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

Richard Howitt, Mélanie Tauber and Elizabeth Pienaar
Department of Agricultural and Resource Economics
University of California, Davis
Davis, California

May 8, 2003

1. The Model Used: The Statewide Water and Agricultural Production Model

1.1 Brief Presentation of the Model[1]

The Statewide Water and Agricultural Production Model (SWAP) is an economic optimization model that identifies demand for water for different regions in California, along with the resulting value of agricultural output. This model is unique in its ability to identify specific agricultural water allocations that are consistent with observed water use and 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 impute 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.

---

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

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 “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, substitution between these inputs can take the form of stress irrigation or 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:

$$y = f(x_1, x_2, x_3)$$

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

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

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:

$$\text{Max} \quad \Sigma_G \Sigma_i \quad p_i f_{Gi}(x_1, x_2, x_3) - \omega_1 x_1 - \omega_2 x_2 - \omega_3 x_3$$

$$\text{subject to} \quad \Sigma_{Gi} x_{1Gi} \le X_1 \qquad (\text{Land})$$
$$\Sigma_{Gi} x_{2Gi} \le X_2 \qquad (\text{Water})$$

1.2 SWAP Regions

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

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 have the same crop categories for all the regions, but the data are not reported consistently. The difference in crop categories does not influence the conclusions that result from the SWAP runs because optimization is done for each region.

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	

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. Table 2 shows the parameters that were changed and their relationship to other parts of the overall study. The changes in parameters were done 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 the year 2100 (see table 2.) The scenarios differed by the assumptions on the level of California's population in 2100. The "high" scenario designated (H) is for a population of 93 million in 2100 and the "low" scenario (L) assumes a population of 69 million. Other parameters that effect the SWAP projections are the rate of exogenous technological progress, the temperature and precipitation changes due to climate change, and the effect of increased carbon dioxide.

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	Carbon dioxide (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	Hadley 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. Population forecasts and resulting forecasted land use estimates were used to calculate the increase in urbanized land and the decrease in agricultural land and are based on the projections by Landis et al. in Appendix III of this report.

Urbanization may eliminate irrigated acreage in one area, but 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, two scenarios for the agricultural land availability in 2100 were also used. Most of the results reported are for the high-population scenario.

Decrease in agricultural land in northern regions and specific assumptions

It should be noted 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).

Note that 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. The decrease in acres that affects the SWAP regions was then calculated 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.

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

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

Output prices can be considered as constant for individual firm –(here 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 a lot of 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 & field" SWAP category in the Southern regions.

4.3 Parameter Changes due to 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.

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. Scenario A was used for the set of yield changes.

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. A technological effect was purposely chosen 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. The figure shows that yields change very 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).

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 Hadley Scenario can be also obtained.

Table 3 presents the runs and their characteristics in terms of parameter changes for 2100. The A, B, and Hadley 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
Hadley run	X	X (High-population scenario)	X (Hadley)	X (Hadley)

a. When nothing is written, Y and W are the changes in yields and water requirements result from the "+3^o 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 into account phenomena such as rotational constraints.

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

Changes in the 2100 cropping pattern are mainly driven by the shift in the demand (compare run 2100_D and run 2100_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 5 shows that the difference in climate change scenario (+3^{o} 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,+18% 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^{o}C, +18% 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 occur because the choice of the climate change scenario does not greatly change the distribution of crop profitability, but 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 Hadley 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 Hadley scenario and under Run A switch between high and low water supplies.

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^{o}C,+18%), 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 scarcer. (See, for example, the highlighted row 3 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

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

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 costal 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 other ones.

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 monthly water demand functions shown in figure 13 for region 1.

It should be noted that the same distribution of water plant requirements across months has been used 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 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 regions and southern regions.

7. Post Processing Results

The demand functions derived above were used in the Calvin model to optimize the water allocations for a year 2100 scenario without climate change, but with a statewide water market. This base run for 2100 is termed the SWM run. For comparison two climate change Calvin water allocations for the water supplies were calculated from the results of the Hadley model and the PCM model of global climate change. These “post processing” results examine the impact of the Calvin optimal allocations on California’s agricultural sector by using the annual regional water allocations generated by Calvin for a 72 year hydrologic record 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 Hadley and PCM climate change on the production, profitability, cropping patterns and water use of the Californian agricultural sector. A brief overview of each model will be presented before detailing the results generated by these models.

7.1 The Statewide Water and Agricultural Production Model (SWAP)

In these SWAP 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 between different months so that the marginal value of water by month and crop is equated.
Climate change has been incorporated 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 the year 2100.

The results from the CALVIN model (see next section) are used in SWAP the model to estimate how the regional demands for water change under various water supply conditions caused 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 supply across 72 years of variable hydrology. Through this process, Calvin models statewide allocations of water based on welfare considerations.

Three water allocation scenarios are generated by CALVIN, they are the base SWM allocations and those that are optimal under the Hadley and PCM scenarios. The allocations are then input into SWAP to determine agricultural production responses to climate change, such as changes in gross revenues and irrigated crop acreage. This information is then used to determine the region-wide economic impacts from changed water availability.

7.2 CALifornia Value Integrated Network (CALVIN)

CALVIN evaluates the potential impact of climate change on California, both with and without population growth and adaptation. CALVIN models a range of climate warming scenarios, but this report focuses on three of those scenarios: the 2100 statewide water market (SWM 2100); the PCM climate change scenario with optimal allocation (PCM 2100); and the 2100 Hadley climate change scenario with optimal allocation (HCM 2100). All three scenarios assume flexible and economically driven water operation and allocation policies. All three scenarios use the same demand for water in 2100. However, PCM 2100 assumes a dry climate warming hydrology, while HCM 2100 assumes a wet climate warming hydrology (see Table 8).

These three scenarios are used to project water demand in the year 2100 due to climate warming. The non-climate impacts on water demand include: population changes; changes in urban water demands; changes in land use; changes in wealth; technology improvements that increase crop yields; more efficient water use technologies; improved water treatment technologies; changes in world agricultural commodity and land markets; and changes in Californian water demands.

7.2.1 Method

SWM 2100, PCM 2100 and HCM 2100 yielded three optimal water allocations for the Californian agricultural sector. Two comparisons were used to measure the effect of climate change on the agricultural sector. First, the net effects on the agricultural sector from changes in the resource base and crop agronomy for the 2100 extrapolation were analyzed. Second, the optimal water allocations from the PCM 2100 and HCM 2100 climate change scenarios were compared to the optimal water allocation that was calculated using SWAP (2100 SWP). These two comparisons provided a direct measure of the effect of climate change in 2100 by separating the effects of climate change from extrapolations of the driving variables.

7.2.2 Effects of the Economic and Agronomic Shifts from 2020-2100

Water supplies are variable in time and space. As such, climate change is expected to change 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. It is clear from Figure 15a that there is significant variability in the annual reductions in water supply to the Sacramento valley 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.

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

Raw Water Availability Estimates and Changes (without operational adaptation, in maf/yr)

	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		Oct-Mar		Apr-Sep	
	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		Oct-Mar		Apr-Sep	
	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		Oct-Mar		Apr-Sep	
	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		Oct-Mar		Apr-Sep	
	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		Oct-Mar		Apr-Sep	
	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 & California’s Water Future”, Lund et al.

7.3 Extrapolating Economic Impacts from 2020-2100

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. Figure 16 presents the percentage 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 theorem proves that, for nonlinear response functions of stochastic variables, that the expected value (average) of the function has to 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 one considers 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 highlights 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 reduced. The large increase in expected net income should be interpreted cautiously. This measure of expected profits is based on the assumption that Californian crop production will remain relatively competitive in the future.

Given the excessively long projection period of 100 years it would only take a small shift in relative market growth to greatly reduce this predicted profit growth of 251 per cent that is based on a predicted increase of 121 per cent in output value. Even given this caveat, it seems fairly certain that the relative position of Californian crop production should improve in terms of output, profit and employment over the medium run. This is currently an unfashionable prediction, and is subject to substantial error, but 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. It shows 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 sec3enarios 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, there is an increase in net income occurs despite small reductions in the supplies of irrigated land and water in some regions.

The growth in net income ranges between 100 per cent and 500 per cent over the 100 year time period, which corresponds to a 0.7 to 1.6 per cent 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 percentage increase in income over 100 years is 257 per cent. However, there is a standard deviation of 140.4 per cent, showing that the range of income change has to be extended from 100 per cent to 400 per cent to capture 68 per cent of the observations.

7.4 A Comparison Between the Hadley and SWM Scenarios

In aggregate, there are very slight differences between the economic measures generated by the Hadley 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 Hadley scenarios. Despite these fluctuations in water usage, the aggregate economic measures from the Hadley scenario do not differ significantly from the figures generated by the SWM scenario. As such, the results are not worth presenting in detail.

Essentially, the Hadley 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 difference from the Hadley and SWM scenarios. Accordingly, we will now focus on the comparison between the PCM and SWM scenarios.

Table 9: Regions Included in Sacramento and San Joaquin Valleys

Sacramento Valley	
CVPM/ SWAP Region	**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 ID, Provident, Princeton-Cordora, Maxwell, Colusa Basin Drain MWC, Orland-Artois 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 WC, Pelger Mutual WC, Reclamation Districts 1004 and 108, Roberts Ditch, Sartain M.D., Sutter MWC, Swinford Trac 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.

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
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: CVPIA, 1997, Technical Appendix Volume Eight

7.5 A Comparison Between the PCM and SWM Scenarios

Figure 19 plots the percentage difference between the PCM and SWM scenarios for the three key measures of sectoral viability, namely the percentage 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 land, water 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 per cent. However, unlike the Sacramento valley, these resource reductions only translate into 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 per cent, 46 per cent and 28 per cent 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 water district over 72 years. The fluctuations are not particularly significant, ranging between plus and minus 2 per cent. 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.

