How significant is the impact of irrigation on the local hydroclimate in California's Central Valley? Comparison of model results with ground and remote-sensing data

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[1] The effect of irrigation on regional climate has been studied over the years. However, in most studies, the model was usually set at coarse resolution, and the soil moisture was set to field capacity at each time step. We reinvestigated this issue over the Central Valley of California's agricultural area by: (1) using the regional climate model at different resolutions down to the finest resolution of 4 km for the most inner domain, covering California's Central Valley, the central coast, the Sierra Nevada Mountains, and water; (2) using a more realistic irrigation scheme in the model through the use of different allowable soil water depletion configurations; and (3) evaluating the simulated results against satellite and in situ observations available through the California Irrigation Management Information System (CIMIS). The simulation results with fine model resolution and with the more realistic irrigation scheme indicate that the surface meteorological fields are noticeably improved when compared with observations from the CIMIS network and Moderate Resolution Imaging Spectroradiometer data. Our results also indicate that irrigation has significant impacts on local meteorological fields by decreasing temperature by 3°–7°C and increasing relative humidity by 9–20%, depending on model resolutions and allowable soil water depletion configurations. More significantly, our results using the improved model show that the effects of irrigation on weather and climate do not extend very far into nonirrigated regions.

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1. Introduction

[2] Agriculture is perhaps one of the most important sectors of California's economy and a major provider of agricultural products to the United States and the global markets. However, given the semiarid nature of California's agricultural region and lack of sufficient precipitation, irrigation has been the main method of meeting the water demand and ensuring high crop yields. In relationship to water conservation and addressing water shortages in California, *Hanson et al.* [2004] studied when to irrigate and how much water to apply based on theoretical and experimental methods, in order to maintain optimum yield. They recommended that irrigation should start when the root zone's available soil moisture is less than the maximum allowable depletion of a specific crop.

[3] The relationship between large-scale irrigation and climate has also received much attention, especially in recent years. Qualitatively, irrigation practices have been identified as having both direct and indirect consequences on local, regional, and even global climate (see the review by *Pielke et al.* [2007]). As early as the 1990s, *Pielke and Avissar* [1990] suggested that the temperature change due to landscape change has about the same magnitude as that due to the greenhouse gas increase at regional and local scales. Many studies have quantitatively investigated the impact of irrigation on weather, climate, and hydrology at local, regional, and continental scales, which relied mainly on the use of numerical atmospheric models. While many of the reported studies have been able to simulate some aspects of the feedback mechanisms caused by irrigation, the models have not dynamically determined the amounts of water that should be realistically added into the model soil. For example, *Segal et al.* [1998] investigated the impact of irrigation on summer rainfall in North America using the MM5 at the resolution of 90 km and weekly scale. In their irrigation scheme, the daily prescribed evapotranspiration is used to describe water usage in the fraction of irrigation grid cells. Using RAMS with 10 km resolution, *Adegoke et al.* [2003] investigated the irrigation effect on weather in Nebraska. In their irrigation scheme, the fraction of irrigation grid cells is set up to be saturated at 0000 UTC each day. Using RegCM3, *Kueppers et al.* [2007] simulated the effect of irrigation on regional climate in the Central Valley, California, at interannual scales. To mimic the effects

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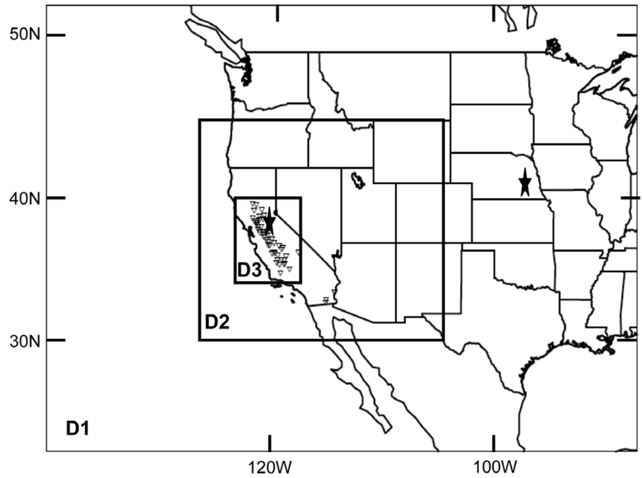

Figure 1. Model domains. The triangles and stars represent the CIMIS site and Ameriflux sites, respectively, selected for this study.

of irrigation, they forced the RegCM3 root zone (top 1 m) soil moisture to field capacity at every time step during the simulation period. *Kueppers et al.* [2008] compared the effects of irrigation on regional climate, with specific emphasis on summer temperatures. Based on simulations by the different Regional Climate Models (RCMs), they found that the behavior of RCMs varied, depending on each model's physics, as well as on irrigation configurations. *Kueppers et al.*'s [2008] treatment of the soil moisture state in different models varied from setting it to saturation in the RSM, field capacity in RegCM3, no specific description in MM5-CLM3, and 4.822×10^{-8} m/s in DRCM, when the topsoil-layer temperature is greater than 12°C and zero when less than 12°C. Irrespective of the various moisture assumptions, almost all of the irrigation water usages are unrealistic, in comparison with the recommended quantities provided by *Hanson et al.* [2004] and now applied in California for large-scale irrigation purposes. Therefore, we conclude that the previous reported results, based on the application of regional climate models, may overestimate or underestimate the effect of irrigation on regional climate.

[4] In fact, how much water should be added into climate model soil is still unresolved and may depend on models. For example, the findings of *Kanamaru and Kanamitsu* [2008] corroborate our conclusion. Using the RSM, they investigated the effects of irrigation on regional climate by prescribing root zone soil moisture to saturated and half-saturated conditions for each time step separately. Their results suggested that the soil-moisture prescription is too high and, hence, causes cool bias. On the other hand, *Lobell et al.* [2009], using the Community Atmospheric Model (CAM3.3) and through prescribing the top 30 cm soil moisture at the irrigation grid for 90%, 50%, 40%, and 30% of soil saturation, found that the impacts of irrigation on air temperature and latent heat fluxes are "extremely insensitive" to soil moisture increases beyond 30% saturation. The results from *Lobell et al.* [2009] may be relevant to the land-surface model, i.e., the Community Land Model (CLM) they used. To further examine the results between *Lobell et al.* [2009] and *Kanamaru and Kanamitsu* [2008], one of our objectives in this study is to investigate whether or not the use of a more realistic and operational irrigation scheme, such as the one described by *Hanson et al.* [2004] into the coupled land-atmosphere model system, will improve the capability of the model in terms of its ability to simulate the state variables and capture the impact of irrigation on the regional climate.

[5] The availability of the California Irrigation Management Information System (CIMIS) observation data sets and some of the MODIS observations provided the unique opportunity of a comparison with the model-generated state variables. Thus, the second objective in this study is to determine if the modified model performance improved as a result of a more realistic irrigation scheme.

[6] In addition to discussing the effect of irrigation on climate with adding water beyond different critical values, *Lobell et al.* [2009] also discussed the effect of irrigation on climate at different horizontal resolutions (1.88° latitude by 2.5° longitude, 0.94° by 1.25°, and 0.47° by 0.63°) and found that the "results are qualitatively identical for all resolutions." In fact, in most of the previous studies on this topic, horizontal resolutions of about 20 km or even coarser [e.g., *Kueppers et al.*, 2007, 2008; *Kanamaru and Kanamitsu*, 2008] have been used. The models at these resolutions show difficulty in resolving spatial variations of the meteorological fields caused by irrigation and other factors. The third objective in this study is to examine if increasing resolution in the RCM can improve the understanding of the impact of irrigation on climate at spatial scale.

