yield changes — northern region of the Central Valley (2000-2100)

Because of the different cultural and harvest impacts of increased temperature and precipitation on crop yields, the effect of these changes is by no means consistent in sign or magnitude across crops. A dramatic example is the different effect of climate change on the yield of orchard versus truck. Although the increased summer precipitation may help orchard production by reducing the need for supplemental irrigation, summer rains will reduce the yield of truck crops that need to be harvested in dry summer conditions. The effect of technological change is always positive.

The regional crop yield changes are introduced in the objective function by multiplying all production functions in each region by a yield increase factor. They were also integrated in the regional market cost because this is a function of the amount of each crop produced.

5. SWAP Model Results under Parameter Modifications

The results from the runs presented below are not likely to be the ultimate ones because some improvements will be seen when we have additional and more precise data on land availability and yield projections. These runs show the effect of the parameter changes on the cropping patterns and in the water demand. It allows us to calculate the sensitivity of the model to each parameter to be changed. Results for scenario A, scenario B (runs A and B), and the HadCM2 scenario can be also obtained.

Table 3 presents the runs and their characteristics in terms of parameter changes for 2100. The A, B, and HadCM2 runs differ from all the other runs by the assumption that the water right is attached to the land and sold with the land. In other words, if the agricultural land is decreased, the availability of water is decreased by the same percentage.

Table 3. Scenario definitions for SWAP runs

Name of the run/data/ solution file	Demand shift (D)	Land shift (L)	Change in yields resulting from climate change (Y)[a]	Water irrigation shift use (W)
2100_D	X			
2100_DLh	X	X (high-population scenario)		
2100_DLl	X	X (low-population scenario)		
2100_DLhY	X	X	X	
2100_DLhW	X	X		X
2100_DLhYW	X	X	X	X
RUN A	X	X (high-population scenario)	X	X
RUN B	X	X (low-population scenario)	X	X
HadCM2 run	X	X (high-population scenario)	X (HadCM2)	X (HadCM2)
PCM run	X	X (high-population scenario)	X (PCM)	X (PCM)

a. When nothing is written, Y and W are the changes in yields and water requirements result from the +3°C and +18% precipitation scenario.

6. Comments on Runs Done with the Model

6.1 Future Modifications to Improve the Results of the Model

When the shift in demand for 2020 is taken into account, it initially results in the disappearance of the grain crops — the land allocation for this crop category decreased from 10% in 2020_base year to 1% in 2020. This phenomenon appears unrealistic because, for example, some rotational constraints exist. We introduced a lower bound constraint for grain crop acreage to take phenomena such as rotational constraints into account.

Changes in land allocation in 2100

Table 4 shows that between 2020 and 2100, the specialization in high-value crops continues. Indeed, the percentage of land used by orchards, truck crops, tomatoes, and fruit and nut crops may represent nearly 70% of the agricultural land available in 2100. See Attachments A and B for detailed results by SWAP crop categories and for pie charts that present these results graphically.

Table 4. Comparison of cropping pattern between 2020 and 2100

	Water rights not sold (%)			Water rights sold (%)	
	2020 base	**2020_DLYW**	**2100_DLhYW**	**Run A[a]**	**Run B[a]**
Field, grain, and rice	27.21	14.81	10.82	10.74	11.24
High-value crop	42.03	64.52	69.37	69.43	68.61
Pasture and fodder	14.99	12.62	12.87	12.63	12.79
Cotton	14.78	7.97	6.10	5.93	6.02
Total	99.01	99.92	99.18	98.73	98.66

a. Runs A and B are the runs with all the parameters modified for the climate change scenario (+3°C, +18% precipitation).

Changes in the 2100 cropping pattern are mainly driven by the shift in the demand (compare Run 2100_D and Run 2020_base in Table 5).

Table 5. Percentage of the available agricultural land used for each type of crop and parameters changed

	Water rights not sold with the land (%)						
	2020_base	**2100_D**	**2100_DLl**	**2100_DLh**	**2100_DLhY**	**2100_DLhW**	**2100_DLhYW**
Field, grain, and rice	27.21	13.02	12.33	11.85	11.08	11.58	10.82
High-value crop	42.03	66.90	68.11	68.87	69.26	68.95	69.37
Pasture and fodder	14.99	13.56	13.52	13.42	13.34	12.91	12.87
Cotton	14.78	5.87	5.78	5.68	6.22	5.55	6.10
Total	99.01	99.36	99.75	99.82	99.89	99.00	99.18

Table 6 shows that the difference in climate change scenario (+3°C and +18% precipitation or HadCM2) does not significantly modify the trend in the cropping pattern. Nonetheless, the acreage of unused agricultural land is significantly increased in the HadCM2 scenario. This phenomenon may be explained by the fact that the water crop requirements are much higher under the HadCM2 scenario.

Table 6. Comparison between 2100 cropping pattern (% of the available acreage by crop) according to the climate change scenario

	Water rights sold	
	Run A	**HadCM2**
Field, grain, and rice	10.74	11.22
High-value crop	69.43	67.87
Pasture and fodder	12.63	12.76
Cotton	5.93	5.10
Total	98.73	96.95

We estimate the effects of different parameter changes in 2100 by running the model several times and integrating gradual changes. This test of sensitivity was done under the +3°C, +18% precipitation scenario.

The marginal value of water is increased by the changes in yield resulting from climate change and technological change because most of the yields are increased by the integration of these two types of change.

The addition of the changes in irrigation water requirements resulting from the climate change effect increases the shadow value of water in 2100, because the crops will need more applied water under the 2100 +3°C, +18% precipitation scenario.

Even though the choice of climate change scenario does not have a strong effect on the cropping pattern in terms of acreage, it does trigger significant changes in the 2100 water demand as shown in Figure 9. We can explain this phenomenon by the fact that the changes in terms of yields and water requirements differ greatly between the different climate change scenarios. These differences in parameters appear to have little influence on the cropping pattern, but they do have a significant effect on the shadow value and water demand curve. This effect seems to take place because the choice of the climate change scenario does not greatly change the distribution of crop profitability, but it does alter the absolute value of the net return from each crop.

Figure 10 shows that for the 2100 runs, the shadow value of water is clearly higher under the HadCM2 scenario than under Run A for low water availability. Under high water availability, we see the opposite effect. Figures 10 and 11 show that the marginal value curves under the HadCM2 scenario and under Run A, the curves switch between high and low water supplies.

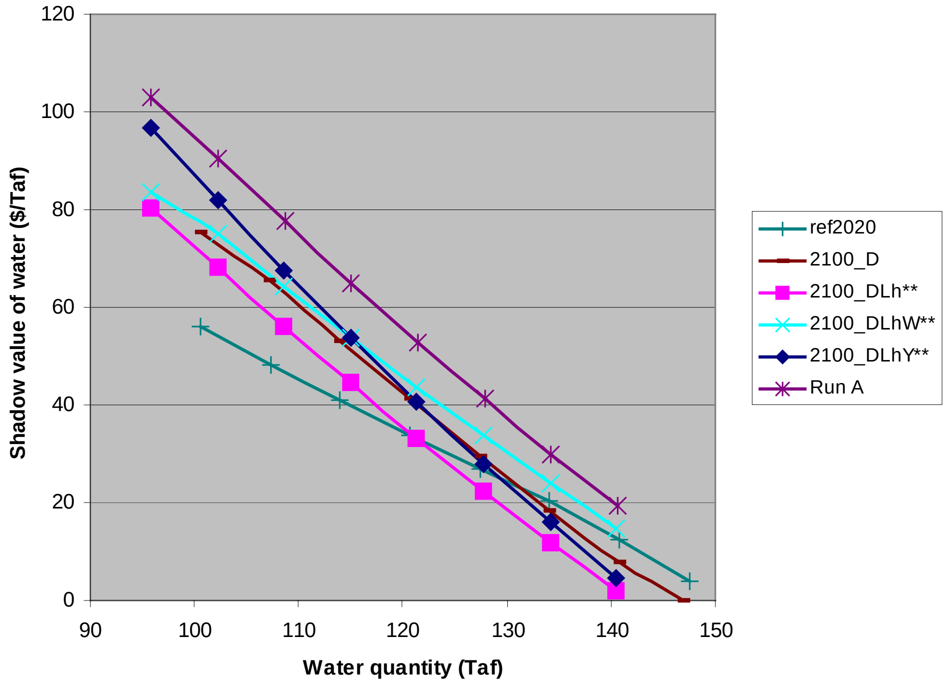


Figure 9. Change in shadow value resulting from gradual changes in parameters in 2100, under the +3°C, +18% precipitation scenario

Note: ** means that the water was sold with the land when the land availability decreased.