In most cases the PCM income values are substantially below the SWM income values, with many years at least 50 per cent below SWM income values. The average reduction in income is 39.6 per cent with a standard deviation of 36.8 per cent. Clearly, sequences of drought years such as the late 1920's and early 1930's 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 percentage deviation of the PCM scenario from the SWM basis, aggregated over all the regions. The message is essentially one of adjustment to resource reduction. The four left-hand histograms depict a systematic adjustment by producers of irrigated crops to water reductions. The aggregate reduction in water supply under PCM is 24.3 per cent. However, due to changes in crops and the adoption of more efficient irrigation practices, the consequent reduction in irrigated land area is only 14.5 per cent. These cuts in crop production are concentrated in the lower valued crops that translates into an 8.3 per cent reduction in the gross value of production. The final reduction in net income of 6 per cent is due in part to changes in crop prices slightly offsetting the reduction in irrigated acres. The average reduction in expenditures by irrigated agriculture is 16.2 per cent. Thus, while some regions will experience significant reductions in water supply and the profitability of production, 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 that are depicted in Figure 19. In short, while 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. These severe local problems are not observed under the substantially wetter Hadley climate change scenario.

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 report, we have attempted to present both the data used, and more importantly, the assumptions 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.

The results can by summarized by stating that the Hadley 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 over regions shows that despite a 24 per cent cut in water supply, the irrigated crop industry has the incentives and capacity to adjust at several margins and reduce this 24 per cent cut in part of the resource base to a 6 per cent 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 with regularity in California.

Attachment A — Change in Cropping Pattern by Crop for 2100 Runs

Run name	2020_base (%)	2100 DLhYW (%)	Run A (%)	Run B (%)	Hadley (%)
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

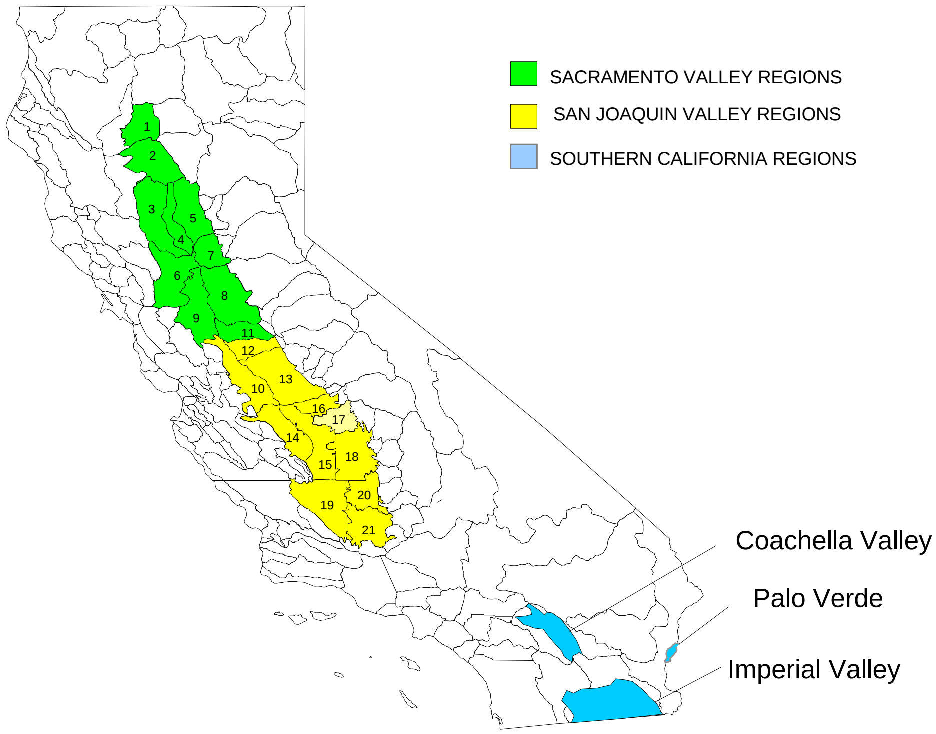


Figure 1. California map with southern and northern SWAP regions

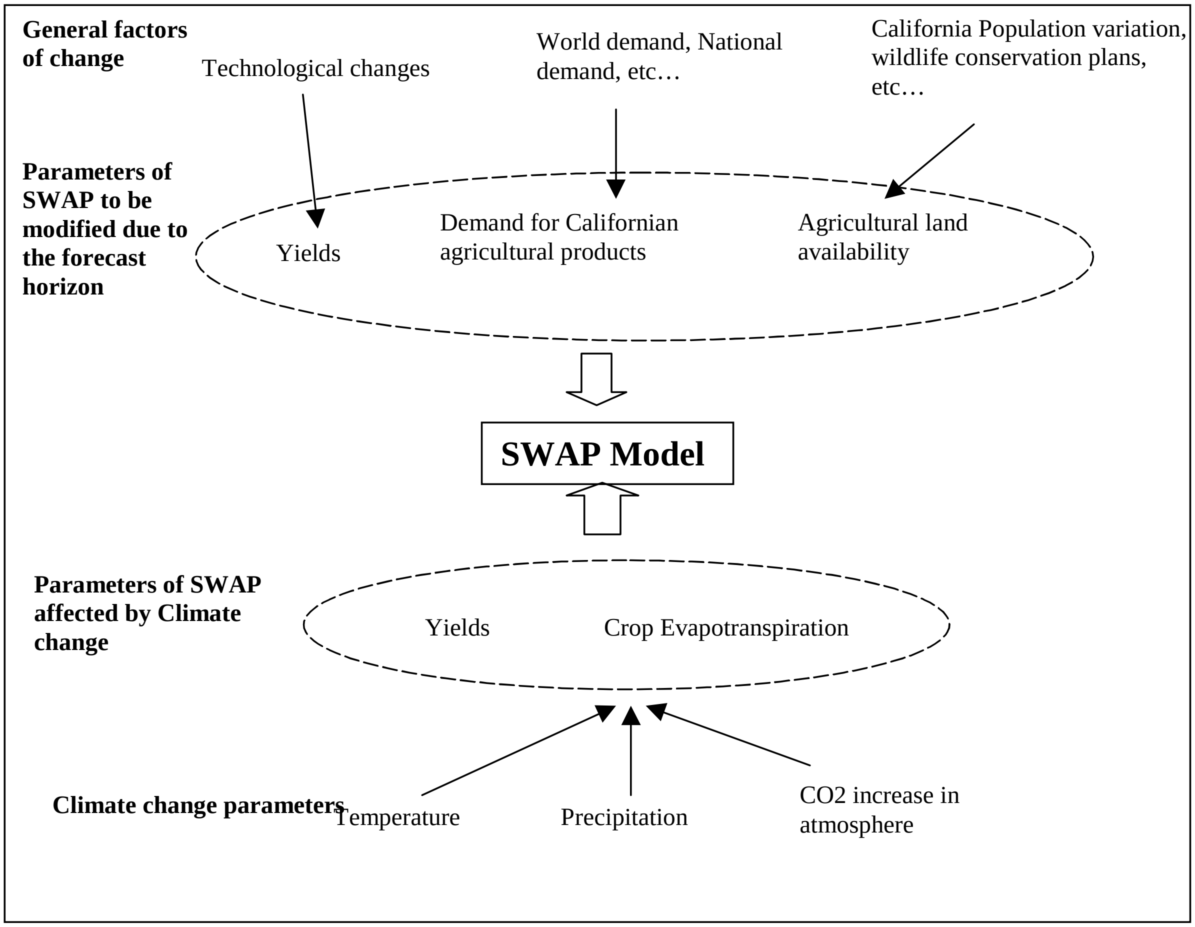


Figure 2. Parameters changed in the initial SWAP model

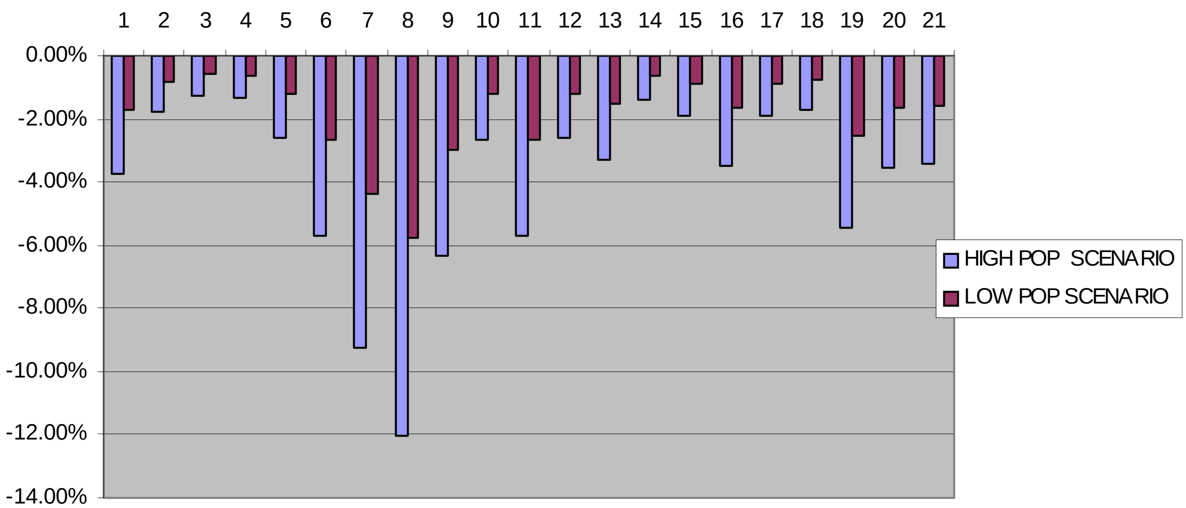


Figure 3. Decrease in agricultural land availability from 2020 to 2100 in the northern SWAP regions