2. Experimental Design and Model Setup

2.1. Study Domain and Model Setup

[7] To resolve the irrigation area in a model, high spatial resolution is needed. In this study, a total of three nested domains, centered at 34°N and 118°W, are used. Domain 1 covers the western and central United States, northern Mexico, and the surrounding oceans with a 36 km horizontal grid mesh (total 169 × 121 grid cells). Domain 2 covers the western mountains of the United States, northwestern Mexico, and surrounding water with a 12 km grid (total 193 × 184 grid cells). Domain 3 is the most inner domain at 4 km resolution, which covers the Central Valley of California, the central coast in California, the Sierra Nevada Mountains, and water (see Figure 1).

[8] The triangle given in Figure 1 indicates the California Irrigation Management Information System (CIMIS) station. With respect to the selected study domain (D-3 in Figure 1), 18 CIMIS stations fall within the Central Valley's irrigation region for the current model configuration, and 27 stations are within the close proximity, but are not categorized as irrigation grids. However, only 8 CIMIS stations are categorized as irrigation grids both at 4 km resolution and 36 km resolution for the current model configurations.

[9] The mesoscale model (NCAR/Penn State MM5), which has been used to study similar topics [e.g., *Segal et al.*, 1998; *Kueppers et al.*, 2008], was employed as the integration model. Based on the sensitivity tests we performed on the schemes of the Planetary Boundary Layer (PBL), cloud microphysics, and radiation, the following setup was adopted. The Grell convective parameterization scheme (CPS) [*Grell*, 1993] is used in Domains 1 and 2. The Goddard Space Flight Center's (GSFC) explicit cloud microphysical solution

[*Tao and Simpson*, 1989], Eta planetary boundary layer [*Janjic*, 1994], and RRTM long-wave radiation [*Mlawer et al.*, 1997] are used in all domains. The Noah Land-Surface Model (LSM) [*Chen and Dudhia*, 2001] with the U.S. Geological Survey (USGS) land use type was used in all domains. In this study, 31 vertical sigma layers are employed from the surface to the top of the atmosphere at 100 mbar. The North America Regional Reanalysis (NARR) data [*Mesinger et al.*, 2006] are used as forcing fields, and the modeling period dates from 1 April to 31 October 2007.

[10] Before investigating the impact of irrigation on meteorological fields using the coupling land-atmospheric model, we tested the model performance on simulating soil and surface fluxes at the irrigation sites using the offline Noah LSM. The forcing data for offline runs were in situ observations either from the CIMIS sites or Ameriflux sites. The missing or nonobserved data for offline forcing data were filled using National Land Data Assimilation System (NLDAS; http://ldas.gsfc.nasa.gov/nldas/) grid data closest to the site.

2.2. Experimental Design

[11] Two basic runs are designed to examine the effect of irrigation on soil, surface fluxes, and/or atmospheric variables both in offline and in coupled models:

[12] 1. The first type is the offline run. The Offline Noah LSM is a 1-D model, although the fraction of vegetation, bare ground, and snow, etc. is considered. The control runs were performed by running the default Noah LSM with relevant forcing data at selected CIMIS and Ameriflux sites. The irrigated runs were performed to mimic irrigation processes by adding water into the model soil. The time period for offline runs was from 2001 to 2004.

[13] 2. The second type is a coupled run. The control run is set to run MM5 from 1 April to 31 October 2007, with default settings for the LSM. The irrigation runs were also performed with MM5 from 1 April to 31 October 2007, with the difference that from 1 May to 31 August 2007, if the root zone soil-moisture conditions (based on *Hanson et al.* [2004] recommendations) identify the need for irrigation, Hanson et al.'s irrigation scheme of adding water to the root zone is included in the Noah LSM, i.e., the top three layers of Noah LSM (irrigated runs).

[14] In the irrigation runs, when the root zone's relative available soil water (SW) content is less than maximum allowable water depletion (SW_m) of soil moisture, i.e., when $SW < SW_m$, irrigation starts; however, when $\theta = \theta_{fc}$, irrigation ends. The variable SW is defined as

$$SW = (\theta - \theta_{wilt}) / (\theta_{fc} - \theta_{wilt}). \tag{1}$$

θ_{fc}, the field capacity, and θ_{wilt}, the wilting point, are prescribed in the Noah LSM and depend on soil texture. Here θ is the model soil moisture and is calculated from the Noah LSM. The SW_m values are obtained from Table E-5 of *Hanson et al.* [2004] and changes depending on vegetation (crop) type. For example, SW_m for wheat (ripening) is 90%; SW_m for alfalfa is 50–55%; and SW_m for onions is 25%. It should be noted that a value of one for SW_m in equation (1) is equivalent to keeping soil moisture at field capacity. Furthermore, the allowable water depletion is defined as a percentage of the available soil moisture [*Hanson et al.*, 2004].

[15] Note that in the Noah LSM, all crops are categorized as one type of land use, and the related vegetation parameters are kept the same. Thus, the maximum allowable water depletion is the average from all crops in the Sacramento and San Joaquin valleys at each month based on data provided by *Hanson et al.* [2004]. Our calculations based on main crop types in the Central Valley indicate that the average SW_m in the Sacramento Valley is about 47–50%, and 45% in the San Joaquin Valley at the seasonal scale. Thus, we call these runs Realistic Allowable Soil Water Depletion (R-ASWD) runs or realistic SW_m runs. To examine whether the value of SW_m affects the model results, we also have performed an irrigation run by setting soil moisture close to field capacity; this is called High Allowable Soil Water Depletion (H-ASWD) run or high SW_m run.

[16] Because the year of 2007 experienced a dry spring, soil dries early and more water may have been used in the following irrigation seasons, assuming that the water was available whenever needed. Using this year as case study to investigate the irrigation influence on meteorological fields, we may see the maximum of the possible effects of irrigation on meteorological fields at the intraseasonal scale.

[17] In our experimental design, we take one month as the spin-up period based on the following reasons: (1) *Liang et al.* [2004] suggested that a 1 month spin-up period was sufficient for their long-term (20 year) runs using MM5-based RCM. *Li et al.* [2007] had tested the MM5 spin-up time in arid/semiarid regions and found that the model topsoil moisture converged closely after 1 week, starting from different days [*Li et al.*, 2007, Figure 3]. (2) Similar to the MM5, the Noah LSM is used in the NARR assimilation system [*Mesinger et al.* 2006], which may reduce spin-up time.

[18] In order to avoid application of water at large solar radiation flux periods, we set the model irrigation to start when available soil moisture is less than the threshold and, at the same time, solar radiation is less than 50 W m^{-2}.

2.3. Observational Data Used in the Study

[19] In order to obtain real weather and climate conditions for the irrigation region, the California Irrigation Management Information System (CIMIS) was established in 1982 by the California Department of Water Resources and the University of California at Davis to assist California's farmers in efficiently managing their water resources. The CIMIS network has over 120 automated weather stations in the state of California. Each CIMIS station routinely monitors and measures meteorological variables, including surface solar radiation, temperature, humidity, precipitation, winds, surface pressure, and soil temperature, on an hourly basis. In most of the CIMIS site, the soil was "well watered" (B. Temesgen, personal communication, 2010; also see the CIMIS Web site). Then, the hourly (or daily) reference evapotranspiration (ET_0) is calculated at the site based on the observed meteorological fields. The nearby farmers will estimate how much water will be needed based on the ET_0, crop coefficient, soil type, vegetation type, season, etc. [*Hanson et al.*, 2004]. The quality of the CIMIS database is considered to be very high because it is well quality-controlled, and all of the meteorological equipment is calibrated annually (B. Temesgen, personal communication, 2008). In CIMIS data, the missing or problematic hourly data are flagged and are not used in this study. Details about data information can be found on the Web site ((http://wwwcimis.