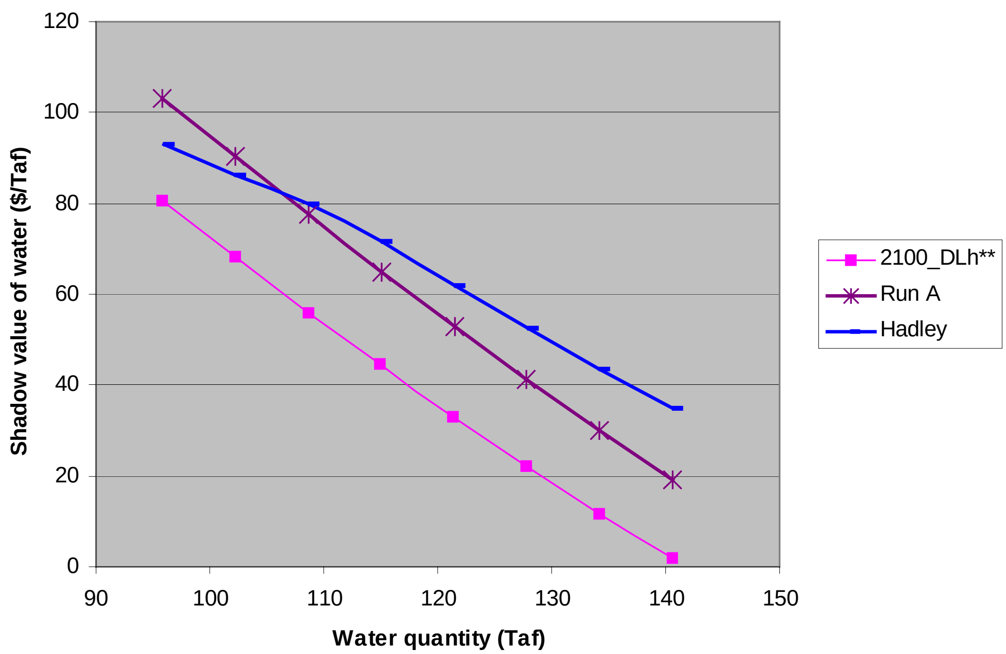


Figure 10. **Agricultural water demand in Region 1 under several climate change scenarios**

Note: ** means that the water was sold with the land when the land availability decreased.

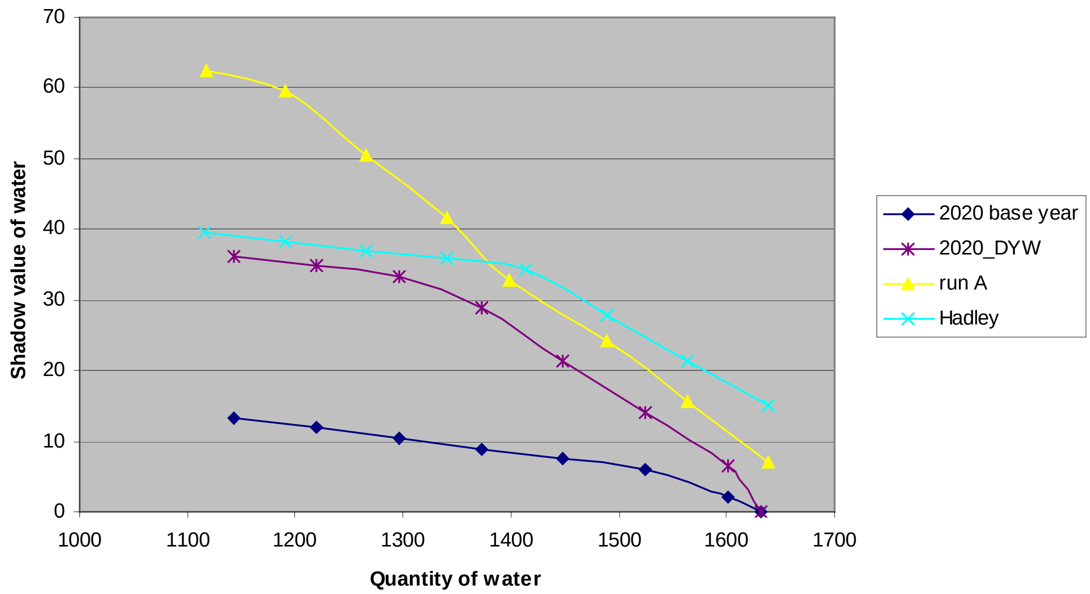


Figure 11. Comparison of water demand in Region 3 under different scenarios

Figure 12 compares the shadow value of water resulting from the climate change scenarios in 2020 and in 2100. Under the same climate change scenario (+3°C, +18% precipitation), the shadow value of water in 2100 is not always higher than the value in 2020. The assumption about whether the water right is also sold when the land is sold for another use results in an increase of the shadow value because water has become more scarce (see, for example, the third row in Table 7). This increase in the shadow values shown in Table 7 is quite significant. The shadow value differs by $11.3/TAF between the 2100_DLhYW run and Run A. The only difference in the run specification is that water is assumed sold along with urbanized land.

The shift in the demand curve is extremely important for Region 25 (San Diego). In the "complete" run (that has changes in demand, land, yield, and water requirements), the shadow value of water can reach $1,750/TAF with a decrease of 25% in water availability. In comparison, for the other regions, the shadow value of water for a 25% decrease in water availability varies from $23 to $600/TAF.

This may be explained by the fact that the increase in water requirements resulting from climate change in 2100 is much more important for the coastal region (San Diego) than for other SWAP regions. Another reason could be that the fruits and nuts category, for which the shift in demand is important, is the almost unique production of this region. Finally, the increase in yields might be more important for this region than for the others.

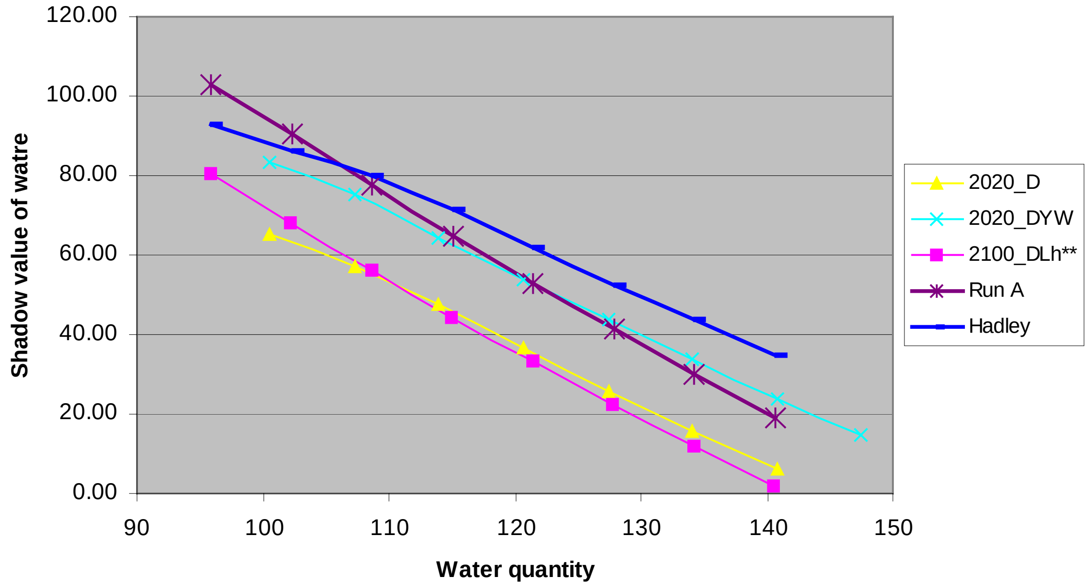


Figure 12. Changes from climate change effects in Region 1, comparison between 2020 and 2100

Note: ** means that the water was sold with the land when the land availability decreased.

Table 7. Data for water demand curves

Change in supply	Water quantity (TAF)	Shadow value water, base_ 2020 ($/TAF)	Water quantity (TAF)	Shadow value for water, 2100_DlhYW ($/TAF)	Water quantity (TAF)	Shadow value for water, Run A ($/TAF)
+10%	147.5	4.1	147.6	8.2	140.6	19.2
+5%	140.8	12.6	140.9	18.8	134.2	29.9
Reference	134.1	20.5	134.2	29.9	127.8	41.2
-5%	127.4	26.9	127.4	41.5	121.4	52.9
-10%	120.7	33.8	120.7	53.7	115.1	64.9
-15%	114.0	40.9	114.0	66.3	108.7	77.6
-20%	107.3	48.3	107.3	79.7	102.3	90.5
-25%	100.6	56.0	100.6	93.6	95.9	103.0

Water demand curves by month in 2100

We assume that the water supply can be reallocated between months during any irrigation season, so the opportunity cost of water will be the same for all months.