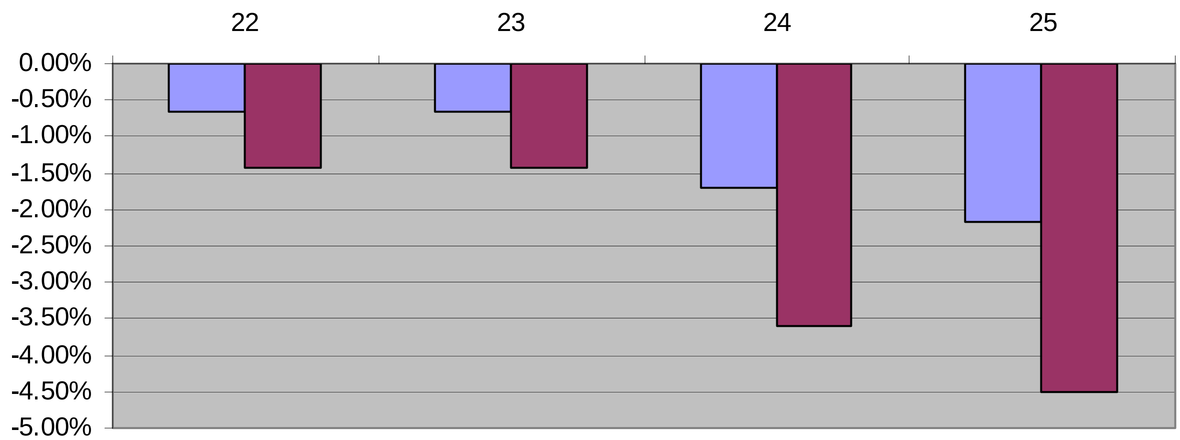


Figure 4. Decrease in agricultural land availability from 2020 to 2100 in the southern SWAP regions

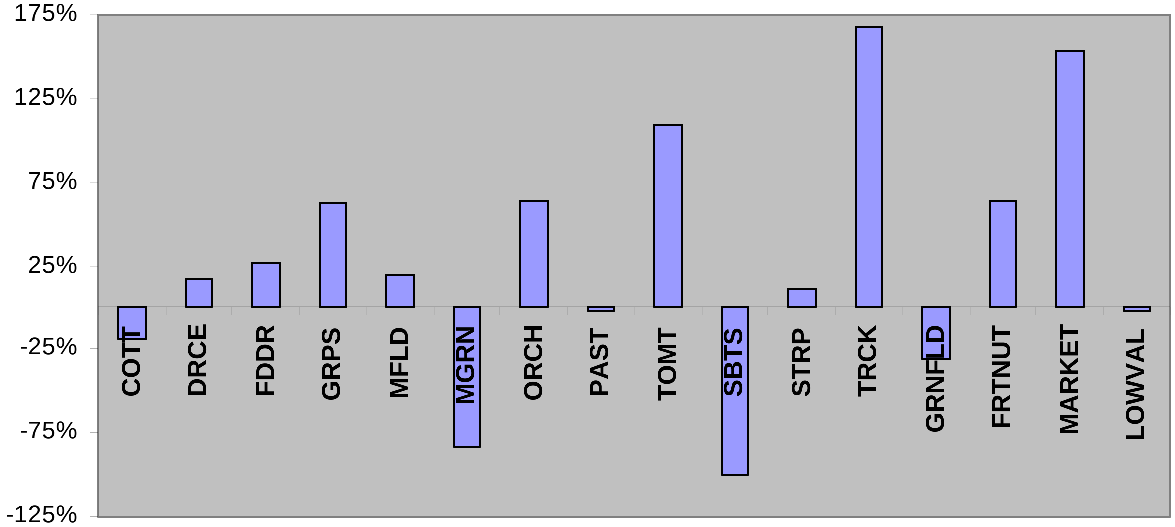


Figure 5. Shift in the Californian crop demand in 2100

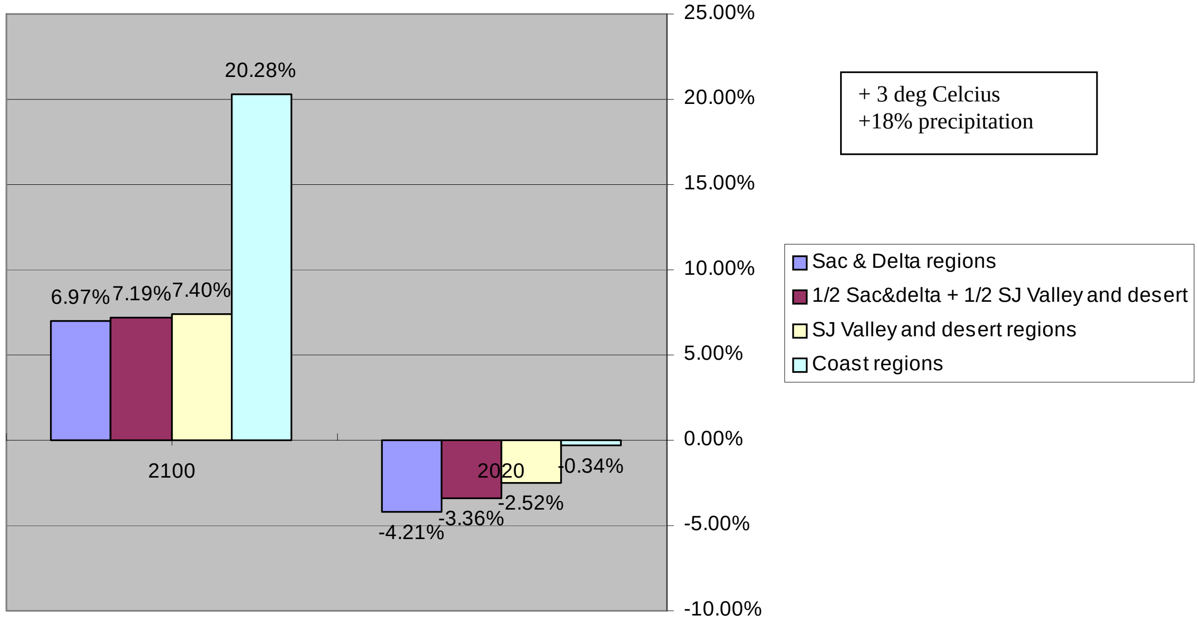


Figure 6. Change in % in water requirements in 2100 and 2020 under (+3°C, +18% precipitation) scenario

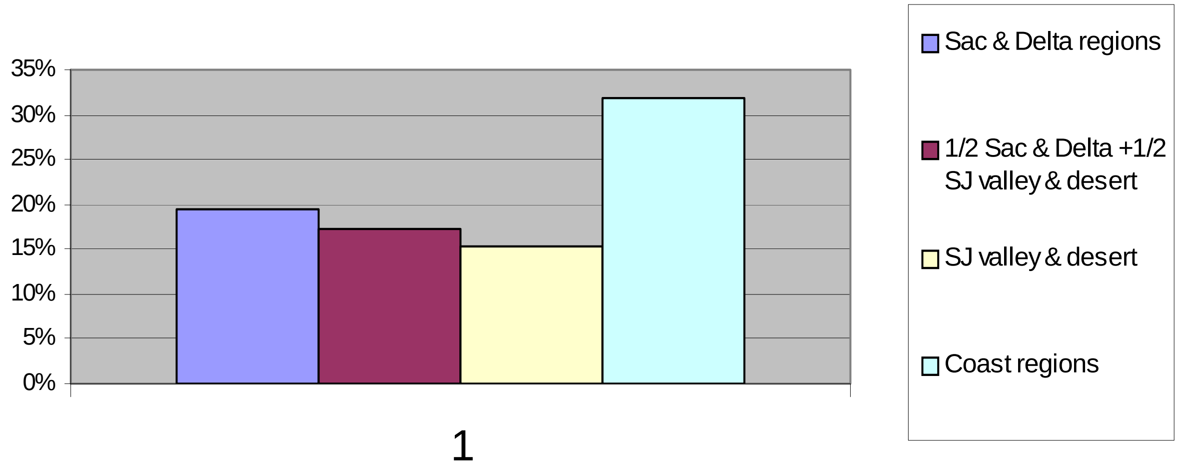


Figure 7. Regional changes in % in water requirement in 2100, under the Hadley scenario