Table 1. The Statistics Results of Daily Soil Temperature at 13 CIMIS Sites From May to September From 2001 to 2004[a]

	Mean (°C)	RSME (°C)	Correlation Coefficient	Bias (°C)
CIMIS	24.0	4.1		
Control runs	26.5	5.0	0.81	2.42
Irrigation runs	23.6	4.0	0.84	−0.36

[a]Given the significant level (0.05 here) with Student's *t* test, the model results are statistically improved in terms of biases (model - observation).

water.ca.gov/cimis/). Currently, the data are used mainly to support the farmers in making decisions regarding when to start irrigating and how much water to apply. In our study, we found great value in the CIMIS data set for validation of climate model performance over the Central Valley irrigation region of California.

[20] In addition to the CIMIS data set, the hourly/30 min in situ observations of level 2 with gap-filled data from Ameriflux sites (http://public.ornl.gov/ameriflux/fairuse.cfm) and the 8 day MODIS (combined Aqua with Terra) skin temperature with 0.05° gridded (CMG) (https://lpdaac.usgs.gov/lpdaac/products/modis_products_table) at daytime (1330 LST) are used to test and validate the model results.

3. Results and Discussion

3.1. Offline Simulation Results

[21] Using the offline Noah LSM, we first examined the model performance over the California irrigation regions of the Central and Imperial valleys. We tested 16 stations whose observation missing data are relatively less than the other stations during the selected period. We found that for the simulation period of 2001–2004, integrating *Hanson et al.*'s [2004] irrigation scheme in the Noah LSM improved the 15 cm soil temperature, observed from CIMIS.

[22] In comparison with CIMIS observations and control runs, our tests indicated that for the 16 sites, the improvements from the irrigation runs are consistently in eight sites (CIMIS numbers 071, 087, 105, 002, 007, 041, 068, 124, 135, and 151). However, at three sites (CIMIS numbers 012, 030, and 032), the results from irrigation runs get consistently worse. In these three sites, there were cool biases from both control runs and irrigation runs, in comparison with CIMIS observations. To examine if the biases are from the observation side, the authors examined the three stations from CIMIS website CIMIS Sites 12 and 32 are characterized as "a little used flood/sprinkle irrigated pastures," which possibly suggest that the area around these two sites were not heavily irrigated. The land cover in CIMIS 12 is bare soil and no photos can be found for the other two sites. We also compared the Noah LSM outputs (with the irrigation scheme) at 5 cm depth with the CIMIS observations (15 cm depth) and found they matched very well The results from the remaining sites (CIMIS numbers 015, 056, and 140) show that during some time periods the model results improved. However, the results also revealed no improvement during some periods when the irrigation scheme was added. Table 1 lists the statistical results of daily soil temperature at the 13 sites. The statistics does not include data from the three sites where the Noah LSM performed poorly and only account for the daily data from 1 May to 30 September from 2001 to 2004. Table 1 also indicates that over the 13 sites, in comparison with CIMIS and control run soil temperatures, the results from the irrigation run improved, and the improvement is statistically important using Student's *t* test at significance level = 0.05. The cool bias in the irrigation runs may be partly due to the fact that the model soil depth is at 20 cm, while the CIMIS soil depth is at 15 cm.

[23] In order to test the consistency of the modified Noah LSM, it was applied to two irrigated Ameriflux sites (Maize, 41.1651°N, 96.4766°W, and Mead Irrigated Rotation, 41.1649°N, 96.4701°W) in Nebraska, where surface fluxes and top-layer soil temperatures are observed. The modeling period selected was similar to the California simulation offline run period.

[24] The surface sensible heat, latent heat flux, ground heat flux, and 4 cm soil temperature from the Noah LSM and observations were checked. Adding the irrigation scheme in the Noah LSM can improve latent heat, sensible heat, and ground heat fluxes during the irrigation season (Table 2). This conclusion is drawn based on the use of same statistical method and significant level used in Table 1. However, the modeled 4 cm soil temperature does not show any improvement. In Table 2, we only account for the daily data in June, July, and August for the years from 2001 to 2004. We note that during the snowmelt season, the model overestimates latent heat and underestimates sensible heat flux. While our proposed modification is able to address the irrigation period model deficiency, it is unable to improve the simulation capability in the snow season. Most recently, using the same LSM (i.e., Noah) and the same method described in section 2.2, *Ozdogan et al.* [2010] studied the ET variation in the Maize and Soybean Ameriflux sites and found that ET is improved by setting the SW_m to 50%.

[25] In summary, from our offline simulation study, we conclude that the modification of the Noah LSM through the use of *Hanson et al.*'s [2004] irrigation scheme improves the model simulation capability. In addition, the Hanson et al. irrigation scheme, even though developed for application in

Table 2. The Statistics Results of Daily Soil Temperature at Two Ameriflux Sites From June to August From 2001 to 2004[a]

	Sensible Heat Flux (W/m^2)			Latent Heat Flux (W/m^2)			Geothermal Flux (W/m^2)			4 cm Soil Temperature (°C)		
	Obs	Ctrl	Irri	Obs	Ctrl	Irri	Obs	Ctrl	Irri	Obs	Ctrl	Irri
Mean	−3.6	3.5	−3.8	134.4	98.6	109.0	5.1	3.7	4.1	23.0	22.2	20.7
RSME	33.6	15.0	13.5	41.3	39.0	45.1	9.5	6.7	7.0	2.8	3.1	2.9
Correlation coefficient		0.39	0.48		0.81	0.76		0.88	0.91		0.89	0.87
Bias		7.6	0.22		−35.6	−25.6		−1.4	−1.1		−2.1	−2.4

[a]Given the significant level (0.05 here and N = 551) with Student's *t* test, the statistics are significantly important, including the sensible heat flux. Obs, observation; Ctrl, control run; Irri, irrigation run.

Table 3. Statistics of Surface Variables Observed at the CIMIS Station and Model Output at Grid Closest to the CIMIS Site When Both 36 km and 4 km Resolutions Are Categorized as Irrigation Grids[a]

	Variables	RH	T_2	T_{max}	T_{min}	T_{smax}
		36 km				
Ctrl	Mean	28.5	29.8	38.9	21.7	50.5
	RSME	5.1	1.5	1.2	1.9	1.5
	Corr.	0.251	0.72	0.83	0.62	0.13
	Bias	−25.2	6.29	6.2	7.1	9.6
R-ASDW	Mean	37.8	26.7	33.3	20.8	36.1
	RSME	3.8	1.3	1.0	1.6	1.0
	Corr.	0.3	0.6	0.79	0.67	0.5
	Bias	−16.0	3.15	0.68	6.2	−4.78
H-ASDW	Mean	40.6	26.1	32.5	20.2	34.1
	RSME	3.5	1.5	1.0	1.7	0.9
	Corr.	0.26	0.58	0.50	0.67	0.04
	Bias	−13.2	2.52	−0.11	5.7	−4.78
		4 km				
Ctrl	Mean	31.7	28.9	38.0	20.8	49.4
	RSME	7.8	2.2	1.7	1.9	2.3
	Corr.	0.22	0.83	0.85	0.75	0.35
	Bias	−21.6	5.37	5.4	6.18	8.51
R-ASDW	Mean	41.7	25.8	32.9	19.7	37.7
	RSME	4.3	1.5	1.3	1.8	3.5
	Corr.	0.35	0.71	0.22	0.80	0.80
	Bias	−12.1	2.23	0.14	5.10	−3.9
H-ASDW	Mean	40.5	25.7	32.7	19.5	36.0
	RSME	5.0	1.3	1.3	0.73	3.3
	Corr.	0.43	0.72	0.2	0.31	0.78
	Bias	−10.6	2.06	−0.11	4.89	−5.0
		CIMIS/MODIS				
	Mean	52.5	23.8	32.6	14.6	40.9
	RSME	5.5	1.5	1.7	1.2	3.0

