

1 **Assimilation of NASA’s Airborne Snow Observatory snow measurements for**
2 **improved hydrological modeling: A case study enabled by the coupled LIS/WRF-**
3 **Hydro system**

4 **Timothy M. Lahmers**^{1,2}, **Sujay V. Kumar**¹, **Daniel Rosen**³, **Aubrey Dugger**⁴, **David J.**
5 **Gochis**⁴, **Joseph A. Santanello**¹, **Chandana Gangodagamage**^{1,2}, and **Rocky Dunlap**³

6 ¹Hydrological Sciences Lab, NASA Goddard Space Flight Center (NASA-GSFC), Greenbelt,
7 MD, USA.

8 ² Earth System Science Interdisciplinary Center (ESSIC), University of Maryland, College Park,
9 MD, USA.

10 ³NOAA/Earth System Research Laboratory, Boulder, CO, USA.

11 ⁴National Center for Atmospheric Research, Boulder, Colorado, USA.

12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27 Corresponding author: Timothy Lahmers (timothy.lahmers@nasa.gov)

28 **Key Points:**

- 29 • SWE data-assimilation improves hydrologic response in the coupled LIS/WRF-Hydro
30 model for a case study in the Tuolumne River basin.
- 31 • Horizontal surface routing increases soil moisture and ET downstream near channels in
32 LIS/WRF-Hydro, compared to an LSM-only simulation.

33 **Abstract**

34 The NASA LIS/WRF-Hydro system is a coupled modeling framework that combines the
35 modeling and data assimilation (DA) capabilities of the NASA Land Information System (LIS)
36 with the multi-scale surface hydrological modeling capabilities of the WRF-Hydro model, both
37 of which are widely used in both operations and research. This coupled modeling framework
38 builds on the linkage between land surface models (LSMs), which simulate surface boundary
39 conditions in atmospheric models, and distributed hydrologic models, which simulate horizontal
40 surface and sub-surface flow, adding new land DA capabilities. In the present study, we employ
41 this modeling framework in the Tuolumne River basin in central California. We demonstrate the
42 added value of the assimilation of NASA Airborne Snow Observatory (ASO) snow water
43 equivalent (SWE) estimates in the Tuolumne basin. This analysis is performed in both LIS as an
44 LSM column model and LIS/WRF-Hydro, with hydrologic routing. Results demonstrate that
45 ASO DA in the basin reduced snow bias by as much as 30% from an open-loop (OL) simulation
46 compared to three independent datasets. It also reduces downstream streamflow runoff biases by
47 as much as 40%, and improves streamflow skill scores in both wet and dry years. Analysis of
48 soil moisture and evapotranspiration (ET) also reveals the impacts of hydrologic routing from
49 WRF-Hydro in the simulations, which would otherwise not be resolved in an LSM column
50 model. By demonstrating the beneficial impact of SWE DA on the improving streamflow
51 forecasts, the article outlines the importance of such observational inputs for reservoir operations
52 and related water management applications.

53 **Plain Language Summary**

54 Land surface models are useful because of their ability to resolve surface-atmosphere feedbacks,
55 including those with vegetation. Land surface models also have the capability to assimilate
56 surface observations, usually measured through remote sensing techniques, into the model.
57 Hydrologic models have the strength of resolving horizontal movements of water both on the
58 surface and through the sub-surface. In the present study, we combine the data-assimilation
59 capabilities of the NASA-LIS land surface model with the WRF-Hydro hydrologic model to
60 combine the utility of both systems. We use this new system to demonstrate the impact of
61 assimilating snow water equivalent, measured from an aircraft, on both the land surface and
62 streamflow from the model in the Tuolumne River basin in Central California. Results show that
63 assimilation of snow water equivalent into the coupled model corrects snow errors and improves
64 the streamflow in both wet and dry years. We find that hydrologic processes that are now added
65 to the land surface model impact simulated soil moisture and evapotranspiration. These findings
66 are important because the ability for a model to better resolve streamflow, from snow
67 assimilation, could be beneficial for water management.

