1 Human-induced modifications to land surface
2 fluxes and their implications on water management
3 under past and future climate change conditions
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Abstract

We used a coupled land-atmospheric simulation framework to quantify the feedback impacts of water resources in a changing climate. The simulations dynamically downscaled data from the North American Regional Reanalysis (NARR) data, Climate Forecast System (CFS) Version 2 and the North American Regional Climate Change Assessment Program (NARCCAP), to investigate irrigation effects on temperatures and surface fluxes under current and future scenarios in Southern Idaho. This study implements irrigation schemes within the Noah Land Surface Model (LSM) coupled with the Weather Research and Forecast (WRF) 3.4 at a 4-km resolution to diagnose irrigation-induced changes to surface energy fluxes and boundary layer properties. Our results suggest that induced cooling via evaporation causes a decrease of 0.8°C to the air temperature over April - October, a decrease of up to 90 meters of the planetary boundary layer depth and an increase of 2.0°C in the dew point over the irrigated areas. On average, the growing season start date trends 0.46 days/year earlier and the growing season termination date trends 0.60 days/year later. A decrease in precipitation with time is also seen at all elevation ranges from the year 2040-2070, with the lowest elevation levels seeing a bigger decrease than the higher levels. Thus, irrigation-induced increases in growing degree days and modifications to surface fluxes are shown in the basin and it is critical to consider when planning both crop and water management.

Key Words: Irrigation, Surface Fluxes, Climate Change, Modeling

1. Introduction

The Snake River, which is the largest tributary of the Columbia River and the ninth largest river in the United States, drains a semi-arid region that covers approximately 281,000 km². Agriculture in this basin, without irrigation, is not sustainable due to the dry hot summers. Irrigation diversion canals are the lifeblood of agriculture in Idaho. Water from the Snake River is used to irrigate over 14,100 km² of cropland. Milner Dam diverts the entire river in the summer to 1,600 km of canals near Twin Falls, Idaho (Slaughter, 2004). Climate change impacts on hydrology and water resources in many basins in the Northwest region are causing some concern in terms of future water availability, agricultural practices, and water management (Jin and Sridhar, 2012; Sridhar et al. 2013). However, coupled feedback analysis under climate change conditions in this managed water system has not been studied previously (Sridhar, 2013). The motivation for this study stems from the need for understanding the impact of land surface feedbacks on evapotranspiration and consumptive water use estimates in order to effectively allocate limited water resources available for irrigation. The hypothesis of this study is that irrigation mitigates warming on a local scale by evaporative cooling under future climate scenarios. There is no study that integrates irrigation effects on boundary layer fluxes for this basin. However, many investigations suggested that the regional climate and land surface fluxes needed to be assessed for current as well as future climate conditions.

Numerous irrigation-related land-atmosphere studies conducted in the Great Plains of the United States have identified importance of irrigation in modifying the

66 boundary layer properties (Adegoke et al. 2003; Barnston and Schickedanz, 1984;
67 DeAngelis et al. 2010; Harding and Snyder 2012a, 2012b; Lobell et al. 2008; Mahmood
68 and Hubbard 2004; Mahmood et al. 2006; Mahmood et al. 2008; Moore and Rojstaczer
69 2001, 2002; Ozdogan et al. 2010). Adegoke et al. (2003) used the Regional Atmospheric
70 Modeling System (RAMS) to perform four 15-day simulations using different vegetation
71 datasets in the U.S. High Plains. Simulations of irrigation schemes watered the top soil
72 daily at 0000 UTC to saturation down on average to a depth of 0.2 m. A 36% increase in
73 surface latent heat flux, a 2.6°C increase in dew point temperature, a 15% decrease of
74 surface sensible heat flux, and a 1.2°C decrease in air temperature was observed
75 between the irrigated and a dry (non-irrigated) simulation. Furthermore, Adegoke et al.
76 reported a decrease in observed long-term (1921-2000) monthly mean and monthly
77 mean maximum temperature at the irrigated site (York, NE), while the non-irrigated site
78 (Halsey, NE) reported an increase in mean monthly and mean maximum temperature
79 during the same time period. DeAngelis et al. (2010) concluded that irrigation could
80 have increased the precipitation up to 15-30% downwind of the Ogallala Aquifer from
81 eastern Kansas to Indiana. DeAngelis et al. (2010) and Harding and Snyder (2012)
82 employed a dynamic recycling model (DRM) developed by Dominguez et al. (2008), and
83 Dominguez and Kumar (2008). The DRM uses a Lagrangian method to track the
84 atmospheric vapor transport and calculates the amount of ET-based precipitation in the
85 Ogallala Aquifer region based on North American Regional Reanalysis (NARR) data. In
86 their DRM study, DeAngelis et al. (2010) found that ET contributes to a 0.3-0.5 mm/day
87 or 2-6% increase in downwind July precipitation. Harding and Snyder (2012a, b)

reported precipitation attributed to irrigation was found to be responsible for precipitation increases on average of 1% over the Great Plains and 1.6% over north central Nebraska. Furthermore, they reported a significant amount of moisture was advected out of their study region before falling as precipitation which resulted in a net loss in water balance. They raised the concern that this phenomenon would create a positive feedback mechanism in the Great Plains that would further reduce the total soil moisture and ground water aquifer supply, which have agricultural implications due to future water shortages within the Ogallala Aquifer. Ozdogan et al. (2010) combined a MODIS irrigated area map, a 1-km land cover use global map, and incorporated 19 crop types at 1-km resolution within the Land Information System (LIS) which used the Noah-LSM across the continental United States to investigate irrigation. They assigned maximum root depth values and represented seasonal variability in greenness fraction and reported a 4% increase in ET across the continental United States during 2003, which is substantial on a nationwide scale.