[a]RH, relative humidity; ET, evapotranspiration; Q2, 2 m air mixing ratio; T2, 2 m air mean daily temperature; T_{max}, daily maximum temperature; T_{min}, daily minimum temperature; T_{smax}, daily ground surface maximum temperature from the model runs; R-ASWD, Realistic Allowable soil water Depletion; H-ASWD, High Allowable soil water Depletion.

California's real-time irrigation management, can be applied to other places.

3.2. Coupled Simulation Results

[26] In this section, we mainly show some results that are from MM5 simulations with and without irrigation that are to be added in the model from April to October 2007.

[27] To examine how much irrigation water should be added in the MM5 during simulation (May–August), we first compared the amount of water estimated from the model and that from recommended values provided in the *Hanson et al.* [2004] handbook. Our tests indicate that the amount of model water use is about 107.5 mm per month in the whole domain-3 at the irrigation grids. This amount compares well with the amount of water usage of 108.2 mm per month in the Sacramento Valley and 106 mm per month in the San Joaquin Valley (based on Table C-16 of *Hanson et al.* [2004]). Therefore, we have confidence that the proposed modified irrigation scheme adds a reasonably correct amount of irrigation water at the monthly scale.

[28] Next, we focus on investigating the results from June, July, and August 2007, which is the peak of the irrigation season, and September and October after model irrigation ceased. Table 3 provides statistical results of averaged surface variables between observation (CIMIS data and MODIS data) and model results at different model configurations in June, July, and August. There are eight CIMIS sites that are categorized as irrigation grids, both at 36 km and 4 km resolution. Model results are biased in control runs but, when the irrigation scheme is integrated into the model, results are improved in the mean daily air temperature, daily maximum temperature, and relative humidity, as well as daytime skin temperature in comparison with observations (CIMIS and MODIS data) (Table 3), while the amounts of the improvements depend on model resolution and allowable soil water depletion (i.e., SW_m). Note that the mean daily minimum temperature improved slightly (<1.0°C) from the irrigation run in comparison with the control run. However, in comparison with observations, the bias of the minimum temperature reaches about 5°C.

[29] We conclude that the results from the model with high SW_m irrigation and high resolution are relatively better than the other results, except daily maximum variables, of which the model with low SW_m and high resolution performed better. This conclusion is reasonable because the meteorological fields at the CIMIS site are measured under the condition that soil moisture is close to saturation, as mentioned in section 3.1. In actuality, for most of the crops, the soil is not required to be saturated. Thus, the real effects of irrigation on meteorological fields at the irrigation region must be less than the results from high SW_m and resolution. To examine this hypothesis, we compared the model results with the MODIS skin temperature observations.

[30] In comparison with the MODIS daytime skin temperature, the control run has a warming bias of about 8.5°C at the 4 km run and 9.6°C at the 36 km run. The irrigation run at 36 km resolution causes a cooling bias of about 4.78°C at different SW_m. However, at the 36 km resolution runs, the model results are not statistically significant. At the 4 km runs, the irrigation causes a cooling bias of 4°C at low SW_m and 5°C at high SW_m. Thus, in comparison with MODIS data, the results from the 4 km resolution with low SW_m are relatively better and more reasonable than the rest.

[31] Figure 2 shows the comparison of the mean surface temperature at 2100 UTC with the MODIS remotely sensed skin temperature at 2130 UTC (1330 local time). The results from the NARR and MM5 control runs at different resolutions (Figure 2a, top) only show the terrain-caused climate pattern and do not show the irrigation-caused surface temperature variations exhibited in the MODIS data. When the maximum allowable soil water depletion SW_m in the MM5 is fixed to 90%, the irrigation-caused surface temperature variation is reproduced by the model at different resolutions (Figure 2a, bottom). Figure 2b shows the modeled surface temperature at different resolutions when the maximum allowable depletion SW_m of soil in the MM5 is set up according to the recommendation of *Hanson et al.* [2004] (i.e., realistic SW_m). In comparison with the map from MODIS and model results shown in Figure 2a, Figure 2b indicated that the surface temperature using the recommendation method to determine model irrigation time is improved.

[32] In summary, in comparison with MODIS data, high-resolution model runs have performed well, especially at the low SW_m irrigation setup. The detailed differences between the MODIS data and the modified model results in the irrigation area may be because the Noah LSM only pre-

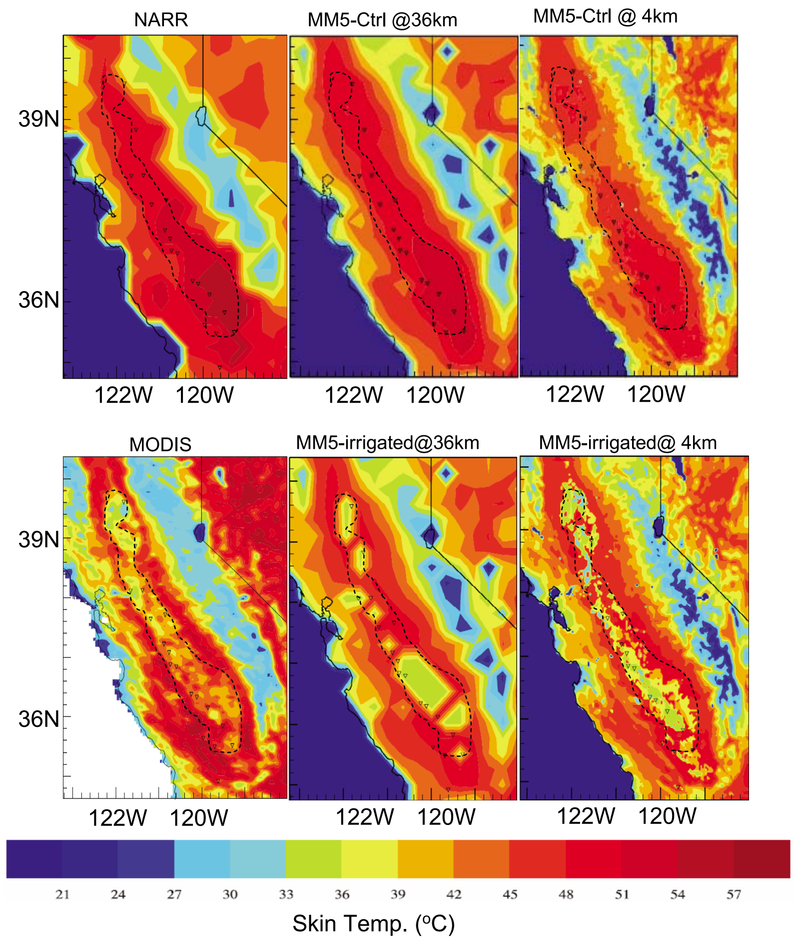

Figure 2a. Surface temperature comparisons. The time of the MODIS overpass is about 0130 LST (2130 UTC), while the other plots are at 2100 UTC. The triangles represent the CIMIS stations where the MM5 at 4 km resolution is identified as irrigated grids. The dashed line surrounds the approximate boundary of irrigated area in the Central Valley. The irrigation runs are set at the maximum allowable depletions of soil moisture and set at the fixed value of to 0.9.

scribes one crop, while there are various crop types in the real world. On the other hand, there are also various irrigation schemes, including flood irrigation and fallow land, that vary at the same spatial scale as crop type, which could influence MODIS observations.