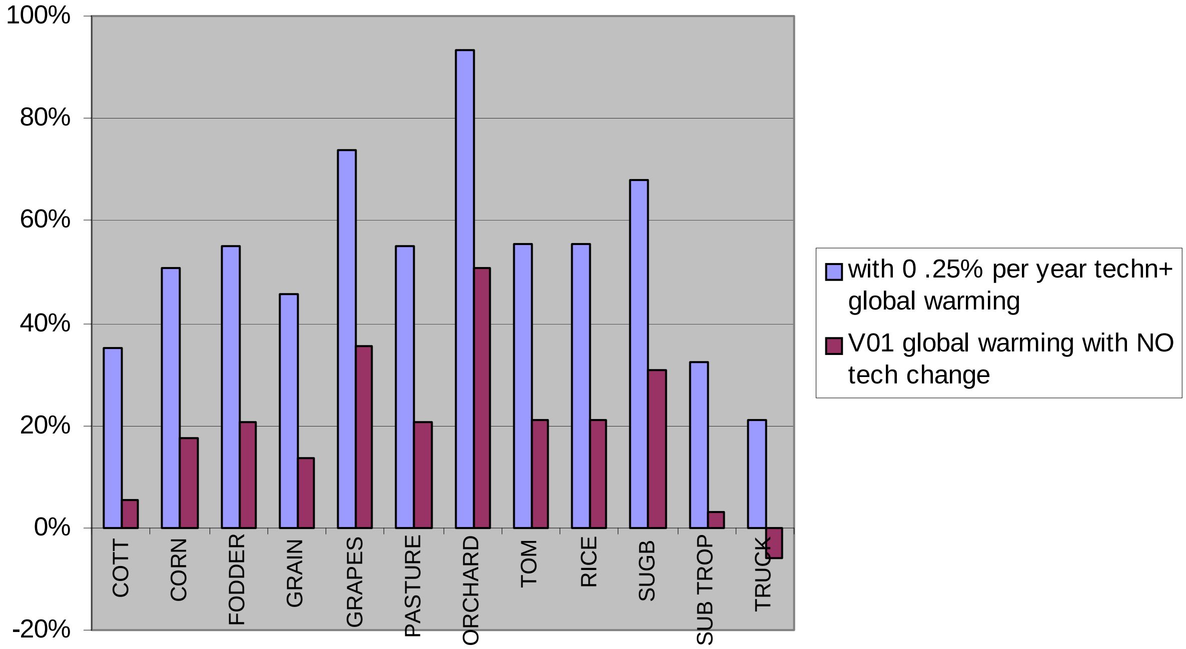


Figure 8. The basis of yield changes — North Valley (2000-2100)

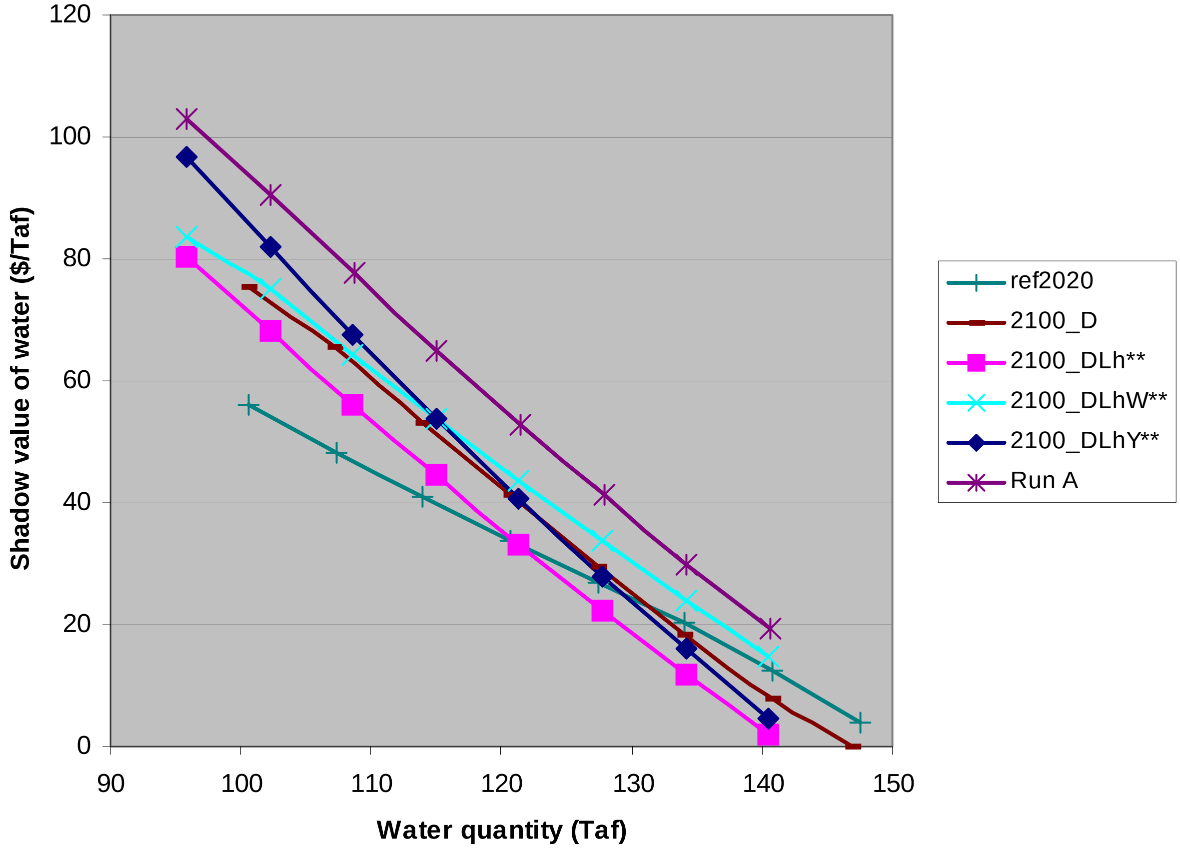


Figure 9. Change in Shadow Value due to gradual change in parameters in 2100, under "+3,+18%" scenario

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

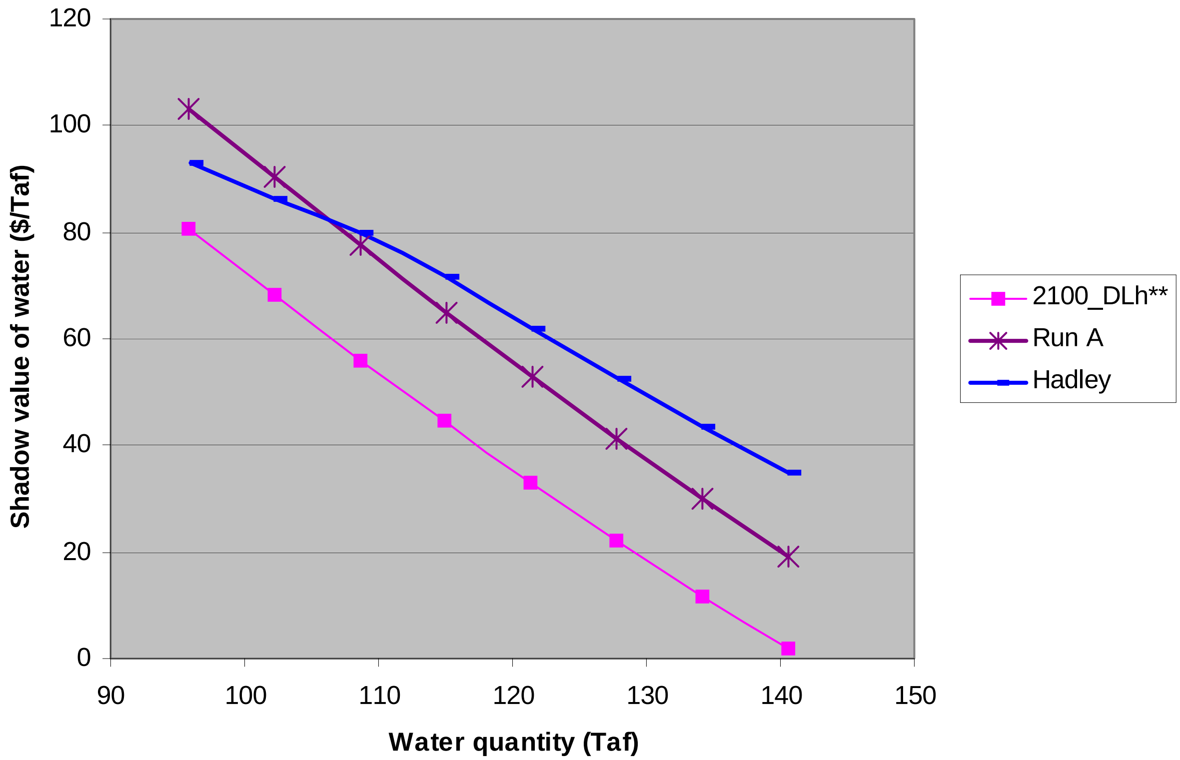


Figure 10. **Agricultural water demand in Region 1 under several climate change scenarios**