When we know the quantity of water used each month by a crop and the cropping pattern chosen when a given quantity of water is available, we can derive the monthly plant water demand functions shown in Figure 13 for Region 1.

Note that we have used the same distribution of plant water requirements across months for the reference year and for 2100 despite the climate change effect. This distribution may be different across the year because the distribution of precipitation across the year will certainly be affected by the climate change. However, because no reliable data about this change in distribution were available, we decided to keep the actual distribution of plant water requirements at this point.

As expected, the willingness to pay for a given quantity of water is higher during the summer months than during the winter months.

Figure 14 shows the monthly demand for July across different regions. We see that the differences are important, especially between the northern and southern regions.

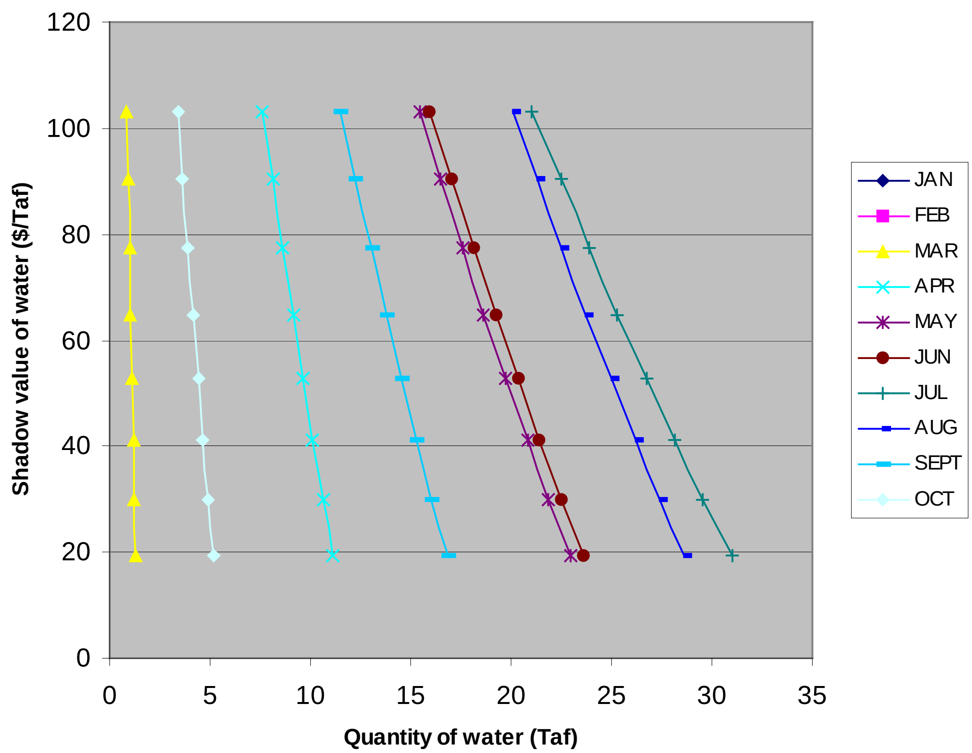


Figure 13. Monthly water demand curves for Region 1, Run A

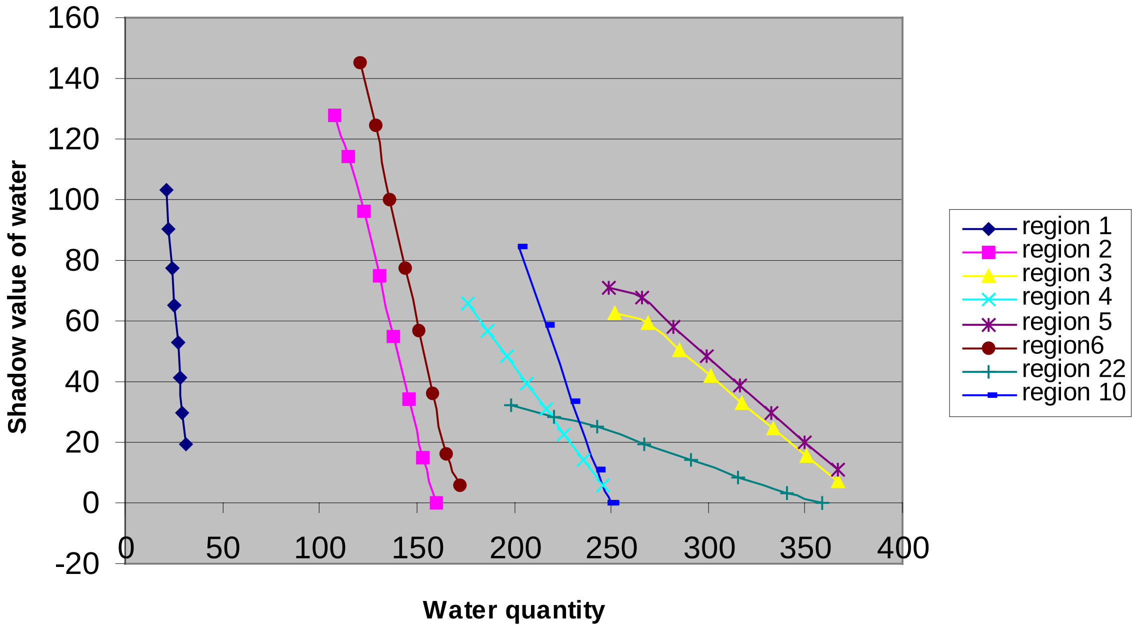


Figure 14. Agricultural water demand curves for July, for several regions, Run A

7. Postprocessing Results

The demand functions derived above were used in the CALVIN model to optimize the water allocations for the 2100 scenario without climate change, but with a statewide water market (SWM). The resulting base run for 2100 is termed the SWM run. To study the impact of climate change on the California agricultural sector, the HadCM2 model and the PCM model of global climate change were used to model optimal water allocations under climate change. The postprocessing results described in this section examine the impact of the CALVIN optimal water allocations on California's agricultural sector: the annual regional water allocations generated by CALVIN for a 72-year hydrologic record are used as constraints on annual solutions to the SWAP model. By averaging over the 72 years and calculating the variability of the effects on agricultural production, we can compare the incremental effects of the HadCM2 and PCM climate change models on the production, profitability, cropping patterns, and water use of California's agricultural sector. We present a brief overview of each model before detailing the results generated by these models.

7.1 The SWAP Model

This model is used to estimate the response of agricultural producers in different regions of California to changes in annual water allocations. SWAP allows water to be transferred among different months so that the marginal value of water by month and crop is equated.

We have incorporated climate change into the SWAP model by modifying two of its agronomic parameters: crop yields and the amount of irrigation water used. SWAP recognizes that any given climate change scenario will not have the same impacts across regions and crops. Accordingly, the effects of climate change on crop yields and irrigation water use are differentiated by region and by crop. In the base SWM run, regional water use changes are projected for 2100.

We used the results from the CALVIN model (see Section 7.2) in the SWAP model to estimate how regional demands for water change under various water supply conditions brought about by climate change. Specifically, the CALVIN model uses monthly estimates of the economic valuation of water for 25 regions of SWAP to determine the statewide allocation of water across 72 years of variable hydrology. Through this process, CALVIN models statewide allocations of water based on welfare considerations.

CALVIN generates three water allocation scenarios — the base SWM allocations and those that are optimal under the HadCM2 and PCM scenarios. These allocations are then put into SWAP to determine agricultural production responses to climate change, such as changes in gross revenues and irrigated crop acreage. Next, this information is used to determine the region-wide economic impacts from changed water availability.

7.2 The CALVIN Model

CALVIN evaluates the potential impact of climate change on California, both with and without population growth and adaptation. Although CALVIN models a range of climate warming scenarios, this appendix focuses on three: the 2100 SWM (SWM 2100); the PCM climate change scenario with optimal allocation (PCM 2100); and the 2100 HadCM2 climate change scenario with optimal allocation (HCM 2100). All three scenarios assume flexible and economically driven water operation and allocation policies. PCM 2100 assumes a dry climate warming hydrology, and HCM 2100 assumes a wet climate warming hydrology (see Table 8).