Coleman et al. (2010) reported that irrigation improved the simulation of daytime surface temperature by decreasing the warm bias via evaporative cooling but enhanced the nighttime temperature cold bias over heavily irrigated areas of Bakersfield in California. Sorooshian et al. (2011) implemented irrigation schemes using a maximum allowable water depletion method in the Penn State University-National Center for Atmospheric Research (NCAR) Mesoscale model (MM5). They reported the temperature surrounding otherwise non-irrigated grids is only slightly impacted by irrigation, showing decreases of less than 0.5°C. Furthermore, increasing model

resolution from 36-km to 4-km improved the simulated temperature and humidity biases by 1°C and 5%, respectively. Sorooshian et al. (2012) set up three experiments using the MM5 model coupled with the Noah-LSM: one with soil moisture conditions at field capacity, a no-irrigation run, and a realistic run. The realistic run applies water to the soil column when the soil moisture is less than the maximum allowable water depletion; a method practiced closely by irrigators in California. They reported the water depletion scheme used in their study produces accurate amounts of ET in the Central Valley of California when compared to the MODIS ET observations (Sorooshian et al. 2012).

Jaksa & Sridhar (2015) quantified surface energy fluxes in regions with and without irrigation in arid regions of Southern Idaho using coupled (WRF and Noah-LSM) and uncoupled Noah-LSM runs at 4-km grid-scale resolution and identified the need for a similar study under climate change conditions. The WRF-ARW 3.4 was used to dynamically downscale reanalysis data from three datasets: The Climate Forecast System Reanalysis (CFSR; Saha et al. 2010), The Climate Forecast System Reanalysis Version 2 (Saha et al. 2011), and the North American Regional Reanalysis (NARR; Mesinger et al. 2006). It is important to note that reanalysis datasets such as the CFSR and NARR implicitly include irrigation as a result of the assimilation of meteorological observations (Wei et al. 2013). Irrigation code based on (Sridhar, 2013) was added to the NOAH-LSM code and was adapted for use within the NOAH-MP model. Thus, the objective of this study is to examine the surface energy balance components impacted by irrigation, validate with observational flux data, and to investigate the differences

within the PBL depth, clouds, precipitation, and water balance using the data from North American Regional Climate Change Assessment Program (NARCCAP), NARR and CFSR products, with and without irrigation, for past, present, and projected future climates.

The paper is organized as follows. Section 2 briefly describes the study area, meteorological forcing data for the model, observational datasets, experimental model design, irrigation representation and constraints. Section 3 describes the results of the simulations. Section 4 describes the conclusions and limitations of the study.

2. Methods

2.1 Study Area

The focus of our study area encompasses the concave-shaped Snake River Plain located in southern Idaho, where a majority of irrigation takes place. The domain of the WRF model (Skamarock et al. 2008) used in this study encompasses the Snake River Basin in Southern Idaho. This area extends from 112.5°W to 118.0°W longitude and from 41.8°N to 44.5°N latitude and more than 90% of cropland area of this region is irrigated (Sridhar, 2013). This study used the 20-category MODIS land use dataset, at 30-arcsecond resolution to define vegetation and soil texture. Precipitation in the basin can vary widely and most of it is received in the winter as snow. Topography dictates the pattern and magnitude of rainfall with high mountains receiving over 1600 mm a year and the Snake River plains receiving 200 mm (Fig. 1a). There is a strong correlation between spring soil moisture and summer temperatures in southern Idaho; warmer than usual summer temperatures correlate with below normal spring soil moisture

values (Alfaro et al. 2005). The basin is expected to be impacted by climate change through changing snow to rain ratios, temperature-induced early snowmelt and increased water demand (Hoekema and Sridhar, 2011; Hoekema and Sridhar, 2013).

2.2 Meteorological Forcing Data

2.2.1 Climate Forecast System Version 2 Forecast Data

The operational NCEP Climate Forecast System Version 2 (CFSv2; Saha et al., 2010) was implemented in March 2011 to replace the Climate Forecast System Version 1 (CFSv1). CFSv2 plays a substantial role in operational forecasts for 6-10 days up to 2 weeks. CFSv2 provides forecasts of 3-6 weeks of forecasts for use in operations at the Climate Prediction Center (CPC; Saha et al. 2011). Saha et al. (2011) report that CFSv2 is superior to the CFSv1 on the intraseasonal time scales from the improved resolution, data assimilation, and physics in the model. CFSv2 data are used to initialize the past climate runs. For the 3D model boundary conditions, specific humidity, zonal wind component, meridional wind component, vertical wind component, geopotential height, and temperature were downloaded at 25 pressure levels ranging between 1000 and 100 hPa. For the 2D model boundary conditions, surface data were obtained for temperature, relative humidity, zonal wind component, meridional wind component, pressure, sea-level pressure, precipitation, and snow depth.