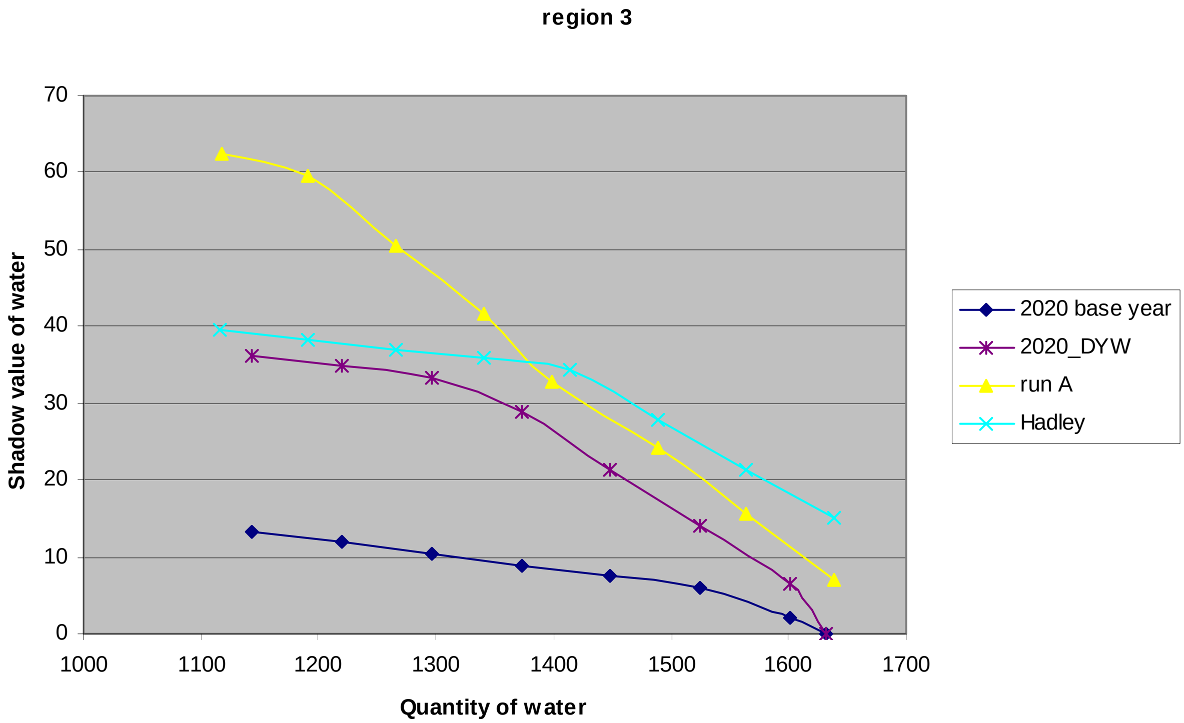


Figure 11. Comparison of water demand in region 3 under different scenarios

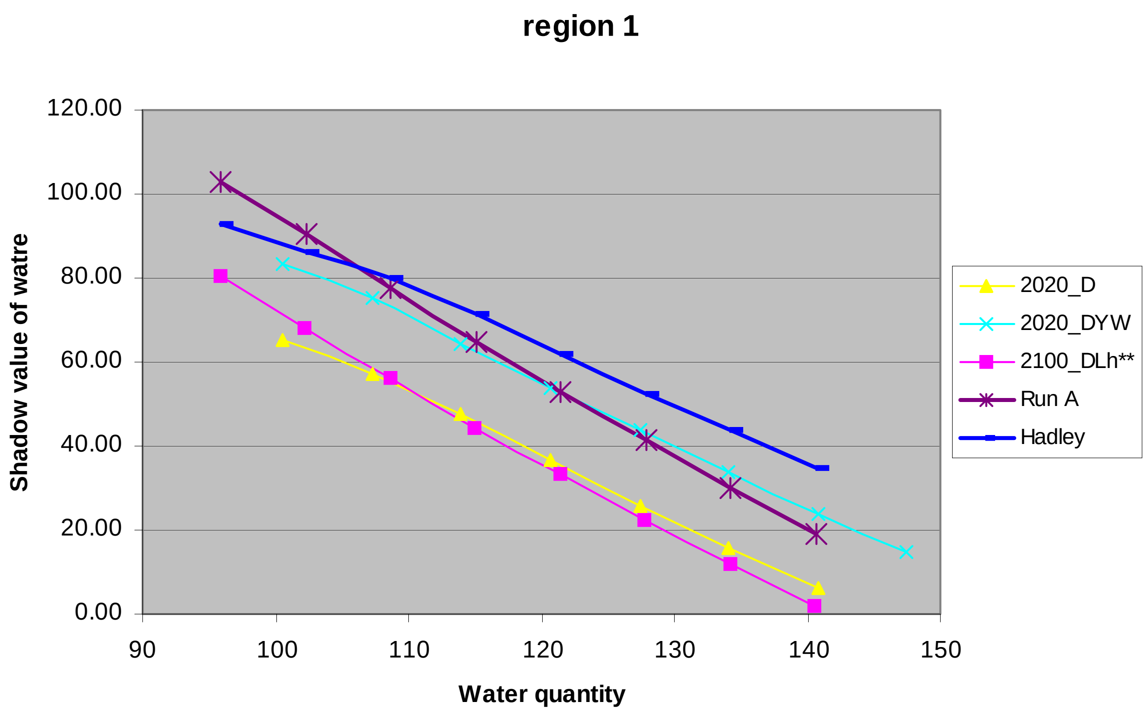


Figure 12. Changes from climate change effects in Region 1, comparison between 2020 and 2100

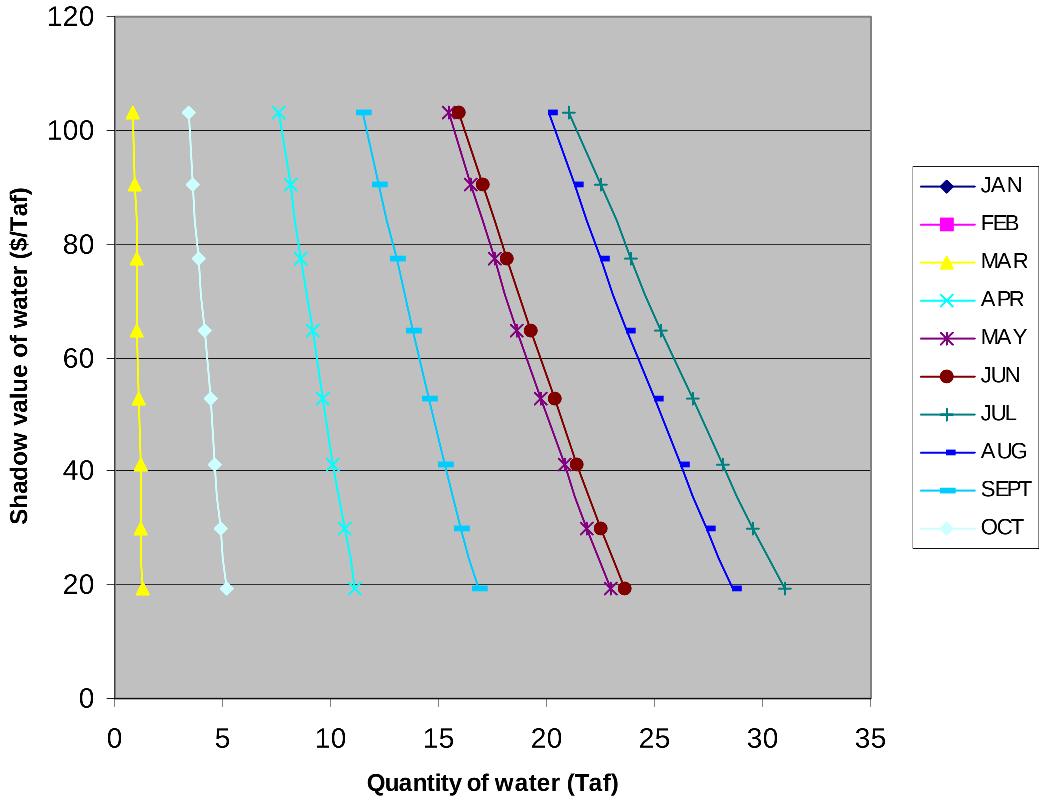


Figure 13. Monthly water demand curves for region 1, Run A

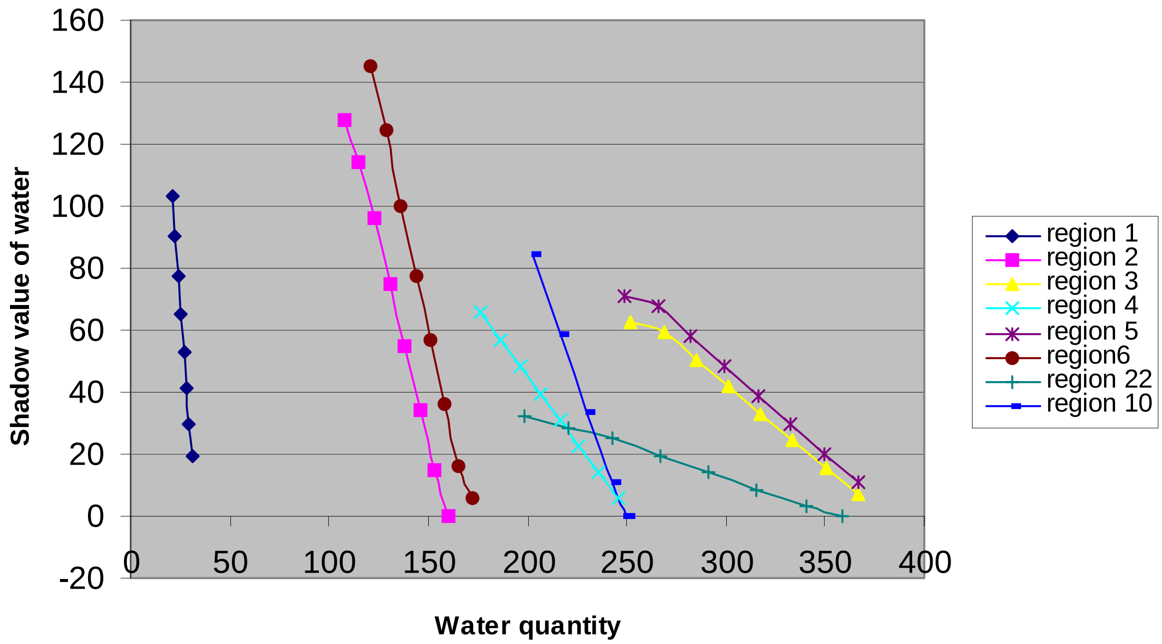
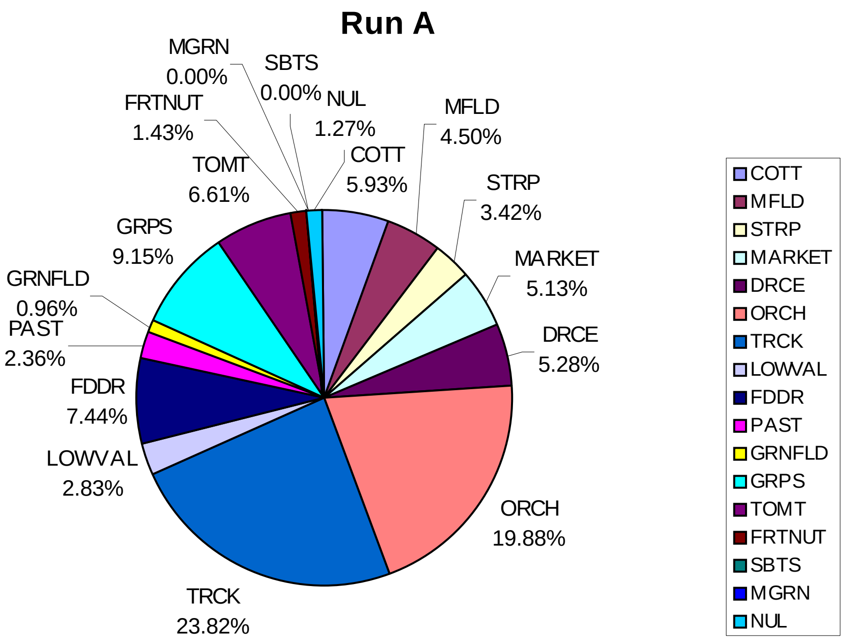