We used these three scenarios to project water demand in 2100 as a result of climate warming. The nonclimate impacts on water demand include population changes, changes in urban water demands, changes in land use, changes in wealth, technology improvements that increase crop

Table 8. Specifics of HCM 2080-2099 and PCM 2080-2099

Raw water availability estimates and changes (without operational adaptation, in MAF/year)

	Volume (MAF)	Change (MAF)	Change (%)
HCM	42.2	4.6	12.1
PCM	28.5	-9.4	-24.8
Historical	37.8	-	-

Overall rim inflow quantities and changes

	Annual		October-March		April-September	
	Quantity (MAF)	Change (%)	Quantity (MAF)	Change (%)	Quantity (MAF)	Change (%)
HCM	49.8	76.5	33.3	134.4	16.6	18.1
PCM	21.1	-25.5	12.2	-14.2	8.9	-36.9
Historical	28.2	-	14.2	-	14.0	-

Local surface water accretion quantities and changes

	Annual		October-March		April-September	
	Quantity (MAF)	Change (%)	Quantity (MAF)	Change (%)	Quantity (MAF)	Change (%)
HCM	11.41	158.1	9.72	174.3	1.69	92.8
PCM	3.17	-28.2	2.36	-33.2	0.81	-7.8
Historical	4.42	-	3.54	-	0.88	-

Groundwater inflow quantities and changes

	Annual		October-March		April-September	
	Quantity (MAF)	Change (%)	Quantity (MAF)	Change (%)	Quantity (MAF)	Change (%)
HCM	8.37	23.5	5.08	41.1	3.29	3.5
PCM	6.21	-8.5	3.08	-14.5	3.12	-1.7
Historical	6.78	-	3.60	-	3.18	-

Surface reservoir evaporation quantities and changes

	Annual		October-March		April-September	
	Quantity (MAF)	Change (%)	Quantity (MAF)	Change (%)	Quantity (MAF)	Change (%)
HCM	1.98	21.7	0.52	40.7	1.46	16.2
PCM	1.98	21.6	0.55	49.9	1.43	13.4
Historical	1.62	-	0.37	-	1.26	-

Overall water quantities and changes

	Annual		October-March		April-September	
	Quantity (MAF)	Change (%)	Quantity (MAF)	Change (%)	Quantity (MAF)	Change (%)
HCM	67.6	78.9	47.5	126.6	20.1	19.3
PCM	28.5	-24.8	17.1	-18.6	11.4	-32.5
Historical	37.8	-	21.0	-	16.8	-

Source: “Climate Warming and California’s Water Future,” Lund et al., Appendix VII.

yields, more efficient water use technologies, improved water treatment technologies, changes in world agricultural commodity and land markets, and changes in water demands in California.

Method

SWM 2100, PCM 2100, and HCM 2100 yielded three optimal water allocations for California's agricultural sector. To measure the effect of climate change on the agricultural sector, we first analyzed the net effects on the agricultural sector from changes in the resource base and crop agronomy for the 2100 extrapolation. Second, we compared the optimal water allocations from the PCM 2100 and HCM 2100 climate change scenarios to the optimal water allocation that was calculated using SWAP (2100 State Water Project [SWP]). These two comparisons gave a direct measure of the effect of climate change in 2100 by separating the effects of climate change from extrapolations of the driving variables.

Effects of the economic and agronomic shifts from 2020 to 2100

Because water supplies are variable in time and space, climate change is expected to alter the timing, spatial distribution, and variability of water supplies. Figures 15a and 15b show that water allocations to both the Sacramento Valley regional group and the San Joaquin Valley regional group should fall in response to climate change. Figure 15a plots the difference in SWM 2100 and CALVIN 2020 base year water allocations for the Sacramento Valley. It shows the differences in mean water allocations and the standard deviation of water supply for the 72 years that were simulated by CALVIN. We can see clearly in Figure 15a that the annual reductions in water supply to the Sacramento Valley vary significantly over this time period. Figure 15b shows that the average reduction in water use in the San Joaquin Valley is greater than in the Sacramento Valley, but the variability of water use is less. Also, the standard deviation of water usage in the San Joaquin Valley is similar to the standard deviation of water use in the Sacramento Valley, despite larger average losses.

7.3 Extrapolating Economic Impacts from 2020 to 2100

Figure 16 depicts the economic impacts of reduced water allocations, focusing on water use, irrigated land, the gross value of production, net income from crops, and expenditures on agricultural inputs. These measures are based on the annual regional water allocations for SWM 2100. The figure shows the percent difference between SWM 2100 and CALVIN 2020 estimates of the five economic measures. Each measure is averaged across the 72 years of data for both the Sacramento and San Joaquin valleys. There is an alternative means of obtaining the data presented in Figure 16 — the economic impacts of changes in expected water deliveries could be measured directly. However, Jensen's inequality theorem proves that this approach would underestimate the economic impacts of reduced water deliveries. Essentially, Jensen's inequality