The data is produced daily and land surface files include 2 meter temperature, 2 meter specific humidity, surface snow water equivalent, u-component and v-component of wind at 10 meters, surface pressure, surface geopotential height, surface ice cover,

175 surface land cover, and volumetric soil moisture content at four layers (0.0-0.1 m, 0.1-
 176 0.4 m, 0.4-1.0 m, and 1-2 m). Atmospheric data are archived on a 720×361 Gaussian
 177 Grid at $0.5^\circ \times 0.5^\circ$ grid resolution from 0°E to 359.5°E longitude and 90°N to 90°S
 178 latitude. Atmospheric files include geopotential height, pressure reduced to MSL
 179 pressure, relative humidity, temperature, and u-component and v-component of wind.
 180 The atmospheric files include these variables at 37 levels ranging between 1000 hPa and
 181 1 hPa.

182 *2.2.2 NARCCAP Data*

183 The North American Regional Climate Change Assessment Program (NARCCAP;
 184 Mearns et al. 2007; 2009) data were used for our analysis. Specifically, we employed
 185 Phase II that used boundary conditions from Atmosphere-Ocean General Circulation
 186 Model (AOGCM) for 30 years of current climate (1971-2000) and future climate (2041-
 187 2070). The future climate scenarios used the A2 emissions scenario (Mearns et al.
 188 2012). For the 3D model boundary conditions, specific humidity, zonal wind component,
 189 meridional wind component, vertical wind component, geopotential height, and
 190 temperature were downloaded at 25 pressure levels between 1000 and 100 hPa.

191 For the 2D model boundary conditions, surface data was obtained for
 192 temperature, relative humidity, zonal wind component, meridional wind component,
 193 pressure, sea-level pressure, precipitation, and snow depth. The data does not include
 194 soil moisture so WRF must be initialized with soil moisture from a different data source
 195 and run with a long enough spin-up time to ensure soil moisture and temperature
 196 equilibrium within the model. NCAR Command Language (NCL) scripts were made

available to convert the NetCDF data into WRF intermediate format (M. Bukovsky,
personal communication, July 12, 2012).

2.2.3 Observation Datasets

Modeled data are compared to AgriMet, flux tower and Snow Telemetry (SNOTEL) observations in the following sections. Temperature, dew point temperature, and precipitation from the WRF runs driven by NARR and CFSR data are compared at six AgriMet observation sites located in Idaho: Aberdeen, Grandview, Nampa, Parma, Rupert and Twin Falls. AgriMet is a network of automated agricultural weather stations operated and maintained by the United States Bureau of Reclamation. The stations are located in irrigated agricultural areas throughout the Pacific Northwest to improve irrigation efficiency. AgriMet weather stations are equipped with sensors that include: air temperature, precipitation, solar radiation, wind speed and direction, pan evaporation at select sites, and relative humidity. Fig. 1b shows the AgriMet, SNOTEL and Flux Tower site locations that were employed for validation and it is worthwhile to note that the inner domain described earlier for the study area is used for computing averages with irrigation in the Southern Idaho region.

Meteorological flux tower sites were installed in late 2009 at Hollister and Raft River sites in Idaho to measure meteorological variables such as temperature, humidity, turbulence, surface energy fluxes, wind speed and soil characteristics such as soil moisture and soil temperature. The Hollister flux tower site is mainly sagebrush and located at 42.33°N, 114.7°W. The Raft River site is mainly cheat grass and is located at 42.58°N, 113.41°W. The instruments include large aperture scintillometers which

estimate sensible heat flux by measuring variations in temperature, humidity and pressure along 800-1600 meter transects. Each site includes three 3D sonic anemometers for measuring boundary-layer turbulence, and hygrometers to measure ET and CO₂ via the eddy covariance method. Soil properties such as soil heat flux, soil water content, soil temperature, and net radiation are measured at these sites. This instrumentation project was sponsored by NSF Idaho EPSCoR and is operated jointly by Boise State University, Idaho State University and University of Idaho.

2.3 Experimental Design

The simulations of WRF driven by CCSM for the period of 2038-2049 and CGCM for the period 2038-2070 were conducted. For all NARCCAP simulations, a 15-month spin-up was performed so that soil variables reached dynamical equilibrium between the boundary conditions and model dynamics, since the GCM boundary conditions data lack soil variables necessary to initialize the land surface model. For historic simulations, the soil moisture variables were initialized using a climatological mean for 1-October (1980-2000) and then each simulation was started on 1-October before the year of interest because the soil moisture is at the climatologically lowest values of any given season in Idaho. The NARR and CFS boundary conditions data included all soil variables necessary to initiate the land surface model so the model spin-up time was reduced from 15-months to 7-months as each simulation was started on 1-October of the year of interest and examined from 1-April of the following year.

The simulations of WRF driven by CCSM for the past were also performed from 1 August 1991 to 20 July 1996. The CFSv2 Forecast was spun up from 8 October 2012 to 1

May 2013 and from 6 December 2012 to 1 July 2013 to examine the driving model's feasibility in future operational use.