Figure 14. Agricultural water demand curves for July, for several regions, Run A

Attachment B — Change in Cropping Pattern by Crop for 2100 Runs



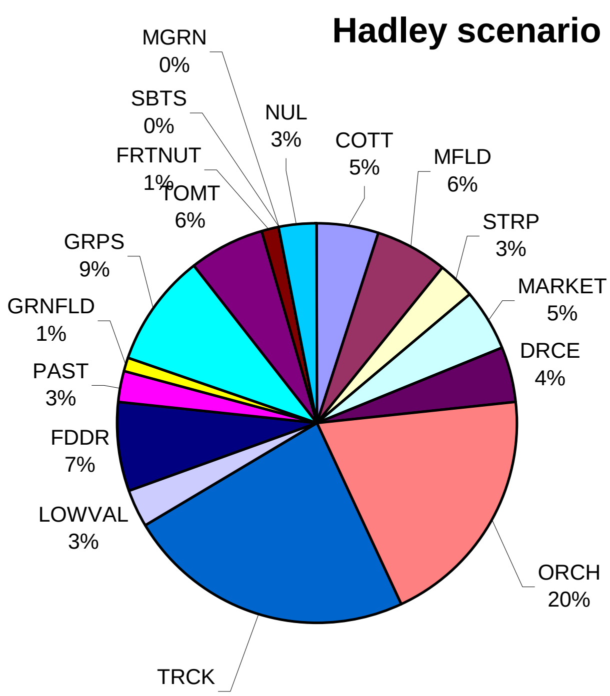


Figure 1a: Change in Water Usage - Sacramento Valley - SWM

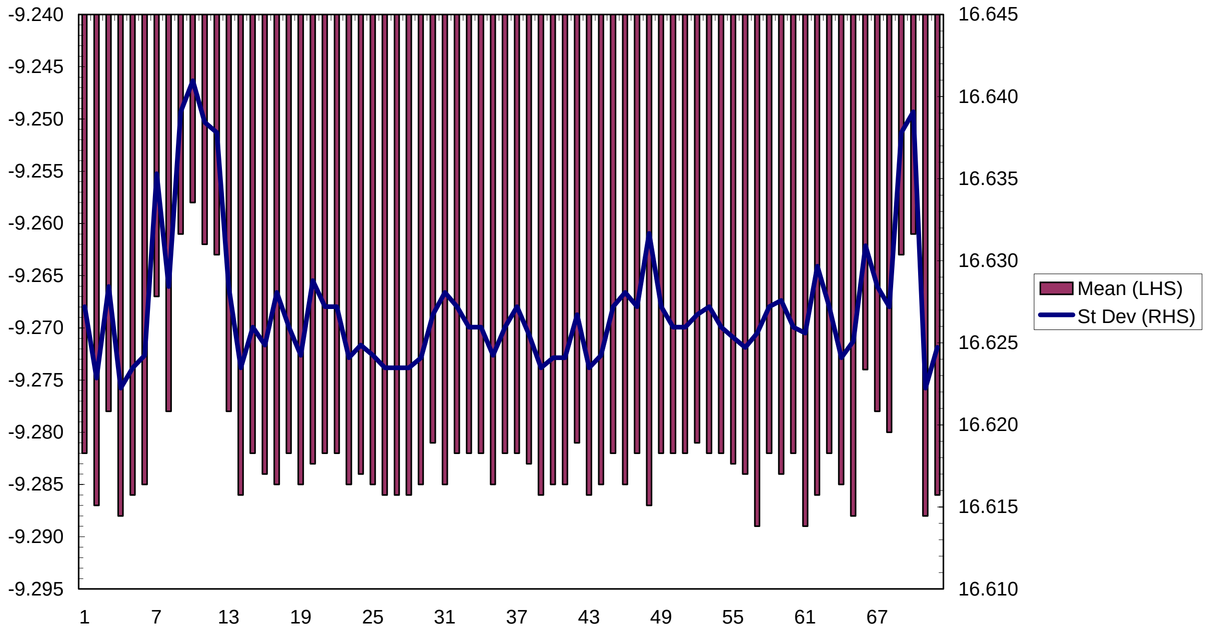
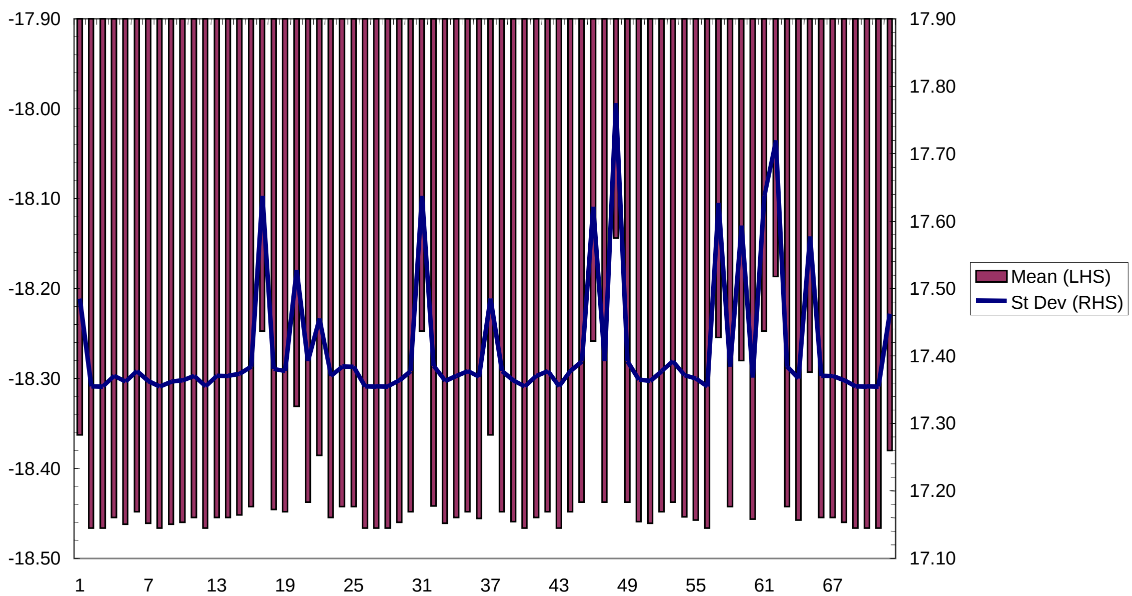


Figure 1b: Change in Water Usage - San Joaquin Valley -



Water Usage By Crop Type – SWM 2100				
	Field	**Fodder**	**Vegetables**	**Fruit and Nuts**
V01	1.2	116.5	8.3	19.8
V02	33.8	181.8	35.1	435.9
V03	872.0	212.7	259.3	213.7
V04	511.7	38.6	278.7	134.0
V05	964.7	141.7	45.8	520.5
V06	58.0	176.4	271.4	136.1
V07	211.2	139.1	5.2	48.0
V08	10.2	50.2	149.9	371.2
V09	154.5	207.7	548.5	116.3
V10	28.0	57.9	613.3	141.0
V11	25.6	22.1	43.0	273.6
V12	91.1	97.9	32.4	375.8
V13	116.7	286.3	126.4	879.7
V14	199.1	21.9	869.0	163.3
V15	487.7	936.9	93.7	400.3
V16	0.0	0.0	18.3	111.4
V17	0.0	0.0	21.7	493.3
V18	584.9	543.4	75.8	794.0
V19	295.1	196.1	58.2	271.2
V20	0.0	0.0	62.6	356.5
V21	0.0	90.5	335.7	247.7
V22	0.0	0.0	0.0	0.0
V23	0.0	0.0	0.0	0.0
V24	0.0	0.0	0.0	0.0

Irrigated Acres By Crop Type – SWM 2100				
	Field	**Fodder**	**Vegetables**	**Fruit and Nuts**
V01	0.3	21.6	6.2	5.6
V02	8.7	34.0	25.0	137.4
V03	159.7	43.1	138.1	67.0
V04	97.9	7.5	151.9	38.6
V05	167.2	26.0	31.1	156.4
V06	19.2	31.1	130.1	46.2
V07	30.7	25.0	3.1	14.6
V08	1.1	6.9	95.0	116.1
V09	54.0	33.6	274.8	37.3
V10	6.3	8.3	384.2	39.8
V11	6.2	3.4	28.9	94.4
V12	22.3	19.2	21.4	141.9
V13	23.6	44.3	71.3	298.8
V14	48.8	3.7	444.3	49.6
V15	169.5	231.0	43.5	139.5
V16	0.0	0.0	7.6	27.5
V17	0.0	0.0	12.3	134.1
V18	194.5	128.2	51.0	291.1
V19	93.6	41.3	35.0	87.4