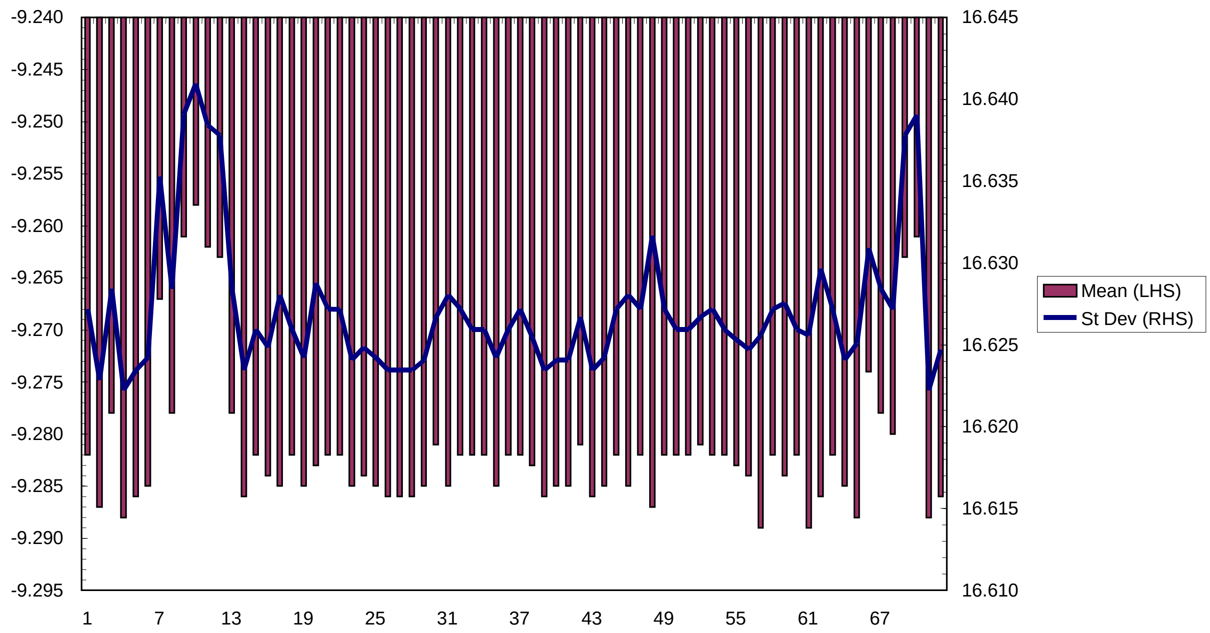


Figure 15a. Changes in water usage, Sacramento Valley

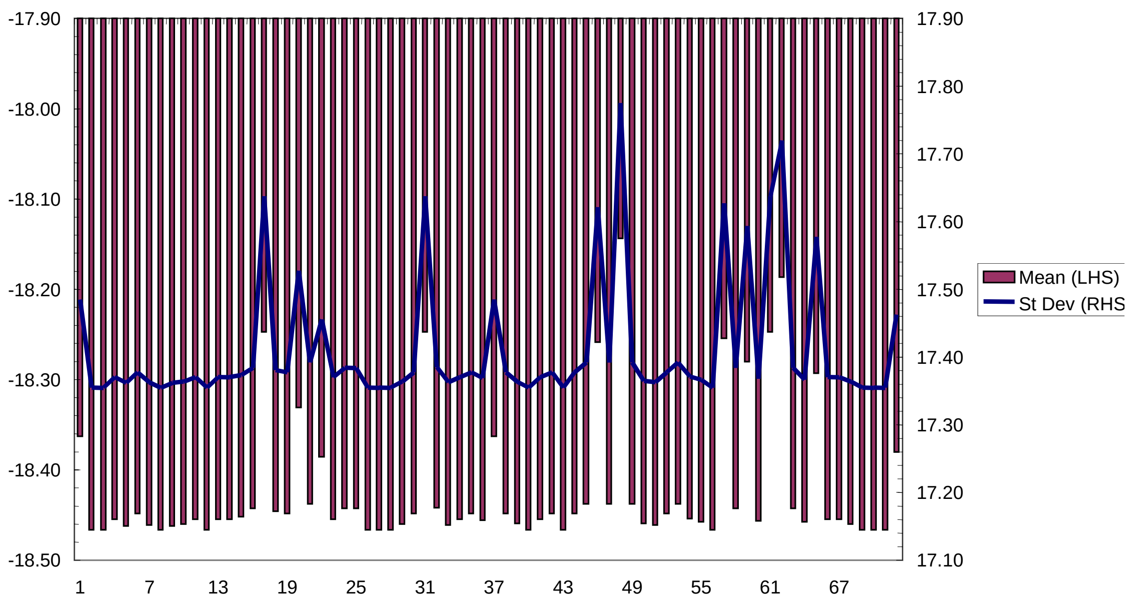


Figure 15b. Changes in water usage, San Joaquin Valley

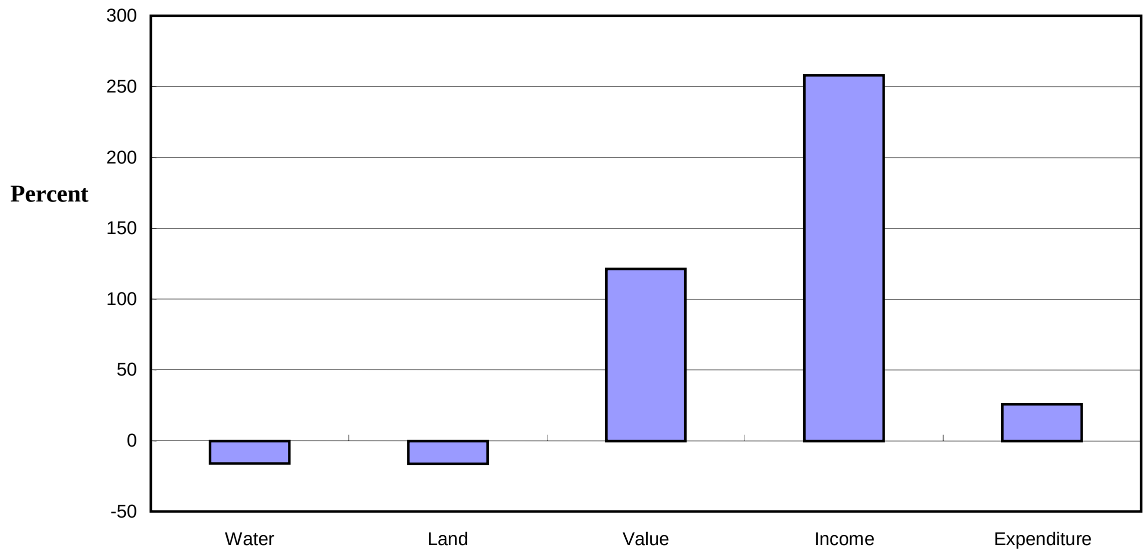


Figure 16. Regional average, 2020

theorem proves that, for nonlinear response functions of stochastic variables, the expected value (average) of the function must be calculated individually for each of the realized values. If we simply calculate the expected value of the water inflow and use it in the value function, it will underestimate the average cost of shortfalls in water supply. This is intuitive when we consider that the benefits of excess water in high flow years do not compensate for the very high costs of shortages in dry and drought years.

Figure 16 illustrates that the gross value of production, net income from crops, and expenditures on agricultural inputs will continue to increase even when water allocations are reduced. However, the quantities of land and water used in irrigated crop production will be slightly lower. The large increase in expected net income should be interpreted cautiously. This measure of expected profits is based on the assumption that crop production in California will remain relatively competitive in the future.

Given the excessively long projection period of 100 years, it would take only a small shift in relative market growth to greatly reduce the predicted profit growth of 251%, which is based on a predicted increase of 121% in output value. Even with this caveat, it seems fairly certain that the relative position of California's crop production should improve in terms of output, profit, and employment over the mid term. Although this is currently an unfashionable prediction, and is subject to substantial error, it is based on parameter values that are consistent with the data and with conservative projections.

Figure 17 summarizes the regional differences for water, land, and net income. We can see that changes in water, land, and net income differ widely across different regions. All regions, except Palo Verde, record an increase in net income over the CALVIN 2020 base case. Note that the water allocations from CALVIN are the outcome of efficient market and spatial allocation for all three scenarios considered. In all three scenarios, the optimization inherent in CALVIN directs the Palo Verde region to sell all its water. Accordingly, this region is omitted from all the comparisons between the scenarios. For all other regions, net income increases despite small reductions in the supplies of irrigated land and water in some regions.

The growth in net income ranges between 100% and 500% over the 100-year time period, which corresponds to a 0.7% to 1.6% annual growth rate in net income. These numbers demonstrate that very conservative growth rates in net income may compound into large differences over a 100-year period. Figure 17 also demonstrates that smaller increases in net income are associated with regions that have larger reductions in land and water availability. The economic extrapolations to 2100 show a wide range of variability. The mean percent increase in income over 100 years is 257%. However, there is a standard deviation of 140.4%, showing that the range of income change has to be extended from 100% to 400% to capture 68% of the observations.

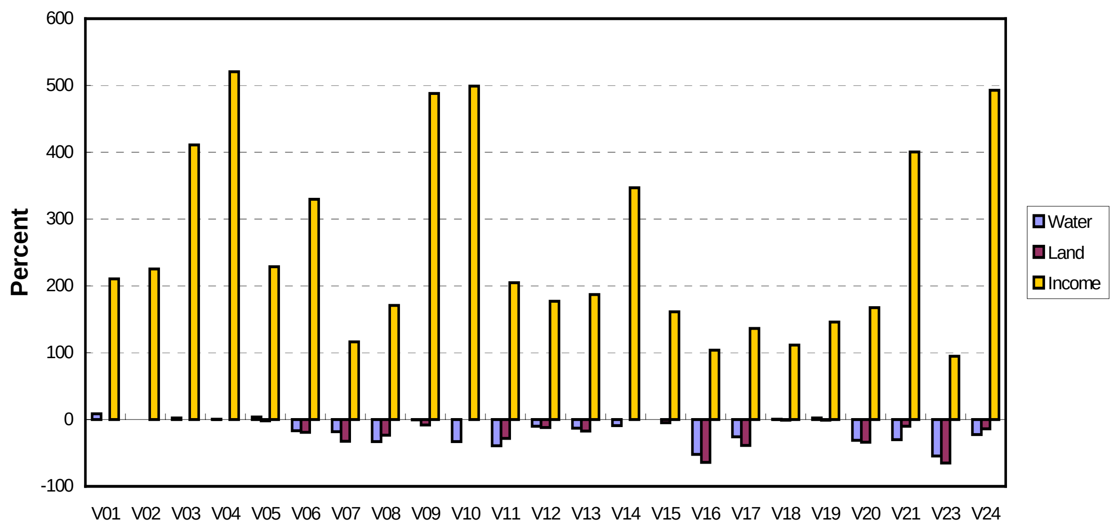


Figure 17. Regional changes, 2020-2100

7.4 A Comparison Between the HadCM2 and SWM Scenarios

In aggregate, very slight differences are seen between the economic measures generated by the HadCM2 and SWM scenarios. However, some regions differ in their water usage. Figures 18a and 18b plot the differences in regional water usage by the main agricultural regions of the Sacramento and San Joaquin valleys (see Table 9 for identification of these regions). The stacked columns show that the V05 and V08 regions in the Sacramento Valley absorb most of the fluctuations between the SWM and HadCM2 scenarios. Despite these fluctuations in water usage, the aggregate economic measures from the HadCM2 scenario do not differ significantly from the figures generated by the SWM scenario. For this reason, the results are not worth presenting in detail.

Essentially, the HadCM2 scenario suggests that changes in water supply will not impose significant costs on California's irrigated crop sector. Minor changes in regional water supply do not translate into notable differences in any of the economic measures of output value, net income, or input expenditures. However, the water supply reductions in the PCM scenario are dramatically different from the HadCM2 and SWM scenarios. Accordingly, we will now focus on the comparison between the PCM and SWM scenarios.