[33] The 2 m air temperature was also checked in September and October using 4 km model output based on H-ASWD at 90% when the model irrigation stopped. In comparison with the control run (21°C in September and 17.7°C in October), the 2 m temperature from irrigated runs with realistic SW_m in September and October are 19.9°C and 17.4°C, respectively, while the CIMIS observations are 19.7°C and 15.4°C, respectively. Results from September–October (when the model irrigation stopped) indicate that with this model configuration, irrigation-caused soil memory from the previous period results in wetter and cooler surface air lasting for a maximum of one month, which means that the impact of irrigation on regional and/or local weather and climate is at the scale from intraseasonal to seasonal.

[34] Figure 3 provides the example of the comparison of diurnal variation of 2 m air temperature and relative humidity. The data represent the averages from June, July, and August. Again, when applying the H-ASWD at 90% irrigation scheme into the model, the model results at 4 km resolution are much closer to the observations, as compared to the default run. Note that the modified model results get worse at around 0300 UTC (1900 LST), which may be related to the abrupt application of water in the irrigation-modified model around this period. In actual practice, automatic irrigation systems usually spray water at some time from late afternoon to early morning and during the time of day when evaporation is at its lowest level (e.g., http://www.clemson.edu/extension/hgic/plants/other/irrigation/hgic1804.html).

[35] Another state variable we checked in the 18 stations was the mean wind components from June, July, and August (see Figure 4). While there still remain some differences between observations and modeling results at the same setup as in Figure 3, the modified model is improved, as compared to the control run. In comparison with observations, the model generates large U-component biases (~1–2 m s^{-1} differences from 0000 to 0300 UT) during the daytime and large V-component ~1 m s^{-1} biases from late afternoon to

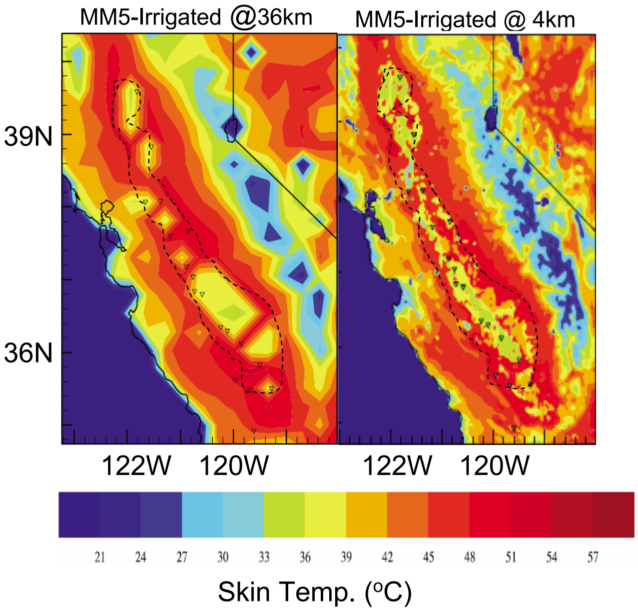

Figure 2b. The same as Figure 2a but for model skin temperature when the maximum allowable depletions of soil moisture are used as the recommended values (R-ASMD).

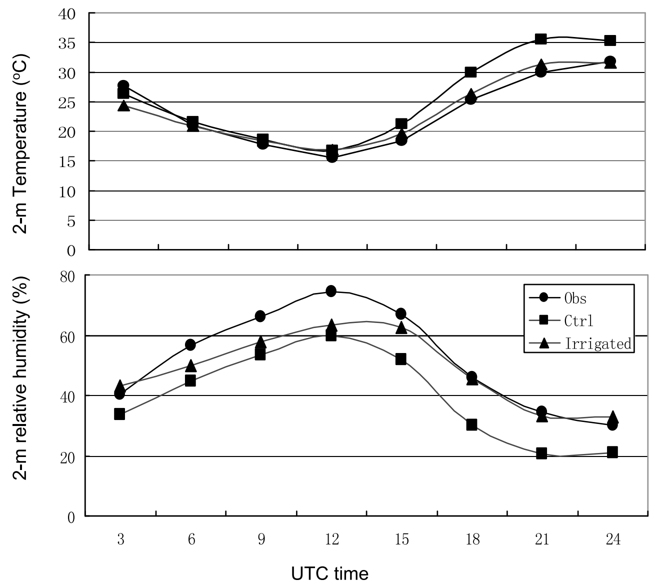

Figure 3. Mean diurnal cycle comparison of 2 m temperature and relative humidity between CIMIS observations and results of 4 km resolution modeled grid data closest to the station in the control run and the irrigation run with high allowable soil water depletion scheme. Total of 18 CIMIS stations are categorized as irrigation grid at 4 km resolution. The averaged months are June, July, and August 2007.

nighttime. Two reasons may cause the wind differences. One reason may come from the model boundary layer scheme's deficiency, namely that Eta PBL is unable to reproduce surface wind very well, even if it can simulate surface temperature perfectly [*Zhang and Zhang*, 2004]. The second reason may come from the fact that the observations are "point" values and observed at 1.5 m, while model estimates are "areal" values for 4 × 4 km grids at 10 m height. We checked the U- and V-component station by station and found the variability of wind to be very large.

[36] Figure 5 shows the differences of the irrigation-grid model results from the runs of different maximum allowable soil water depletion (H-ASWD at 90% minus R-ASWD) at different resolutions. Figure 5 indicates that in the irrigation areas, either at 36 km or at 4 km resolution, the MM5 run with H-ASWD at 90% generates high evapotranspiration (ET), high near-surface air mixing ratio(Q_2), cool daily mean temperature(T_2) and maximum (T_{max}) temperature, and cool ground surface maximum temperature (T_{smax}), in comparison with R-ASWD run. The interesting thing is that in comparison with the result from different resolutions, the model at coarse resolution generates high ET, high Q_2, low T_2 and T_{max}, and low T_{smax} for most of the days, in comparison with high resolution. Figure 5 indicates that model resolution can also affect the results in simulating the impact of irrigation on surface meteorological fields.