V20	0.0	0.0	37.2	100.3
V21	0.0	13.9	207.7	81.7
V22	0.0	0.0	0.0	0.0
V23	0.0	0.0	0.0	0.0
V24	0.0	0.0	0.0	0.0

Production By Crop Type – SWM 2100

	Field	Fodder	Vegetables	Fruit and Nuts
V01	1.6	1103.8	52.6	5.2
V02	49.2	1459.3	209.4	171.3
V03	713.8	817.1	2039.7	85.1
V04	475.7	82.9	2168.8	21.4
V05	744.2	1098.8	298.5	104.1
V06	130.5	637.1	2416.9	44.9
V07	147.3	1072.5	37.1	8.3
V08	10.5	555.2	1102.5	468.4
V09	391.5	876.6	3297.5	82.9
V10	33.0	312.7	4126.8	56.3
V11	47.1	37.5	222.7	146.4
V12	142.7	169.6	152.1	206.5
V13	126.3	1904.8	876.0	1075.9
V14	202.5	99.9	6974.4	102.0
V15	552.8	2433.2	684.5	747.1
V16	0.0	0.0	86.6	308.8
V17	0.0	0.0	115.4	874.8
V18	733.4	1308.2	415.8	1161.7
V19	288.3	525.1	311.3	143.3
V20	0.0	0.0	348.1	517.2
V21	0.0	268.4	1778.3	465.7
V22	0.0	0.0	0.0	0.0
V23	0.0	0.0	0.0	0.0
V24	0.0	0.0	0.0	0.0

Gross Value By Crop Type – SWM 2100

	Field	Fodder	Vegetables	Fruit and Nuts
V01	220.8	16,125.4	34,160.1	15,453.2
V02	6,809.3	26,578.1	131,851.3	392,595.4
V03	128,993.5	33,546.3	641,841.8	181,747.7
V04	79,141.5	6,013.9	687,497.6	106,562.1
V05	131,364.0	18,632.1	163,126.0	430,689.4
V06	17,484.1	28,296.4	513,530.3	111,925.1
V07	25,816.9	16,938.3	13,474.0	34,432.5
V08	1,897.6	7,793.5	444,200.1	306,684.9
V09	52,473.4	33,416.7	1,230,759.7	93,990.1
V10	13,501.5	11,249.6	1,758,762.8	146,307.1
V11	5,717.1	3,993.4	121,032.2	327,645.9
V12	17,143.0	18,045.0	92,490.3	468,062.1
V13	36,324.6	48,669.0	306,840.8	1,083,831.2
V14	70,764.7	6,051.3	1,925,361.9	179,422.3
V15	159,825.9	197,057.6	177,212.3	541,537.3

V16	0.0	0.0	51,324.3	194,007.6
V17	0.0	0.0	68,411.3	703,131.2
V18	155,961.6	104,125.9	230,405.4	1,004,153.6
V19	92,163.6	54,966.1	154,974.4	287,170.7
V20	0.0	0.0	198,219.3	476,816.7
V21	0.0	28,057.4	1,000,376.1	339,754.6
V22	0.0	0.0	0.0	0.0
V23	0.0	0.0	0.0	0.0
V24	0.0	0.0	0.0	0.0

Net Return By Crop Type – SWM 2100

	Field	Fodder	Vegetables	Fruit and Nuts
V01	126.0	12,052.3	22,721.1	11,182.3
V02	3,325.7	15,515.2	85,436.5	273,633.7
V03	39,111.3	18,687.9	431,941.5	128,634.7
V04	34,549.8	3,613.7	457,327.1	78,660.3
V05	44,204.1	13,146.3	107,839.7	315,211.3
V06	10,280.3	15,106.0	337,803.5	75,479.3
V07	8,632.2	11,257.2	8,386.2	23,554.8
V08	948.6	4,754.0	280,926.4	202,861.6
V09	34,903.1	22,458.4	779,590.1	65,407.8
V10	8,820.6	7,544.1	1,090,542.6	114,700.4
V11	3,467.7	2,586.0	68,555.3	256,738.2
V12	9,664.0	11,072.6	52,899.2	362,545.7
V13	19,658.6	27,060.8	188,047.6	823,939.7
V14	25,570.7	3,435.2	1,207,399.9	131,839.9
V15	37,715.6	61,314.9	108,061.8	401,766.0
V16	0.0	0.0	37,039.9	167,834.6
V17	0.0	0.0	45,235.1	577,967.5
V18	52,123.1	46,474.3	135,320.0	709,012.3
V19	18,207.6	27,427.7	88,654.4	202,135.5
V20	0.0	0.0	127,445.1	376,327.2
V21	0.0	14,661.9	590,658.5	245,554.6
V22	0.0	0.0	0.0	0.0
V23	0.0	0.0	0.0	0.0
V24	0.0	0.0	0.0	0.0

Water Usage By Crop Type – Difference Between HCM 2100 and SWM 2100

	Field	Fodder	Vegetables	Fruit and Nuts
V01	0.0	-0.1	0.0	0.0
V02	0.8	0.6	0.0	0.4
V03	3.3	-3.0	0.0	0.0
V04	0.5	-0.5	0.0	0.0
V05	0.5	-0.4	0.0	0.0
V06	0.5	-1.4	0.2	0.1
V07	0.3	-0.3	0.0	0.0
V08	0.1	-1.0	0.1	0.2
V09	1.1	-1.6	0.3	0.1
V10	0.4	-2.7	0.3	0.1
V11	0.1	-0.4	0.0	0.1

V12	0.3	-0.7	0.0	0.1
V13	1.8	-5.0	0.1	0.6
V14	0.2	-0.3	0.0	0.0
V15	20.5	51.9	0.1	1.0
V16	0.0	0.0	0.0	0.0
V17	0.0	0.0	0.0	0.0
V18	46.0	109.2	-0.4	7.2
V19	0.5	-1.5	0.0	0.0
V20	0.0	0.0	0.0	0.0
V21	0.0	-2.2	0.4	0.3
V22	0.0	0.0	0.0	0.0
V23	0.0	0.0	0.0	0.0
V24	0.0	0.0	0.0	0.0

Irrigated Acres By Crop Type – Difference Between HCM 2100 and SWM 2100

	Field	Fodder	Vegetables	Fruit and Nuts
V01	0.0	0.0	0.0	0.0
V02	0.1	-0.1	0.0	0.0
V03	0.8	-0.8	0.0	0.0
V04	0.1	-0.2	0.0	0.0
V05	0.1	-0.1	0.0	0.0
V06	0.2	-0.3	0.1	0.1
V07	0.1	-0.1	0.0	0.0
V08	0.0	-0.2	0.0	0.1
V09	0.4	-0.6	0.1	0.0
V10	0.1	-0.4	0.3	0.1
V11	0.0	0.0	0.0	0.0
V12	0.2	-0.2	0.0	0.1
V13	0.4	-0.8	0.1	0.3
V14	0.0	-0.1	0.0	0.0
V15	-1.7	9.4	-0.1	-0.2
V16	0.0	0.0	0.0	0.0
V17	0.0	0.0	0.0	0.0
V18	-9.2	12.9	-0.5	-3.1
V19	0.2	-0.3	0.0	0.0
V20	0.0	0.0	0.0	0.0
V21	0.0	-0.4	0.3	0.2
V22	0.0	0.0	0.0	0.0
V23	0.0	0.0	0.0	0.0
V24	0.0	0.0	0.0	0.0

Production By Crop Type – Difference Between HCM 2100 and SWM 2100

	Field	Fodder	Vegetables	Fruit and Nuts
V01	0.0	0.3	0.0	0.0
V02	0.6	3.8	0.0	0.0
V03	3.0	-3.9	0.0	0.0
V04	0.5	-0.7	0.0	0.0
V05	0.4	-0.9	0.0	0.0
V06	0.8	-0.2	0.7	0.0
V07	0.3	-1.0	0.0	0.0

V08	0.1	-2.5	0.3	0.1
V09	2.1	-2.5	0.8	0.0
V10	0.5	-4.6	1.5	0.0
V11	0.1	-0.5	0.0	0.0
V12	0.7	-1.2	0.0	0.0
V13	2.0	-3.7	0.4	0.3
V14	0.1	-0.8	0.2	0.0
V15	10.3	115.1	-0.2	-0.2
V16	0.0	0.0	0.0	0.0
V17	0.0	0.0	0.0	0.0
V18	3.3	138.8	-1.6	-3.4
V19	0.5	-1.9	0.0	0.0
V20	0.0	0.0	0.0	0.0
V21	0.0	-5.7	1.2	0.4
V22	0.0	0.0	0.0	0.0
V23	0.0	0.0	0.0	0.0
V24	0.0	0.0	0.0	0.0