The configuration of WRF is shown in Table 1 following the recommendations of Warner (2011), except the vertical grid spacing. Horizontal grid spacing in this study is 4 km and the vertical grid should not be specified independently. The recommended vertical and horizontal model grid spacing is based on the following equation:

$$\Delta Z_{opt} = s\Delta y \quad (1)$$

where s is the frontal slope, Z_{opt} is the optimal vertical grid increment, and Δy is the horizontal grid increment. The adaptive time-step option is enabled within WRF to reduce the wall-clock time due to the amount of processing time required to complete a simulation of 30 years. The adaptive time step increases the model time step in fair weather and reduces the model time step when winds are strong in the vertical or horizontal (e.g., thunderstorms or jet streams). The vertical grid number is the same as those used within the University of Washington (UW) Atmospheric Science WRF model due to the extensive modeling experience in the complex terrain of the Northwestern United States, with the MM5 and its successor, the WRF-ARW (Mass & Ovens 2012). The model uses 38 full-sigma vertical levels.

2.4 Irrigation Representation

The irrigation scheme allows for customization of the land use categories, start date, end date, amount to water and minimum amount of soil moisture availability to initiate irrigation (Sridhar, 2013). The scheme begins by performing a land class check and determines whether the cell should be irrigated or not. For the study, the default

MODIS 20 land use categories were used, and irrigation was enabled for ‘croplands’, which is land use category 12 within the model. Irrigation canals in Southern Idaho generally carry water from April 1 through October 31 of each year and characterize the growing season in this study. The scheme checks whether or not the date is within the growing season to irrigate the grid cells.

Irrigation is simulated by applying water to the top model soil layer when any one of the soil layers gets too dry. The irrigation scheme does not change the physics of the existing Noah-LSM. The scheme simply adds water to the top soil layer when it reaches a defined threshold. After the soil water is added, the Noah-LSM calculates fluxes, runoff, and evaporation accordingly. The soil moisture (SM) percentage is used to determine whether irrigation is required. Minimum soil moisture percentage (Min %) is set to 60% for this study. We used this percentage based on Sridhar (2013) where the irrigation scheduling was taken into account for a given season as well as the water holding capacity of the soil based on the computation on field capacity and wilting point for the soil type in the basin. The soil moisture is computed and is compared to the minimum soil moisture (MSM). MSM is defined by:

$$MSM = (SMCREF - SMCWLT) * Min\% + SMCWLT \quad (2)$$

where SMCREF is the reference soil moisture capacity as defined in the Noah-LSM based on the soil type, and SMCWLT is the reference soil moisture wilting point based on the associated soil type. Each soil layer is crosschecked for MSM and water is added accordingly. When the soil moisture in the crop grid cells falls below 60% (MSM), water is applied to the soil top layer and is moistened until the maximum added soil moisture

(MASM) reaches 85% of the SMCREF. This percentage is based on the assumption that soil column is always irrigated less than the field capacity level to minimize runoff or excess drainage. We considered this as a calibration parameter so that field is always saturated enough to sustain plant life above the soil wilting point.

$$\text{MASM} = (.85) \text{ SMCREF} \quad (3)$$

3. Results and Discussion

3.1 Impact of Irrigation in NARCCAP-CCSM future and past simulations

The NARCCAP-CCSM past (1992-1999) data was compared to the NARCCAP-CCSM Future (2040-2070) data. Figure 2 illustrates impact of irrigation within the model which decreased the latent heat flux, slightly increased the sensible heat flux, and increased the magnitude of ground heat flux. This could be due to the fact that more of the available energy is used to heat the soil, increasing the ground heat flux and thus decreasing the vapor pressure deficit near the surface. While soil temperature increase due to lowering vapor pressure deficit could be a factor in partitioning the available energy, it is the switch between energy limited (under irrigated condition) and soil moisture-limited (under drying conditions) evaporation conditions. The feedback or coupled effect of the land surface and near-surface meteorology dominated the partitioning behavior of the energy. For instance, with increased ET the humidity load increases in the boundary layer, which in turn decreases the vapor pressure deficit forcing the stomata to shut down thereby decreasing ET. This occurs despite the fact that soil moisture is increased due to irrigation which is also adding humidity to the near-surface layer thereby decreasing the evaporative demand. The decrease in latent

heat flux could also be due to the lack soil moisture retention capacity of the soil column despite irrigation recharging it to 85% of the field capacity level.

Our analysis showed an increase in irrigation requirement (3.95 mm/year) and an increase in evaporation (3.25 mm/year) from the results based on the NARCCAP-CCSM simulation. The amount of irrigation added in the model corresponded the most ($R^2=0.6714$) with dew point temperature depression. Average annual temperature compared with average annual irrigation added only yielded a linear regression of $R^2=0.4553$.

3.2 Projected Temperature Trends

Trends for average annual temperature for all irrigated grid cells from 5000-7000 ft (1500-2100 m) MSL (low), 7000-9000 ft (2100-2700 m) MSL (medium), and grid cells higher than 9000 ft (2700 m) MSL (high) suggested that low elevation range exhibited the largest warming trend ($+0.067^\circ\text{C}/\text{year}$) followed by irrigated grid cells ($+0.060^\circ\text{C}/\text{year}$). It is interesting to note the warming trends decrease as elevation increases, with medium ($+0.057^\circ\text{C}/\text{year}$) and high ranges ($+0.055^\circ\text{C}/\text{year}$). Table 2 lists the decadal average daily maximum temperature by month from 2040-2070. As shown in Table 2, July is the hottest month in the future for maximum temperature with an average of 30.6°C . Average Daily Minimum Temperature by month and the average daily difference between the maximum and minimum temperature were analyzed and found they were also substantially higher.