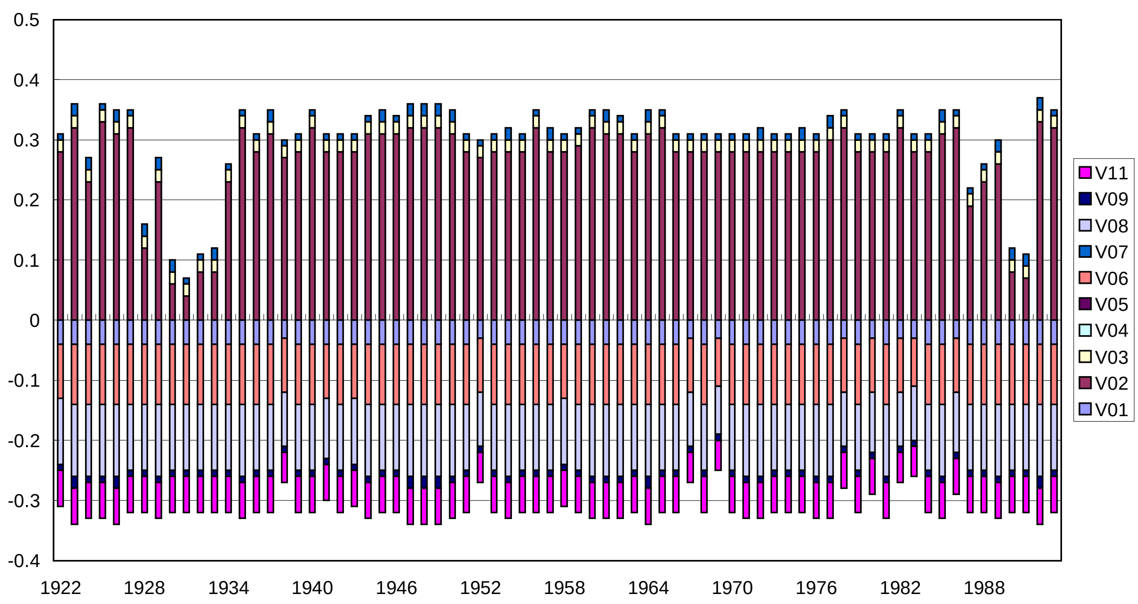


Figure 18a. Changes in water usage, Sacramento Valley

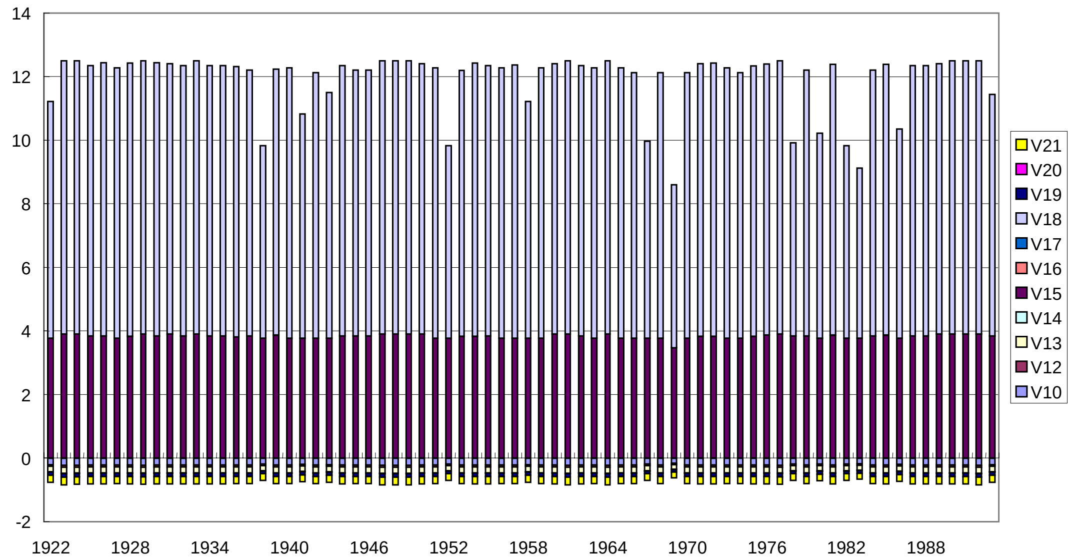


Figure 18b. Changes in water usage, San Joaquin Valley

Table 9. Regions included in Sacramento and San Joaquin valleys

	Sacramento Valley
Central Valley Production Model (CVPM)	**Description**
1	CVP users: Anderson Cottonwood, Clear Creek, Bella Vista, Sacramento River miscellaneous users
2	CVP users: Corning Canal, Kirkwood, Tehama, Sacramento River miscellaneous users
3	CVP users: Glenn Colusa Irrigation District (ID), Provident, Princeton-Cordora, Maxwell, Colusa Basin Drain Municipal Water Company (MWC), Orland-Artois Water District (WD), Colusa County, Davis, Dunnigan, Glide, Kanawha, La Grande, Westside WD, and Tehama Colusa Canal Service Area
4	CVP users: Princeton-Cordora-Glenn, Colusa Irrigation Co., Meridian Farm Water Company (WC), Pelger Mutual WC, Reclamation Districts 1004 and 108, Roberts Ditch, Sartain Municipal District, Sutter MWC, Swinford Tract IC, Tisdale Irrigation, Sacramento River miscellaneous users
5	Most Feather River riparian and appropriative users
6	Yolo and Solano Counties, CVP users: Conaway Ranch, and Sacramento River miscellaneous users
7	Sacramento Company north of the American River, CVP users: Natomas Central MWC, Pleasant Grove-Verona, San Juan Suburban, Sacramento River miscellaneous users
8	Sacramento County south of the American River, San Joaquin Company
9	Delta regions. CVP users: Banta Carbona, West Side, Plainview
11	Stanislaus River water rights: Modesto ID, Oakdale ID, South San Joaquin ID

Table 9. Regions included in Sacramento and San Joaquin valleys (cont.)

San Joaquin Valley	
CVPM/SWAP region	**Description**
10	Delta Mendota Canal. CVP users
12	Turlock ID
13	Merced ID, CVP users: Madera, Chowchilla, Gravley Ford
14	CVP users: Westlands WD
15	Tulare Lake Bed. CVP users: Fresno Slough, James, Tranquility, Traction Ranch, Laguna, Reclamation District 1606
16	Eastern Fresno Company, CVP users: Friant-Kern Canal, Fresno ID, Garfield, International
17	CVP users: Friant-Kern Canal, Hills Valley, Tri-Valley Orange Grove
18	CVP users: Friant-Kern Canal, County of Fresno, Lower Tule River ID, Pixley ID
19	Kern Co. SWP service area
20	CVP users: Friant-Kern Canal, Shafter-Wasco, South San Joaquin.
21	CVP Users: Cross Valley Canal, Friant-Kern Canal, Arvin Edison

Source: U.S. Bureau of Reclamation, 1997. Central Valley Improvement Act, Draft Programmatic EIS, Technical Appendix Volume 8, Sacramento, CA.

7.5 A Comparison Between the PCM and SWM Scenarios

Figure 19 plots the percent difference between the PCM and SWM scenarios for the three key measures of sectoral viability: the percent difference in water used, irrigated land acres, and net income from the crop sector. In contrast to the SWM scenario, the PCM scenario predicts large reductions in water, land, and net income in the Sacramento Valley regions. Regions V15 and V18 in the San Joaquin Valley also record decreases in land and water in excess of 20%. However, unlike the Sacramento Valley, these resource reductions translate into only negligible losses in net income. The values in Figure 19 are average changes over the 72 simulated years. The very large average reductions in income in regions V03, V05, and V07 are 39%, 46%, and 28%, respectively. These average income reductions will translate into substantially larger losses during drought periods.

Figures 20 and 21 show the variability of income under the PCM scenario for two regions in different parts of California. Figure 20 plots the income changes for the Westlands WD over 72 years. The fluctuations are not particularly significant, ranging between plus and minus 2%. Figure 21 plots the distribution of income change for Region V03 in the Sacramento Valley. It shows a very large negative tail to the distribution of income changes.