Gross Value By Crop Type – Difference Between HCM 2100 and SWM 2100

	Field	Fodder	Vegetables	Fruit and Nuts
V01	1.7	-54.3	2.4	3.1
V02	96.2	-202.0	-5.8	110.6
V03	520.2	-756.8	2.3	12.0
V04	88.2	-150.3	-3.3	-2.2
V05	65.9	-138.8	-1.9	2.2
V06	109.8	-532.7	160.9	64.1
V07	51.0	-94.0	-0.1	-0.5
V08	13.1	-194.0	105.0	117.1
V09	279.9	-720.1	299.3	36.4
V10	201.1	-591.3	608.1	52.5
V11	16.2	-101.6	15.5	27.1
V12	80.8	-370.4	14.2	46.8
V13	455.0	-1,094.3	121.0	411.3
V14	49.2	-145.1	9.8	2.2
V15	1,711.7	7,167.0	-122.1	-53.8
V16	0.0	0.0	-10.7	23.2
V17	0.0	0.0	-4.8	72.6
V18	-303.4	10,941.1	-900.7	-2,118.4
V19	156.1	-902.8	8.4	22.2
V20	0.0	0.0	-19.0	68.1
V21	0.0	-994.7	643.3	340.4
V22	0.0	0.0	0.0	0.0
V23	0.0	0.0	0.0	0.0
V24	0.0	0.0	0.0	0.0

Net Return By Crop Type – Difference Between HCM 2100 and SWM 2100

	Field	Fodder	Vegetables	Fruit and Nuts
V01	0.8	-47.0	0.0	1.1
V02	27.9	-171.6	-3.1	62.6
V03	106.3	-482.6	-8.7	5.4

V04	24.4	-104.1	-10.2	-3.6
V05	8.6	-103.7	-2.8	-3.5
V06	51.0	-383.0	24.5	14.0
V07	11.5	-74.6	-0.2	-1.1
V08	5.6	-107.9	27.3	43.1
V09	165.1	-542.1	54.0	10.4
V10	128.1	-401.4	183.2	27.0
V11	8.5	-78.9	1.7	6.3
V12	35.9	-294.9	0.3	3.9
V13	213.9	-660.0	21.5	157.6
V14	13.6	-102.6	-25.3	-1.0
V15	823.8	402.9	4.7	45.7
V16	0.0	0.0	-7.2	20.3
V17	0.0	0.0	-3.0	66.5
V18	736.1	2,307.4	7.1	330.7
V19	-5.9	-706.1	-3.3	1.7
V20	0.0	0.0	-10.3	57.5
V21	0.0	-649.5	124.6	166.7
V22	0.0	0.0	0.0	0.0
V23	0.0	0.0	0.0	0.0
V24	0.0	0.0	0.0	0.0

Water Usage By Crop Type – Difference Between PCM 2100 and SWM 2100

	Field	Fodder	Vegetables	Fruit and Nuts
V01	-1.0	-67.7	0.0	-1.7
V02	-33.8	-181.7	-3.0	-176.6
V03	-746.7	-157.6	-117.2	-125.1
V04	-253.5	-3.8	1.7	-2.0
V05	-883.1	-125.8	-12.7	-367.5
V06	-5.6	14.6	-1.5	-0.3
V07	-192.8	-110.6	-0.3	-10.1
V08	-7.5	-30.8	-17.2	-114.9
V09	-48.1	-126.1	-6.3	-9.0
V10	-4.8	24.4	-3.3	0.3
V11	-6.5	-2.5	-0.4	-11.8
V12	-46.6	-44.9	0.1	-15.5
V13	-59.8	-100.9	0.0	-25.1
V14	-14.7	1.6	0.9	-0.1
V15	-163.6	-316.8	-1.3	-6.1
V16	0.0	0.0	-0.1	0.3
V17	0.0	0.0	-0.1	0.6
V18	-283.3	-278.7	-1.1	-29.0
V19	-52.6	-13.4	-0.3	-4.9
V20	0.0	0.0	-0.3	0.7
V21	0.0	16.4	-3.0	-1.5
V22	0.0	0.0	0.0	0.0
V23	0.0	0.0	0.0	0.0
V24	0.0	0.0	0.0	0.0

Irrigated Acres By Crop Type – Difference Between PCM 2100 and SWM 2100				
	Field	**Fodder**	**Vegetables**	**Fruit and Nuts**
V01	-0.2	-4.2	0.1	-0.1
V02	-8.7	-33.9	-1.7	-31.5
V03	-128.5	-29.6	-53.6	-34.1
V04	-8.0	1.2	3.1	1.1
V05	-150.6	-22.4	-6.8	-93.3
V06	-1.9	3.1	-1.0	-0.2
V07	-26.3	-16.3	-0.1	-1.6
V08	-0.8	-4.0	-4.9	-20.0
V09	3.6	-6.1	2.1	0.2
V10	-1.1	3.5	-2.5	0.1
V11	-1.5	-0.3	-0.1	-0.3
V12	-0.1	-1.8	0.3	1.4
V13	-10.0	-4.1	1.5	5.3
V14	-3.6	0.5	2.5	0.6
V15	-45.6	-72.1	-0.4	-1.2
V16	0.0	0.0	-0.1	0.1
V17	0.0	0.0	-0.1	0.1
V18	-74.3	-52.5	-0.5	-5.8
V19	-10.0	-1.0	0.0	-0.3
V20	0.0	0.0	-0.2	0.2
V21	0.0	3.1	-2.2	-0.9
V22	0.0	0.0	0.0	0.0
V23	0.0	0.0	0.0	0.0
V24	0.0	0.0	0.0	0.0

Production By Crop Type – Difference Between PCM 2100 and SWM 2100				
	Field	**Fodder**	**Vegetables**	**Fruit and Nuts**
V01	-1.0	-355.4	0.2	0.0
V02	-49.2	-1,454.8	-7.5	-25.6
V03	-582.5	-583.9	-797.3	-37.1
V04	-78.6	0.1	14.2	0.1
V05	-671.8	-956.9	-50.9	-55.6
V06	-9.6	40.7	-6.8	-0.1
V07	-126.4	-731.7	-0.6	-0.5
V08	-7.4	-336.2	-78.8	-36.0
V09	-35.8	-405.9	6.7	0.0
V10	-5.4	105.5	-15.6	0.0
V11	-11.2	-4.3	-0.8	-1.0
V12	-29.1	-34.7	0.8	0.0
V13	-58.2	-316.4	4.9	1.2
V14	-12.8	9.7	14.5	0.2
V15	-172.6	-593.7	-3.2	-2.5
V16	0.0	0.0	-0.6	-0.5
V17	0.0	0.0	-0.6	-3.4
V18	-309.6	-462.8	-2.0	-9.2
V19	-33.2	-16.9	-0.4	-0.4
V20	0.0	0.0	-1.3	-1.3
V21	0.0	47.7	-9.9	-2.6

V22	0.0	0.0	0.0	0.0
V23	0.0	0.0	0.0	0.0
V24	0.0	0.0	0.0	0.0

Gross Value By Crop Type – Difference Between PCM 2100 and SWM 2100				
	Field	**Fodder**	**Vegetables**	**Fruit and Nuts**
V01	-137.9	-4,082.3	260.7	183.7
V02	-6,809.3	-26,508.9	-4,050.8	-62,842.5
V03	-105,183.9	-23,013.2	-217,891.6	-88,828.6
V04	-15,820.4	922.6	8,302.7	3,618.5
V05	-118,666.0	-16,033.8	-21,478.1	-231,096.7
V06	-1,288.0	5,355.9	677.3	2,625.9
V07	-22.474.5	-10,851.4	-108.7	-1,745.0
V08	-1,331.4	-4,202.1	-15,167.9	-51,199.2
V09	-4,817.0	-8,246.0	8,155.4	1,367.7
V10	-2,170.2	5,998.4	754.1	3,793.3
V11	-1,352.6	-64.0	154.0	4,726.0
V12	-3,492.4	-2,066.4	870.4	10,977.2
V13	-14,817.1	-6,111.4	3,978.2	19,296.2
V14	-4,167.1	1,180.2	13,034.3	4,616.2
V15	-37,931.3	-48,930.5	157.6	3,850.3
V16	0.0	0.0	-147.6	1,773.5
V17	0.0	0.0	-51.8	8,990.9
V18	-51,969.8	-37,191.3	-79.5	6,013.6
V19	-9,568.1	4,124.4	580.7	5,899.1
V20	0.0	0.0	102.9	7,628.6
V21	0.0	8,026.4	-1,321.3	2,125.8
V22	0.0	0.0	0.0	0.0
V23	0.0	0.0	0.0	0.0
V24	0.0	0.0	0.0	0.0

Net Return By Crop Type – Difference Between PCM 2100 and SWM 2100				
	Field	**Fodder**	**Vegetables**	**Fruit and Nuts**
V01	-82.1	-2,461.2	152.9	270.4
V02	-3,325.7	-15,461.6	-853.1	-33,544.1
V03	-31,177.9	-12,489.4	-139,604.4	-61,554.5
V04	-5,148.3	713.6	3,742.3	2,950.5
V05	-39,837.2	-11,248.8	-9,774.1	-162,070.8
V06	-619.8	4,168.9	1,906.2	2,773.8
V07	-7,244.0	-6,873.8	5.2	-490.7
V08	-646.5	-2,398.0	-7,630.5	-32,105.3
V09	-4,091.6	-5,180.3	5,286.1	1,377.8
V10	-1,373.2	4,422.3	5,000.3	3,720.8
V11	-805.9	68.4	363.0	5,247.7
V12	-2,307.2	-711.9	420.1	10,535.8
V13	-7,688.6	-227.7	1,632.0	16,801.1
V14	-1,011.2	949.6	9,325.0	4,250.2
V15	-6,196.7	-4,037.2	695.2	5,275.0
V16	0.0	0.0	-18.4	1,718.6
V17	0.0	0.0	122.3	9,007.5

V18	-14,038.9	-10,717.1	927.7	12,550.7
V19	129.8	5,551.7	639.6	6,582.7
V20	0.0	0.0	516.2	7,485.3
V21	0.0	5,520.0	2,892.8	3,060.6
V22	0.0	0.0	0.0	0.0
V23	0.0	0.0	0.0	0.0
V24	0.0	0.0	0.0	0.0