3.3 Growing Season and Degree Days

Growing season begins at the start of germination and terminates when the crop is harvested or mature. Typically it starts in April and ends in October. Growing degree days expressed as heat units, usually represent the timing of biological processes and it is computed using daily minimum and maximum temperature and the base temperature (McMaster and Wilhelm, 1997). Growing season days, were examined from 2040-2070. Growing degree days (GDD) with a base of 50°F (10°C) were calculated and the computation of growing degree days is as follows:

$$GDD = \left[\frac{T_{max} + T_{min}}{2} \right] - T_{base} \quad (4)$$

where T_{max} is the maximum daily temperature (°F), T_{min} is the minimum daily temperature (°F). T_{base} is the base temperature (°F) for plant growth and is usually set to 50°F (10°C). The growing season length trend is illustrated in Figure 3a and exhibits an increase of +1.07 day/year and an increase of 16 annual growing degree days (Fig. 3b). The number of days per year where the maximum temperature exceeded 86°F (30°C; Fig. 3c) exhibited an increase of +0.47 days/year. Lastly, the number of days per year where the minimum temperature dropped below 32°F (0°C; Fig. 3d) displayed a decrease of -0.70 days/year.

The growing season start date trended 0.46 days/year earlier and the growing season termination date trended 0.60 days/year later. The implications of this extended growing season can be profound; it might increase the number of irrigation events for a given season and the amount of water required to meet the crop water demand.

3.4 Observed and simulated energy budget comparisons

Flux tower observations were used to examine the model's ability to simulate latent, sensible, and ground heat fluxes for the natural ecosystem (non-irrigated). Modeled data from the WRF driven by CFSv2 and NARR between 1 April 2010 and 31 October 2012 was examined because of the availability of flux tower data for this time period. The following section will illustrate the model performance with respect to observations from two flux tower sites, Hollister, ID and Raft River, ID.

Hourly growing season latent heat flux was evaluated at Hollister (Fig 4a) and Raft River (Fig. 4b) along with a one-standard deviation of the range of monthly observed data from 2010-2012. The latent heat flux was either underestimated by the sensor or overestimated by the model. The observed and modeled data showed good agreement in April and October when the soil moisture was high but diverged from May through September (Fig. 4a). Both datasets generally stayed within one-standard deviation of observations with the exception of the NARR (July) and CFSv2 (July, August). At Raft River, the CFSv2 resembled observations in April and May and diverged from June through September. The NARR compared relatively well with observations from June through October, but underestimated latent heat flux in April and May (Fig. 4b). The CFSR overestimated latent heat flux in July and August and was outside the one-standard deviation of observations.

Hourly growing season sensible heat flux was analyzed at Hollister (Fig. 5a) and Raft River (Fig. 5b). Overall, the differences in modeled and observed sensible heat resembled that of the latent heat flux in that the observed data were less than the

modeled data. Unlike sensible heat, the differences between modeled and observed were similar from April through September. The NARR overestimated the sensible heat flux more than the CFSv2 (Fig. 5a) at Hollister. At Raft River, the NARR overestimated the sensible heat flux and was outside the one-standard deviation of the observed data (Fig. 5b). The CFSv2 also overestimated the sensible heat flux but was on the edge of the one-standard deviation bar. Overall, the latent heat flux peaked earlier in the season for the cheatgrass site, unlike the sagebrush ecosystem and model-derived latent heat fluxes were higher than observed fluxes. We also analyzed the closure of energy budget at the flux tower sites at Hollister and Raft River and found that the sensors at the two sites underpredicted the turbulent fluxes (latent and sensible heat flux) with respect to available energy (net radiation – ground heat flux).

3.5 Comparison of irrigation and no-irrigation simulation

Irrigation clearly alters the surface energy partitioning of latent and sensible heat fluxes, especially from June through October. The latent heat flux increased from 2.1 to 97.3 W m⁻², with August and September seeing the greatest difference during the year. The average latent heat flux increased (+46.9 W m⁻²) in all irrigated grid-cells with the addition of irrigation (evaporation). Furthermore, the added irrigation caused evaporative cooling, which decreased the sensible heat flux by an average of 41.0 W m⁻². Sensible heat flux decreased on average from 3.3 to 86.0 W m⁻², with the greatest differences at the driest time of the year, August and September. August 2012 was a warm and dry month, which produced the greatest changes in sensible and latent heat

flux from the no-irrigation to the irrigated simulation. April and May 2011 was a particularly moist spring, and the soil moisture carried over into the summer; this result confirms the findings of Alfaro et al. (2005). Ground heat flux did not substantially change with respect to average ($+0.2 \text{ W m}^{-2}$) with the addition of irrigation when compared between the no-irrigation and irrigated experiments. Spatial plots of the differences in surface energy fluxes showed that net radiation increased as a result of the irrigation between April and October 2012 (from 2.7 W/m^2 in April, 12.5 W/m^2 in May, 19 W/m^2 in June, 27.3 W/m^2 in July, 18.4 W/m^2 in Aug, 36.9 W/m^2 in Sep and 2.2 W/m^2 in Oct). The net radiation increase is consistent with the findings of Roy et al. (2011) in which net radiation increased as a result of the increased soil moisture.