[37] Based on our study, the MM5 with the new irrigation scheme is capable of simulating the surface meteorological features caused by irrigation with relatively reasonable accuracy, especially during the daytime. The vertical cross-section analysis of temperature and relative humidity differences (figure not shown) indicates that the irrigation-induced cool and wet phenomena can extend to the entire boundary layer, and thus may affect the surrounding areas by modifying the local and mesoscale circulations, which is consistent with previous studies [e.g., *Kueppers et al.*, 2007]. The surface wind field result indicates that the net surface wind vector (difference between wind of irrigation run minus the wind of control run) is toward the nonirrigation area from irrigated area at daytime (data at 2100 UTC are checked). To

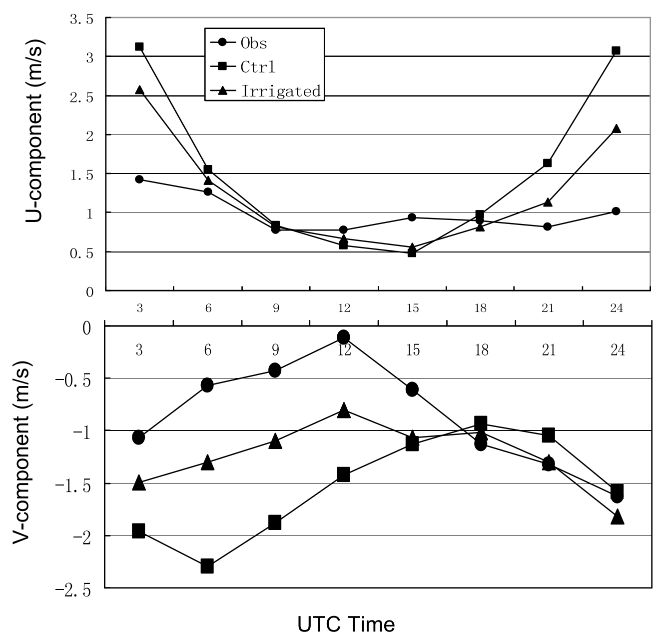

Figure 4. The same as Figure 3 but for wind components.

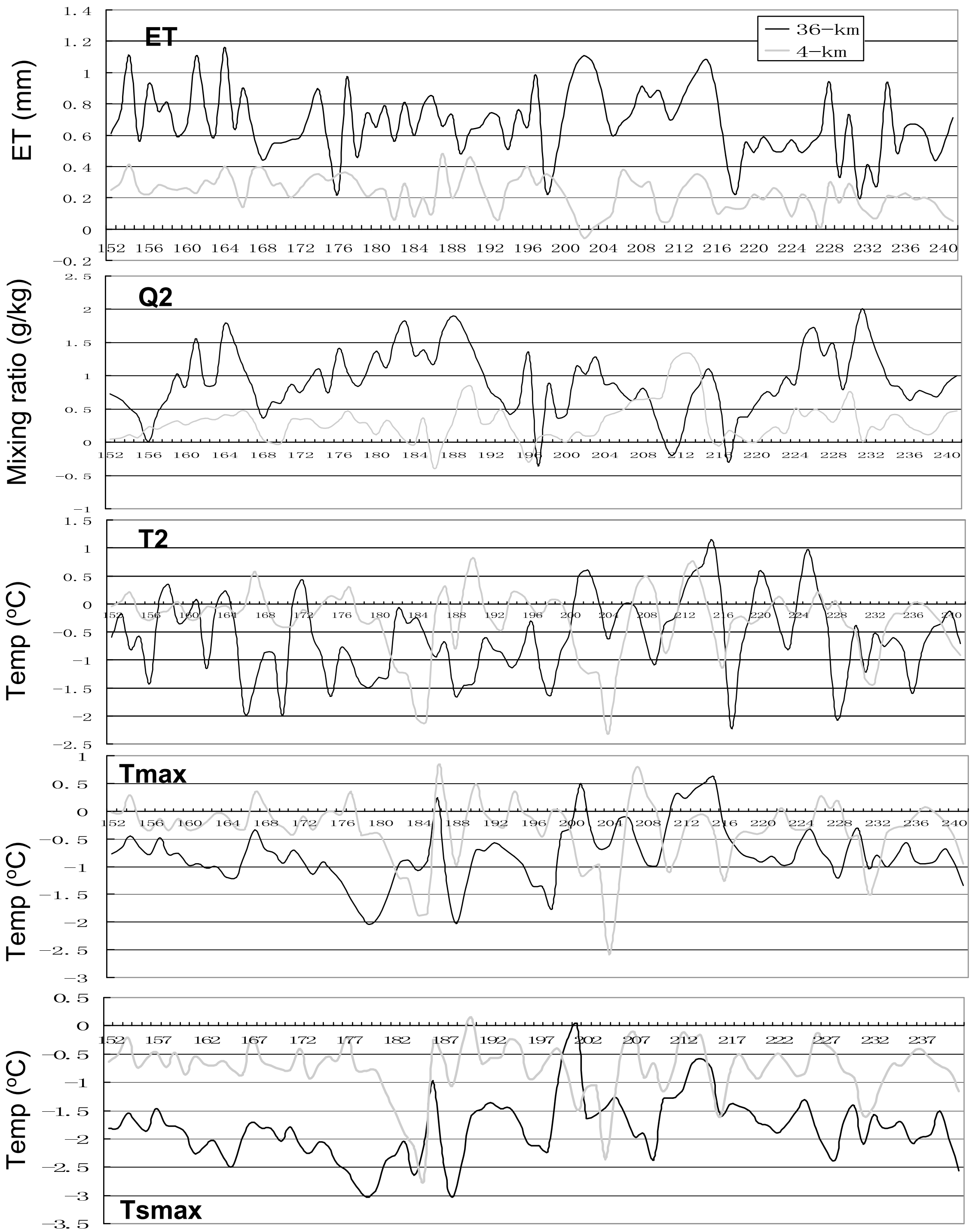

Figure 5. Surface meteorological field differences between high allowable soil water depletion and low allowable soil water depletion (HAD minus RAD) at different resolutions. ET, evapotranspiration; Q2, 2 m air mixing ratio; T2, 2m air mean daily temperature; Tmax, daily maximum temperature; Tsmax, daily ground surface maximum temperature from the model runs.

Table 4. Statistics of Surface Variables Observed at the CIMIS Station and Model Output at Grid Closest to the CIMIS Site When Both 36 km and 4 km Resolutions Are Categorized as Nonirrigation Grids[a]

	Variables	RH	T_2	T_{max}	T_{min}	T_{sfc}
		36 km				
Ctrl	Mean	29.9	28.8	37.0	21.1	47.9
	RSME	9.1	2.5	2.8	2.5	2.9
	Corr.	0.4	0.25	0.21	0.48	0.06
	Bias	−17.3	4.51	3.44	6.14	4.03
R-ASWD	Mean	32.2	27.9	35.6	20.7	46.8
	RSME	4.8	2.3	2.4	2.5	2.4
	Corr.	0.49	0.22	0.14	0.49	−0.01
	Bias	−14.9	3.61	2.05	5.68	2.89
H-ASWD	Mean	32.5	27.9	35.4	20.7	46.7
	RSME	4.3	2.3	2.3	2.6	2.4
	Corr.	0.44	0.22	0.13	0.46	0.0
	Bias	−14.3	3.63	1.85	5.73	2.78
		4 km				
Ctrl	Mean	31.8	28.8	37.6	20.9	47.8
	RSME	7.4	2.1	2.2	1.9	2.4
	Corr.	0.7	0.69	0.23	0.72	0.33
	Bias	−15.3	4.4	3.84	5.87	3.74
R-ASWD	Mean	33.6	27.9	36.0	20.7	45.9
	RSME	6.3	2.1	2.0	1.9	3.6
	Corr.	0.79	0.71	0.31	0.73	0.37
	Bias	−13.7	3.47	2.35	5.52	1.89
H-ASWD	Mean	34.2	27.8	35.9	20.7	45.7
	RSME	6.2	2.0	2.0	1.9	3.7
	Corr.	0.81	0.71	0.36	0.74	0.39
	Bias	−13.3	3.43	2.0	1.22	1.69
		CIMIS/MODIS				
	Mean	47.1	24.4	33.7	15.3	43.9
	RSME	9.1	2.1	2.0	2.0	3.1

[a]RH, relative humidity; T2, 2 m air mean daily temperature; T_{max}, daily maximum temperature; T_{min}, daily minimum temperature; T_{sfc}, ground surface temperature; Ctrl, control; R-ASWD, Realistic Allowable soil water Depletion; H-ASWD, High Allowable soil water Depletion.

examine the extent to which irrigation can affect the surrounding regions, we analyzed the surface meteorological fields based on observation and models.