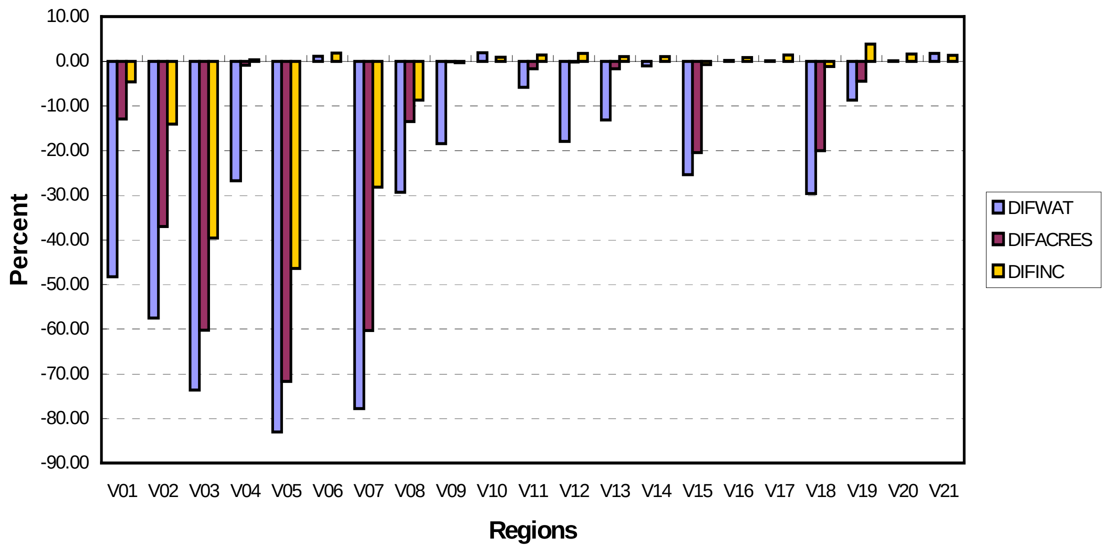


Figure 19. Comparison between the PCM and SWM scenarios

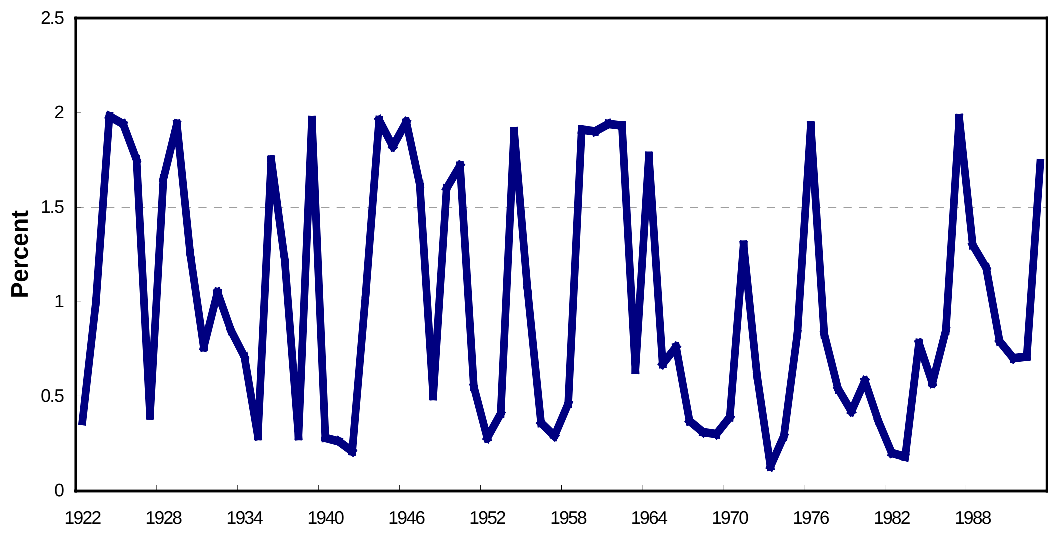


Figure 20. Annual income changes: SWM, PCM, Westlands WD

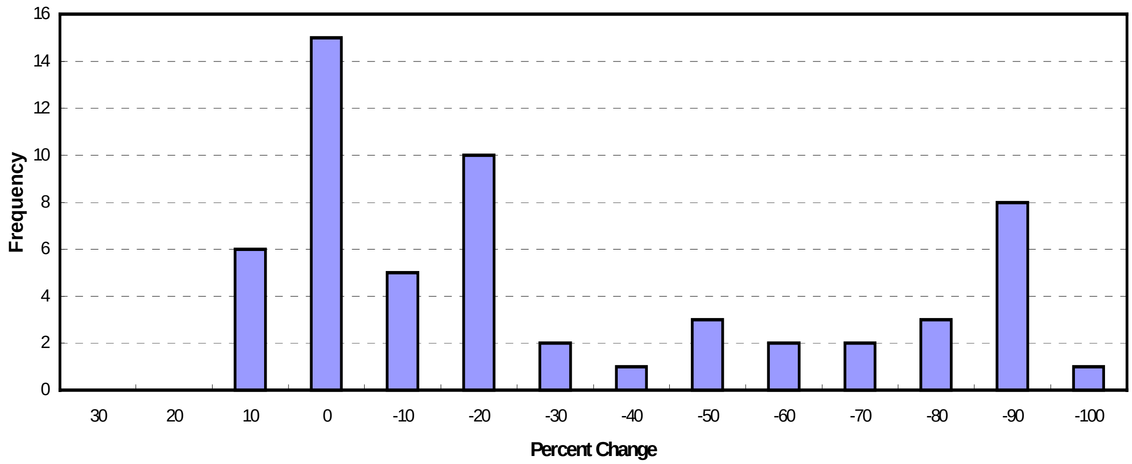


Figure 21. Percent income changes: PCM, Region VO3

In most cases the PCM income values are substantially below the SWM income values, with many years having income values at least 50% below those obtained from the SWM. The average reduction in income is 39.6% with a standard deviation of 36.8%. Clearly, sequences of drought years such as the late 1920s and early 1930s — coupled with the PCM climate change — are sufficient to significantly damage the capital structure of irrigated agriculture in the susceptible regions of the Sacramento Valley.

Figure 22 shows the percent deviation of the PCM scenario from the SWM basis, aggregated over all the regions. Essentially, the message is one of adjustment to resource reduction. The four left-hand histograms depict a systematic adjustment to water reductions by producers of irrigated crops. The aggregate reduction in water supply under PCM is 24.3%. However, because of changes in crops and the adoption of more efficient irrigation practices, the consequent reduction in irrigated land area is only 14.5%. These cuts in crop production are concentrated in the lower valued crops, translating into an 8.3% reduction in the gross value of production. The final reduction in net income of 6% is due in part to changes in crop prices, which slightly offset the reduction in irrigated acres. The average reduction in expenditures by irrigated agriculture is 16.2%. Thus, although some regions will experience significant reductions in water supply and production profitability, the average overall economic impact under the PCM scenario is manageable. This relatively small average effect should not mask the wide range of regional and temporal impacts shown in Figure 19. In short, although the average statewide impacts of reduced water availability are manageable for the PCM climate change scenario, the combined CALVIN and SWAP models predict severe local regional problems during dry periods. We do not observe these problems under the substantially wetter HadCM2 climate change scenario.

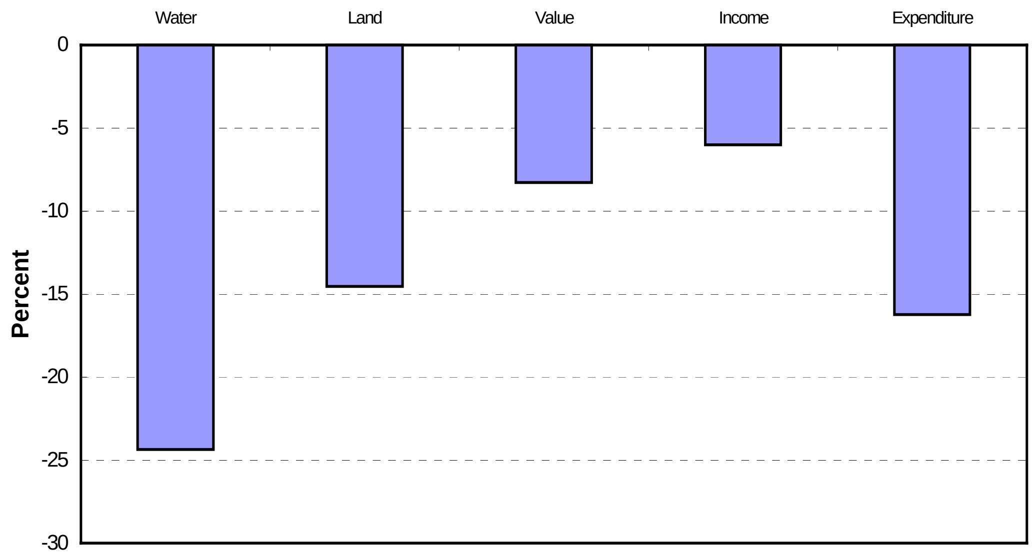


Figure 22. Average PCM effect

7.6 Summary

Any prediction over this length of time horizon is likely to be wrong. The question is not whether the predicted agricultural production in California in 2100 is accurate. Instead, the question is whether the predictions are useful in analyzing the effects of global climate change on the state's water resources and their productivity. To do this with the available data, we have modified the agronomic, economic, land use, and hydrological parameters of the SWAP model to enable us to extrapolate the regional demands for water in 2100. Within the limits of this appendix, we have attempted to present the data we used, and more importantly, the assumptions we made about the main driving forces behind the ever-changing state of agricultural water demands in the state. This will enable readers to judge the likely effects of changes in the assumptions made or the data used on the final demands for agricultural water in the future.