Latent and sensible heat fluxes were examined from the WRF driven by CCSM and CGCM with irrigation, for both past (1992-1996) and future (2040-2070) periods. Fig. 6 shows the future simulations exhibiting the changes in the partitioning of the fluxes in a future climate (Fig. 6) for the irrigated area same domain shown in Fig 1b. Mean annual latent heat flux increased $0.29 \text{ W m}^{-2}/\text{year}$ while sensible heat flux decreased $0.07 \text{ W m}^{-2}/\text{year}$. The general increase in the simulated latent heat flux and the demand for irrigation during the growing season were expected due to the temperature increase.

3.6 Elevation and Snow

Snow water equivalent (SWE) and snow depth were examined to identify trends. Fig. 7 shows the annual SWE curves for high elevations over 1992-1996, 2040-2050, 2051-2060, and 2061-2070 for the CCSM and for 2040-2045 for the CGCM. Clearly, the

declining snowpack in the most distant future period, 2061-2070 was higher than other decades, although there was some interdecadal variability between December through May which matched with snow accumulation and peak melt periods, respectively. The average maximum snow water equivalent date was calculated for each model run at low, medium, and elevations and is listed in Table 3. The low elevation region exhibit the greatest differences in mean peak SWE dates, from Mar 23 (1992-1996) to Feb 20 (2040-2070). In the future, 2051-2060 medium elevations exhibit the earliest dates in the NARCCAP 2040-2070 period but also have the highest future SWE totals.

3.7 Comparison of WRF driven by CGCM and CCSM simulations

The CGCM and CCSM was simulated for 2038-2045 and 2040-2070, respectively. In this section, the average 2-m monthly temperature, dew point, specific humidity, and mixing ratio for the CGCM and CCSM are compared for the 2040-2045 time period. While WRF simulations preserved the differences that existed in these GCMs, this section highlights the differences in the results. When these GCMs were driven with WRF, the internal variability within the GCMs were preserved and our study highlights differences found in the variables such as the average 2-m monthly temperature, dew point, specific humidity, and mixing ratio. Generally, CCSM was considered a warm model that produced less precipitation and snow pack when compared with CGCM. Increased temperature from CCSM resulted in more latent heat as well. The CGCM simulation produced temperatures that were more moderate than the CCSM. For example, the CGCM January mean temperature was warmer (1.1°C) and the July

temperature was cooler (-2.3°C) than the CCSM. The CGCM had lower average dew point and specific humidity with respect to the CCSM simulations.

Accumulated monthly precipitation, evapotranspiration, irrigation, and PBL depth for the CGCM and the CCSM are shown in Table 4. The CGCM had higher summertime precipitation than the CCSM due to thunderstorms and possible monsoonal development. With the higher precipitation in the CGCM, the evapotranspiration was less in the CGCM (274.4 mm) than the CCSM (339.2 mm) and the amount of irrigation applied was also less in the CGCM (278.0 mm) than the CCSM (313.8 mm).

The average monthly latent, sensible and, ground heat fluxes, and net radiation for 2040-2045 based on both the WRF driven-CGCM and CCSM simulations appear in Table 5. The CGCM produced lower average annual latent heat flux (44.5 W m^{-2}) than the CCSM (54.9 W m^{-2}). Sensible heat flux average was slightly higher with the CGCM (32.2 W m^{-2}) compared to the CCSM (27.1 W m^{-2}). Cooler temperatures in the summer for the CGCM are consistent with lower net radiation (76.9 W m^{-2}) compared to the CCSM (82.3 W m^{-2}). The lower annual net radiation in the CGCM may be attributed to more cloudiness, which would moderate the temperatures as discussed earlier.

3.8 Feedback Factor of WRF CGCM with Uncoupled CGCM

The feedback factor was used to investigate the differences between the coupled atmospheric and land surface model combined (i.e., WRF with the Noah-LSM) with an uncoupled land surface model only (Noah-LSM; Chen and Dudhia, 2001; Jaksa and Sridhar, 2015). The spin up for the uncoupled Noah LSM included two years. Huang

and Margulis (2010) define the feedback factor (Φ_x) between coupled and uncoupled models as:

$$\Phi_x = \frac{x_{coupled} - x_{uncoupled}}{x_{coupled}} \quad (5)$$

where x is the temporally averaged flux (W m^{-2}) for a given vegetation type.

The feedback factor was examined over irrigated cropland grid cells on a monthly time scale from 2040-2044, shown in Fig. 8. The feedback factor indicated that the uncoupled model underestimated sensible and ground heat fluxes and overestimated latent heat flux over cropland grid cells. The feedback factor also illustrated the coupled model was simulating changes in the boundary layer relative humidity (vapor pressure deficit) and thus the magnitude of ET was smaller from the coupled model compared to the uncoupled model. Furthermore, the fluxes were partitioned more realistically within the coupled model compared to the uncoupled model.

3.9 PBL Depth

It is widely known in the literature that PBL depth decreases with increased soil moisture (Sridhar, 2013). We used the default PBL depth in the Mellor-Yamada-Janjic (MYJ) PBL scheme formulated in WRF (LeMone et al., 2013). The energy partitioning of sensible heat flux is converted into latent heat flux, which causes less turbulence and thus a lower PBL depth. PBL depth decreased in the irrigated simulations compared to the no-irrigation run. On a daily time scale, the greatest differences in the PBL depth occurred when the atmosphere was fully mixed, usually around 5 PM local time (00

UTC). Also, the greatest PBL depth differences occurred around 5 PM local time (00 UTC).