[38] The effects of irrigation on meteorological fields of surrounding nonirrigation areas are also examined. The possible effects from our study vary depending on resolution and SW_m. Table 4 provides the statistics of surface variables observed at the CIMIS station/MODIS and model output at the grid closest to the CIMIS site, while the model with either 36 km or 4 km resolution is categorized as nonirrigation grid. There are a total of 22 CIMIS stations in this categorization. Generally, in comparison with CIMIS and MODIS observations, the model performed better (in checking correlation, bias) when 4 km resolution is used than when 36 km resolution is used. When 36 km resolution is used, the model results, including the control run and irrigation runs at different allowable soil water depletions, cannot pass the Student's *t* test (0.10 significance level), or the values of the improvement (difference between the model control run and the irrigation run) are smaller than the biases. When 4 km resolution is used, the model with irrigation runs slightly improved the daily mean and maximum temperature, and daytime skin temperature, especially with high SW_m. However, the model still generates a large dry (~−13% to −15%) and warm (~3.4°–3.6°C) bias. As mentioned in section 3.1, the observations of CIMIS data are measured under the condition of high-level soil moisture. Therefore, we may conclude that the effects of normal irrigation on the meteorological fields of surrounding nonirrigated areas are slight, except for daily maximum temperature and daytime surface temperature.

[39] Figure 6 displays daily 2 m temperature differences between the MM5 control runs and the irrigation runs at 4 km resolution. The differences at the model irrigation grids over the Central Valley are masked. Thus, the differences shown in Figure 6 indicate the extent to which large-scale irrigation can affect the weather and climate in nearby nonirrigation areas. Figure 6 indicates that the effect of irrigation on nearby nonirrigation regions' daily average temperature is less than 1°C at most of the surrounding areas, except for the boundary of the southern Central Valley. However, irrigation can affect the daily maximum temperature at the range from 1 to 4°C at the nearby nonirrigation regions. This effect is larger in the San Joaquin Valley than in the Sacramento Valley, both in extent (1°–2°C larger) and in areas, possibly due to the prevalent northerly in the Central Valley during the daytime (see Figure 4).

[40] In comparison with the model results from different resolutions, one can notice the differences in the irrigation regions (Tables 3 and 4), even though the model with different resolutions generates very similar spatial patterns. Higher resolution can generate more detailed spatial variations and cooler skin temperatures at some locations, which is important for understanding the effect of irrigation on the local climate.

[41] Figure 7 provides the 2 m monthly mean temperature comparison between Ameriflux observations and model results at 4 km resolution with/without irrigation at high SW_m. The Ameriflux sites are located in the eastern portion of the large irrigation areas (<50 km in distance but are not irrigated themselves) and are about 30 km from the closest CIMIS station. The result shows that (1) irrigation-caused cooling is not large when comparing the model results with/without irrigation, and (2) model biases are clear in June and October. The results indicate that irrigation-induced cool and wet effects occur mainly at the local scale. The effects of irrigation on weather and climate do not extend very far into nonirrigated regions.

4. Summary and Conclusion

[42] In this study, the effects of irrigation in the Central Valley of California on local/regional climate is reexamined by incorporating more realistic irrigation processes suggested by *Hanson et al.* [2004] into the MM5 Noah land-surface model using different maximum allowable soil water depletion and different resolutions. The following is a summary of the results of our modeling studies.

[43] 1. Relative to the results from the model default runs, the model with the irrigation process of *Hanson et al.* [2004] indicate that the surface meteorological fields are noticeably improved in comparison with observations from the California Irrigation Management Information System (CIMIS) network and MODIS data. This aspect of our findings is consistent with previous studies. However, our results also indicate that the irrigation caused the irrigated grids'

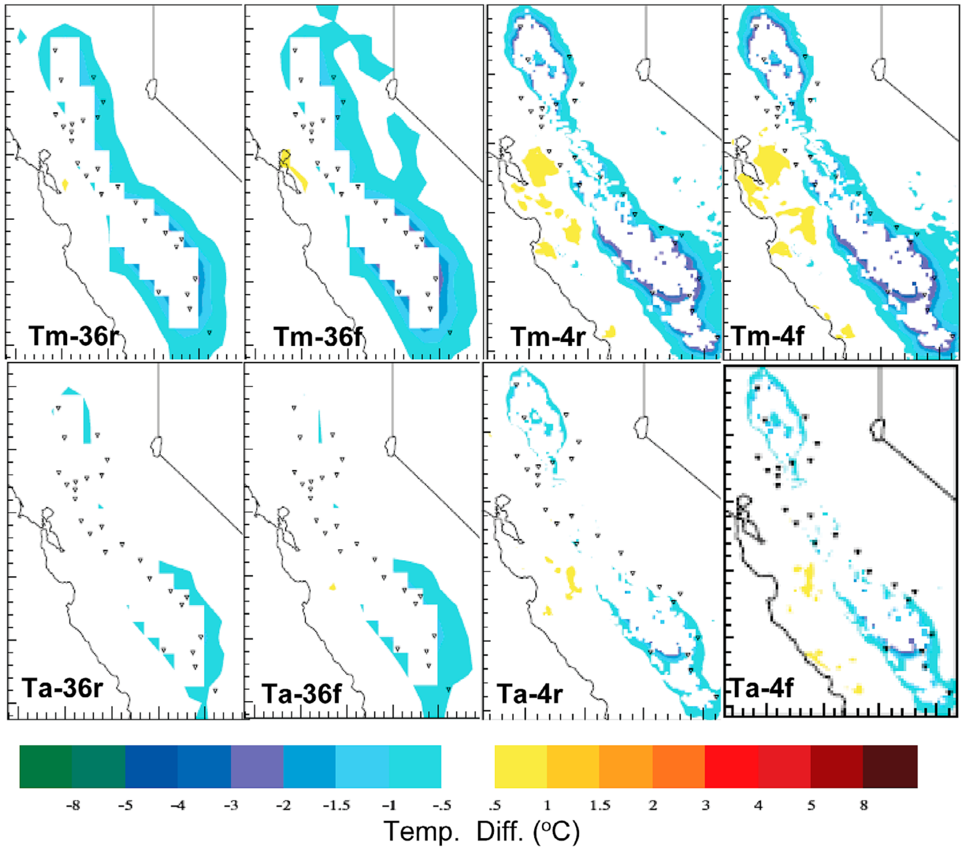

Figure 6. Daily 2 m temperature differences between the MM5 control runs and the irrigation runs. The results at the irrigation grids are masked. The differences indicate the significant effect of irrigation on temperature in nonirrigation areas. The triangles indicate the CIMIS stations near the Central Valley, while the MM5 grid at 4 km resolution does not identify it as an irrigation area. T, temperature; m, daily maximum; a, daily average; 36, 36 km resolution; 4, 4 km resolution; r, R-ASMD irrigation; f, H-ASMD irrigation.

temperature to decrease by about 3°–7°C and humidity to increase by about 9–20%, depending on model resolutions and allowable soil water depletions.