To summarize the results, the HadCM2 climate change scenario does not show any significant water supply effects for irrigated crop production in California. In contrast, the PCM scenario shows severe cuts in water supply for selected dry periods and regions. The statewide average across regions shows that despite a 24% cut in water supply, the irrigated crop industry has the incentives and capacity to adjust at several margins and reduce this 24% cut in part of the resource base to a 6% reduction in average profit. These comforting average values should not disguise the very harsh and disruptive effects that the PCM scenario will have on irrigated crop production in certain local regions during the dry periods that are bound to occur regularly in California.

Appendix X — Attachment A

Change in Cropping Pattern by Crop for 2100 Runs

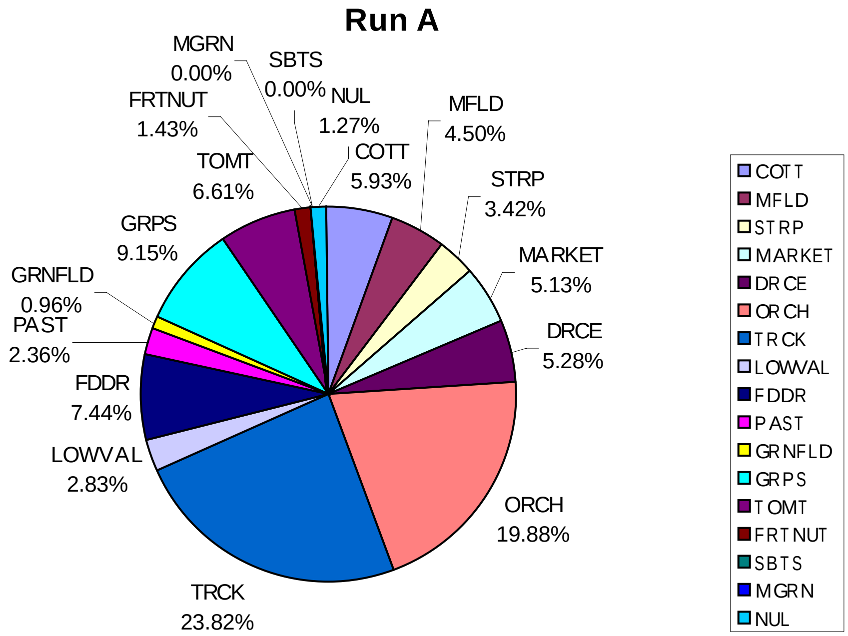
Run name	2020_base (%)	2100 DLhYW (%)	Run A (%)	Run B (%)	HadCM2 (%)
COTT	14.78	6.10	5.93	6.02	5.10
MFLD	10.03	4.41	4.50	4.87	5.65
STRP	3.29	3.41	3.42	3.38	3.04
MARKET	3.23	5.13	5.13	5.04	5.00
DRCE	6.44	5.48	5.28	5.40	4.45
ORCH	15.06	19.87	19.88	19.65	19.81
TRCK	7.15	23.79	23.82	23.55	23.47
LOWVAL	3.22	2.84	2.83	2.83	2.80
FDDR	6.94	7.66	7.44	7.51	7.40
PAST	4.83	2.38	2.36	2.44	2.57
GRNFLD	1.72	0.94	0.96	0.98	1.12
GRPS	7.21	9.14	9.15	9.05	8.95
TOMT	4.76	6.60	6.61	6.53	6.20
FRTNUT	1.35	1.44	1.43	1.42	1.39
SBTS	1.18				
MGRN	7.84				
NUL	0.99	0.82	1.27	1.34	3.05
Total	99.01	99.18	98.73	98.66	96.95

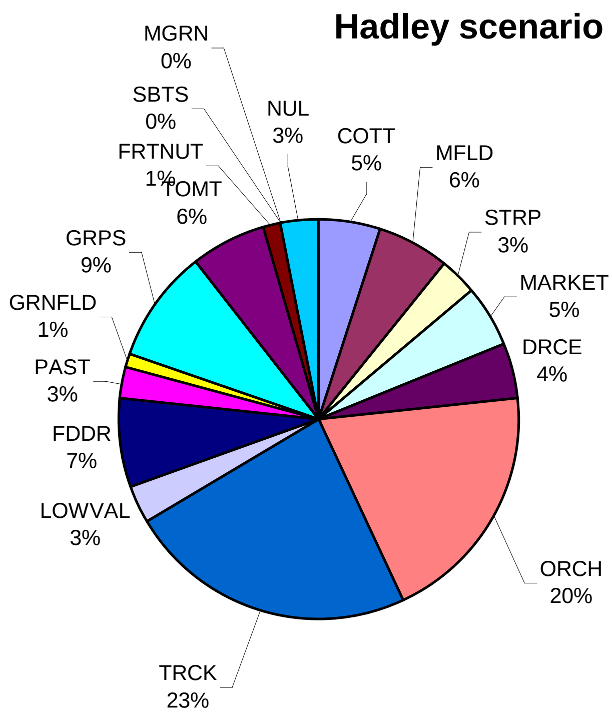
Run name	2020 base (%)	2100 D (%)	2100 DLl (%)	2100 DLh (%)	2100 DlhY (%)	2100 DlhYsT (%)	2100 DLhW (%)	2100 DlhYW (%)
COTT	14.78	5.87	5.78	5.68	6.22	6.22	5.55	6.10
MFLD	10.03	6.42	5.91	5.52	4.28	4.28	5.50	4.41
STRP	3.29	3.32	3.38	3.42	3.40	3.40	3.42	3.41
MARKET	3.23	4.79	4.91	4.99	5.12	5.12	4.99	5.13
DRCE	6.44	5.52	5.35	5.27	5.92	5.92	4.98	5.48
ORCH	15.06	18.39	18.71	18.91	19.83	19.83	18.94	19.87
TRCK	7.15	23.90	24.32	24.59	23.75	23.75	24.62	23.79
LOWVAL	3.22	2.90	2.87	2.86	2.91	2.91	2.81	2.84
FDDR	6.94	7.92	7.97	7.96	8.03	8.03	7.54	7.66
PAST	4.83	2.73	2.68	2.59	2.39	2.39	2.56	2.38
GRNFLD	1.72	1.09	1.07	1.06	0.87	0.87	1.10	0.94
GRPS	7.21	8.80	8.96	9.07	9.13	9.13	9.08	9.14
TOMT	4.76	6.27	6.39	6.47	6.59	6.59	6.47	6.60
FRTNUT	1.35	1.44	1.44	1.44	1.44	1.44	1.43	1.44
SBTS	1.18							
MGRN	7.84							
NUL	0.99	0.64	0.25	0.18	0.11	0.11	1.00	0.82
Total	99.01	99.36	99.75	99.82	99.89	99.89	99.00	99.18

Appendix X — Attachment B

Change in Cropping Pattern by Crop for 2100 Runs —

Graphical Representation


Run A
MGRN 0.00%
SBTS 0.00%
NUL 1.27%
FRTNUT 1.43%
MFLD 4.50%
COTT 5.93%
TOMT 6.61%
STRP 3.42%
GRPS 9.15%
MARKET 5.13%
GRNFLD 0.96%
PAST 2.36%
DRCE 5.28%
FDDR 7.44%
LOWVAL 2.83%
ORCH 19.88%
TRCK 23.82%
COTT
MFLD
STRP
MARKET
DRCE
ORCH
TRCK
LOWVAL
FDDR
PAST
GRNFLD
GRPS
TOMT
FRTNUT
SBTS
MGRN
NUL


Hadley scenario
MGRN 0%
SBTS 0%
NUL 3%
FRTNUT 1%
COTT 5%
MFLD 6%
TOMT 6%
STRP 3%
GRPS 9%
MARKET 5%
GRNFLD 1%
DRCE 4%
PAST 3%
FDDR 7%
LOWVAL 3%
ORCH 20%
TRCK 23%