Spatial plots of PBL depth of the no-irrigation and irrigated simulations were examined (Table 4 and Fig. 9). There is a seasonality component of PBL depth decrease due to irrigation, with the most pronounced effect from irrigation during August. August was the month with the greatest decrease of the PBL depth, with August 2012 (anomalously dry) saw the greatest decrease in monthly average PBL depth over the cropland grid cells at -221.7 m. A three-growing season PBL analysis demonstrated that the differences from season to season PBL depths are related to differences in soil moisture, temperature, and dew point and the overlying atmospheric weather pattern. April and May of 2011 show that the effects of irrigation were mitigated due to abundant precipitation across the Snake Basin, as the soil moisture surrounding the irrigated lands resembled those of the irrigated land.

3.10 Vertical Influence of Irrigation

Vertical cross-section investigations were performed over the cropland grid cells to examine the effect of irrigation on the lower atmosphere. The cross sections were chosen by considering that transects passed through major irrigated areas in the Snake River basin. The data were examined during 2 PM local time (21 UTC), and in August 2012, which was the time of largest irrigation effect. Fig. 10a shows the locations of the cross-section (A-A' and B-B') investigations performed. The impact of irrigation on temperature and dew point temperature were examined at both cross-section locations, shown in Fig. 10b and Fig. 10c.

Due to irrigation, temperature decreased up to 2.8°C and dew point increased up to 5°C approximately 1.5 to 2.0 km above the surface as shown in Fig. 10(b-c). While the irrigation reduced PBL depths and thus the turbulence in both transects, it was more pronounced in the western region as in Fig. 10b. Equivalent potential temperature (Bolton, 1980) is decreased below 2.0 km in the lower atmosphere due to irrigation. From Fig. 11, θ_e increased up to +4.4 Kelvin (°K) on the eastern basin during August 2012 (21 UTC) with darker color showing increased equivalent potential temperatures. Irrigation effect was less pronounced on the western basin, with an increase of +2.1 °K in θ_e . An interesting feature revealed by Fig. 12 is the low equivalent potential temperature on the western side of the domain suggesting that irrigation effects are much stronger (higher temperature and dew point differences) in cross-section A-A'. This also suggested why dewpoint temperature was underestimated in the simulations as discussed earlier. Also, the advection from western side of the domain added to the available energy near A-A' whereas the high mountains on the eastern portion might have modulated temperature and wind. More investigation is needed to characterize whether the representation of land surface conditions impacted the simulation or if this was an artifact generated by the model from domain design or placement.

4. Conclusions

Effective plans for managing land and water resources prudently require an understanding of how the changing climate is impacting the regional water resources.

Another layer of significance is added when human-induced changes to the landscape through irrigation modify the regional climate and near-surface fluxes, as in the Snake River basin. We performed the NARCCAP, NARR and CFSv2-driven WRF simulations with and without irrigation using various data as input for initialization, lateral boundary conditions and validation to investigate the irrigation effect on temperatures and precipitation under current and future scenarios in Southern Idaho.

Overall, irrigation-induced cooling, despite increasing temperatures in the future, is apparent. This also results in decreased planetary boundary layer thickness and increased dewpoint temperatures within model simulations. Because of irrigation, the soil moisture is augmented to the root zone and this increases the latent heat flux in the growing season and decreases sensible heat flux.

The vertical influence of irrigation investigation reveals temperature decreases up to 2.8°C and dew point increases up to 5°C up to approximately 1.5 to 2.0 km in the vertical direction. The growing season start date trends 0.46 days/year earlier and the growing season termination date trends 0.60 days/year later. From the coupled land surface-atmospheric feedback analysis, the magnitude of latent heat flux is slightly mitigated in the coupled simulation along with the underestimation of sensible and ground heat fluxes. Overestimation of latent heat flux over cropland grid cells is apparent when fluxes are simulated in the uncoupled model. This has enormous implications in managing the crop water demand during the growing season, and is crucial to future water management, especially when the snowpack accumulation could

540 be decreasing and snowmelt timing might be advancing in the high mountains that
541 serve as the source region for the Snake River.

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543

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Fig. 12. Average differences (irrigated minus non-irrigated) for equivalent potential temperature ($^{\circ}\text{K}$) at 2 pm local time for August 2012 in a cross-section extending

815 horizontally from B to B' and vertically from 0 to 6 km height. Temperature differences
816 are shown by contour lines, with negative as dashed lines.

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Simulation		CFS Forecast	NARCCAP
Reanalysis Reference		(Saha et al., 2006; 2010, 2011)	(Mearns et al., 2007)
Model Version		WRF version 3.4	WRF version 3.4
WRF Resolution	Horizontal	4-km (175 × 175)	4-km (175 × 175)
	Vertical	38 levels, top at 1 hPa	38 levels, top at 100 hPa
Input Resolution	Horizontal	0.5° × 0.5° ATM, 0.313° Land Surface	50km
	Vertical	38 levels, top at 1 hPa	25 levels, top at 100 hPa
Buffer zone width (km)		5 × 4-km (20-km)	5 × 4-km (20-km)
Spin-up Period		None	Past: 8/1/1991-12/30/1992 Future (CCSM/CGCM3): 1/1/2038-12/31/2039
Integration Period		Forecast 1: 10/8/2012-5/1/2013 Forecast 2: 12/6/2012-7/1/2013	Past: 1/1/1993-7/20/1996 Future: (CCSM) 1/1/2040-12/1/2070 (CGCM3) 1/1/2040-12/31/2049
Physics Configuration	Radiation	CAM	CAM
	Surface	MYJ	MYJ
	PBL	MYJ (Veg Dependent C _{ztl} enabled)	MYJ (Veg Dependent C _{ztl} enabled)
	Cumulus	None	None
	Microphysics	Thompson	Thompson
	Shallow Cu	None	None
	Ocean / Lake	None	None
	Land Surface	Noah-LSM (both coupled and offline)	Noah-LSM (both coupled and offline)