[44] 2. Based on the diurnal cycle analysis, we find that the resulting improvement is especially pronounced in the daytime, when the PBL is unstable and there was strong interaction between land surface and low PBL. However, at nighttime, the model has deficiency in simulating surface wind fields and relative humidity.

[45] 3. Our offline tests indicate that the incorporation of the R-ASWD irrigation method developed by *Hanson et al.* [2004] in California, can be used in other irrigation sites to model the surface fluxes. Our simulation results for this case show improvement in surface flux estimates in Nebraska.

[46] 4. With increasing model resolution from 36 km to 4 km, the modeling results indicate that simulated temperature values are improved by about 1°C and relative humidity by about 5%, in both the control and irrigation runs. Furthermore, the improvements are statistically important. However, some biases from model outputs are still apparent, in comparison with observations. Our tests indicate that model resolution is an important factor in assessing the impact of irrigation on local/regional climate.

[47] 5. Finally, in the fully irrigated grid, using high maximum allowable soil water depletion in the model causes an increase in the near-surface air wet (specific humidity increasing ~0.5–1.5 g/kg) and cool (temperature decreasing ~0.5°–2°C), in comparison with using realistic allowable soil water depletion. In the surrounding nonirrigated grids,

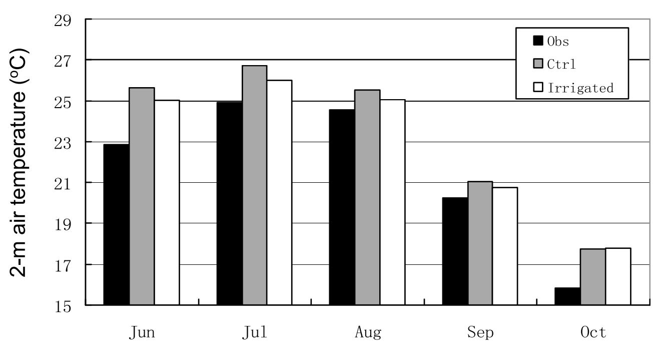

Figure 7. The 2 m monthly mean air temperature comparison between models and observations at two Ameriflux sites, Tonzi Ranch (38.4136°N,120.966°W) and Vaira Ranch (38.4067°N,120.9507°W), and model output closest to the site. The model mean is from the 4 km resolution modeled grid data closest to station in control run and the irrigation run with high allowable soil water depletion scheme.

when the allowable soil water depletion increases from low to high, resulted in a slight decrease of about 0.5°C in the daily maximum temperature. Therefore, we conclude that the impact of irrigation on surrounding nonirrigated grid's daily or monthly mean temperature is very small.

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References

Adegoke, J., R. Pielke Sr., J. Eastman, R. Mahmood, and K. Hubbard (2003), Impact of irrigation on midsummer surface fluxes and temperature under dry synoptic conditions: A regional atmospheric model study of the U.S. High Plains, *Mon. Weather Rev.*, *131*, 556–564, doi:10.1175/1520-0493(2003)131<0556:IOIOMS>2.0.CO;2.

Chen, F., and J. Dudhia (2001), Coupling an advanced land surface-hydrology model with the Penn State-NCAR MM5 modeling system. Part I: Model implementation and sensitivity, *Mon. Weather Rev.*, *129*, 569–585, doi:10.1175/1520-0493(2001)129<0569:CAALSH>2.0.CO;2.

Grell, G. A. (1993), Prognostic evaluation of assumptions used by cumulus parameterizations, *Mon. Weather Rev.*, *121*, 764–787, doi:10.1175/1520-0493(1993)121<0764:PEOAUB>2.0.CO;2.

Hanson, B., L. Schwankl, and A. Fulton 2004: Scheduling irrigations: When and how much water to apply?, *Publ. 3396*, 202 pp., Div. of Agric. and Nat. Resour., Univ. of Calif., Davis.

Janjic, Z. (1994), The step-mountain Eta coordinate model: Further developments of the convection, viscous sublayer and turbulence closure schemes, *Mon. Weather Rev.*, *122*, 927–945, doi:10.1175/1520-0493(1994)122<0927:TSMECM>2.0.CO;2.

Kanamaru, H., and M. Kanamitsu (2008), Model diagnosis of nighttime minimum temperature warming during summer due to irrigation in the California Central Valley, *J. Hydrometeorol.*, *9*, 1061–1072, doi:10.1175/2008JHM967.1.

Kueppers, L., M. Snyder, and L. Sloan (2007), Irrigation cooling effect: Regional climate forcing by land use change, *Geophys. Res. Lett.*, *34*, L03703, doi:10.1029/2006GL028679.

Kueppers, L., et al. (2008), Seasonal temperature response to land-use change in the western United States, *Global Planet. Change*, *60*, 250–264, doi:10.1016/j.gloplacha.2007.03.005.

Li, J., X. Gao, and S. Sorooshian (2007), Modeling and analysis of the variability of the water cycle in the Upper Rio Grande Basin at high resolution, *J. Hydrometeorol.*, *8*, 805–824, doi:10.1175/JHM602.1.

Liang, X., L. Li, K. Kunkel, M. Ting, and J. Wang (2004), Regional climate model simulation of U.S. precipitation during 1982–2002. Part I: Annual cycle, *J. Clim.*, *17*, 3510–3529, doi:10.1175/1520-0442(2004)017<3510:RCMSOU>2.0.CO;2.

Lobell, D., G. Bala, A. Mrin, T. Phillips, R. Maxwell, and D. Rotman (2009), Regional differences in the influence of irrigation on climate, *J. Clim.*, *22*, 2248–2255, doi:10.1175/2008JCLI2703.1.

Mesinger, F., et al. (2006), North American regional reanalysis, *Bull. Am. Meteorol. Soc.*, *87*, 343–359.

Mlawer, E., S. Taubman, P. Brown, M. Jacono, and S. Clough (1997), Radiative transfer for inhomogeneous atmosphere: RRTM, a validated correlated-k model for longwave, *J. Geophys. Res.*, *102*, 16,663–16,682, doi:10.1029/97JD00237.

Ozdogan, M., M. Rodell, H. Beaudoing, and D. Toll (2010), Simulating the effect of irrigation over the United States in a land surface model based on satellite-derived agricultural data, *J. Hydrometeorol.*, *11*, 171–184, doi:10.1175/2009JHM1116.1.

Pielke, R., and R. Avissar (1990), Influence of landscape structure on local and regional climate, *Landscape Ecol.*, *4*(2-3), 133–155, doi:10.1007/BF00132857.

Pielke, R., J. Adegoke, T. Chase, C. Marshall, T. Matsui, and D. Niyogi (2007), A new paradigm for assessing the role of agriculture in the climate system and in climate change, *Agric. For. Meteorol.*, *142*, 234–254, doi:10.1016/j.agrformet.2006.06.012.

Segal, M., Z. Pan, R. Turner, and E. Takle (1998), On the potential impact of irrigated areas in North America on summer rainfall caused by large-scale systems, *J. Appl. Meteorol.*, *37*, 325–331, doi:10.1175/1520-0450-37.3.325.

Tao, W.-K., and J. Simpson (1989), Modeling of a tropical squall-type convective line, *J. Atmos. Sci.*, *46*, 177–202, doi:10.1175/1520-0469(1989)046<0177:MSOATS>2.0.CO;2.

Zhang, D., and W. Zhang (2004), Diurnal cycles of surface winds and temperatures as simulated by five-boundary layer parameterizations, *J. Appl. Meteorol.*, *43*, 157–169, doi:10.1175/1520-0450(2004)043<0157:DCOSWA>2.0.CO;2.

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