Table 1

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Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2040-2050	1.53	3.68	7.85	14.64	21.62	26.13	30.48	29.52	22.73	14.06	8.2	1.04
2050-2059	1.41	5.96	10	15.06	20.39	25.39	30.09	29.17	22.88	16.26	7.9	1.07
2060-2069	3.04	5.12	9.96	16.48	21.81	26.73	31.43	31.27	22.57	15.96	8.96	4.03

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Table 2

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WRF driven by the models and their period	Average Maximum Snow Water Equivalent Date		
	5000-7000 Feet	7000-9000 Feet	9000+ Feet
CCSM 1992-1996	Mar 23 (241.3)	Apr 2 (640.0)	Apr 11 (942.3)
CCSM 2040-2050	Feb 21 (111.8)	Mar 7 (439.4)	Apr 7 (680.7)
CGCM 2040-2045	Feb 28 (181.0)	Mar 30 (654.7)	Apr 6 (942.2)
CCSM 2051-2060	Feb 16 (147.3)	Feb 18 (548.6)	Apr 2 (871.2)
CCSM 2061-2070	Feb 20 (53.3)	Mar 17 (330.2)	Mar 27 (612.1)
CCSM 2040-2070	Feb 20 (104.1)	Mar 7 (436.9)	Apr 6 (713.7)
CFSR 2010-2012	Mar 2 (71.1)	Mar 30 (307.3)	Apr 19 (459.7)
NARR 1999	Feb 23 (71.3)	Mar 5 (335.3)	Apr 14 (500.4)

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Table 3

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	PBL depth		Precipitation		ET		Irrigation	
Month	CGCM	CCSM	CGCM	CCSM	CGCM	CCSM	CGCM	CCSM
Jan	584.5	488.6	584.7	463.5	85.3	70.3	0.0	0.0
Feb	512.0	508.4	224.3	386.8	103.3	112.1	0.0	0.0
Mar	553.7	594.1	281.0	308.9	191.8	203.3	0.0	0.0
Apr	696.0	710.9	206.2	331.6	311.8	356.1	226.9	147.3
May	801.1	784.8	112.8	186.5	424.3	542.6	365.8	400.6
Jun	846.8	811.8	44.4	43.8	489.7	635.3	688.8	758.9
Jul	817.0	778.6	69.3	16.1	529.1	727.3	744.3	970.9
Aug	735.4	710.5	37.4	4.7	466.8	638.8	665.8	870.0
Sep	627.9	628.8	34.2	73.4	331.2	398.1	483.8	483.8
Oct	564.0	574.8	218.1	293.5	189.9	212.2	160.9	133.5
Nov	552.5	559.6	582.2	371.7	105.3	111.0	0.0	0.0
Dec	498.4	477.5	555.4	318.2	64.3	63.5	0.0	0.0
MEAN	649.1	635.7	245.8	233.2	274.4	339.2	278.0	313.8

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Table 4

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	Latent Heat		Sensible Heat		Ground Heat		Net Radiation	
Month	CGCM	CCSM	CGCM	CCSM	CGCM	CCSM	CGCM	CCSM
Jan	14.0	11.5	-8.5	-3.4	5.4	3.4	10.9	11.5
Feb	18.6	20.5	7.0	12.8	2.1	4.5	27.7	37.8
Mar	31.5	33.4	32.7	29.0	-5.0	-5.7	59.2	56.6
Apr	51.7	59.2	47.4	45.6	-9.8	-9.4	89.4	95.4
May	66.7	85.4	73.2	54.5	-6.7	-7.9	133.2	131.9
Jun	79.0	102.4	72.1	61.2	-7.4	-6.3	143.7	157.4
Jul	82.7	113.8	63.4	48.0	-4.0	-6.0	142.2	155.8
Aug	74.0	101.5	53.3	37.9	-2.0	-1.0	125.3	138.3
Sep	55.2	66.4	35.3	28.4	1.4	3.1	92.0	97.9
Oct	30.9	34.5	13.8	14.1	7.1	8.3	51.8	56.9
Nov	18.3	19.2	-1.1	-0.7	11.0	9.9	28.2	28.5
Dec	11.4	11.3	-2.5	-2.0	10.4	10.9	19.3	20.2
Mean	44.50	54.93	32.18	27.12	0.21	0.32	76.91	82.35

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Table 5

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Fig. 1a

Fig. 1b

Fig. 2

Fig. 3

Fig. 4a

Fig. 4b

Fig. 5a

Fig. 5b

Fig. 6

Fig. 7

Fig. 8

Fig. 9

Fig. 10a

Fig. 10b

Fig. 10c

Fig. 11

Fig. 12