68 **Key Words**

- 69 • Hydrologic Modeling
- 70 • Data Assimilation
- 71 • Snow Hydrology

72

73 **1 Introduction**

74 Accurate understanding of the hydrological cycle and the variability of its components is
75 becoming increasingly important for water management, especially in semi-arid environments
76 like the western US. The significant natural heterogeneity and the ubiquitous nature of
77 anthropogenic impacts on the land surface, however, makes it challenging to quantify these
78 complex processes. Detailed representation of the underlying processes through advanced model
79 practices and exploitation of information from remote sensing through methods such as data
80 assimilation (DA) are critical for reducing the uncertainty within global and regional
81 hydrological predictions (Lettenmaier et al. (2015)).

82 Land surface models (LSMs) and hydrological models are two different classes of models
83 that are often used for modeling terrestrial hydrologic processes, but each have a different
84 historical legacy and modeling emphasis (e.g. Clark et al. 2015). The LSM development has
85 been primarily focused on improving representations of vertical surface energy and water flux
86 estimates by incorporating sophisticated parameterizations of vegetation and the root zone
87 (Pitman (2003), Peters-Lidard et al. (2017)). Modern LSMs include multi-layer formulations of
88 the vertical canopy structure for better representations of physical and biological processes
89 related to stomatal control. The LSMs, however, tend to have simplified representations of
90 surface and subsurface hydrological process, particularly processes related to the horizontal
91 transport of water. Most contemporary LSMs are one-dimensional column models that focus on
92 modeling the vertical moisture transport and do not typically include lateral moisture transport
93 formulations (e.g. Maxwell et al. 2011). In addition, most LSMs have shallow subsurface
94 representations where characterization of water table and the effect of groundwater recharge are
95 largely ignored or highly conceptualized. The development of distributed hydrological models
96 (e.g. Hamman et al. 2018; Sun et al. 2019; Regan et al. 2020), on the other hand, has been
97 focused on physically based representations of runoff processes (e.g. Clark et al. 2017),
98 including formulations for 3-d subsurface flow, macropore flow, and surface water flow
99 processes. The representation of land-atmosphere flux processes in these distributed models are
100 often limited as they are largely based on empirical formulations (e.g. Anderson, 1973; Nielsen
101 and Hansen, 1973).

102 As both LSMs and hydrological models have their strengths and weaknesses in their
103 model formulations, linking these two classes of models enables the exploitation of advances
104 made in both modeling communities. The Weather Research and Forecast (WRF) Hydrologic
105 Model extension (WRF-Hydro) modeling system (Gochis et al., 2020) was designed as an
106 architecture to explicitly enable these linkages. Though the use of data assimilation methods to
107 take advantage of remote sensing information has been growing in the LSM community (Reichle
108 et al. 2007, Zaitchik and Rodell 2009, de Lannoy et al. 2012, Barbu et al. 2014, Kumar et al.
109 (2008, 2014, 2019a,b)), its application for hydrological models to date has been limited. To
110 further enhance the WRF-Hydro modeling system with the infusion of land remote sensing and
111 data assimilation capabilities, an advanced terrestrial hydrological modeling system combining
112 the NASA Land Information System (LIS; Kumar et al., 2006; Peters-Lidard et al., 2007) and
113 WRF-Hydro has been developed. LIS is an advanced land surface modeling and data
114 assimilation framework, developed to enable fine-scale land surface modeling and the
115 assimilation of terrestrial hydrology and land surface remote sensing observations. The

116 combination of these DA capabilities with a hydrologic modeling system makes the integrated
117 environment novel.

118 This article describes the application of the coupled LIS/WRF-Hydro system over the
119 Tuolumne River basin in central California, focusing on the use of remotely sensed snow
120 estimates for DA and the impact of lateral flow on the LSM realized through the hydrological
121 model. Specifically, we employ the coupled system to utilize the high-resolution snow water
122 equivalent (SWE) estimates from NASA's Airborne Snow Observatory (ASO;
123 <https://www.jpl.nasa.gov/missions/airborne-snow-observatory-aso/>) over the Tuolumne River
124 basin in central California. Through DA tools, the ASO SWE estimates are employed to improve
125 the realization of snow states. The impact of improved snow simulation on streamflow
126 simulation is then quantified. The study thus focuses on the following specific science questions:

- 127 1. What is the added utility of remotely sensed ASO SWE estimates for improving land
128 surface and hydrologic states, including streamflow?
- 129 2. What are the impacts of additional physical processes realized by WRF-Hydro on LSM
130 variables related to the basin hydrologic response?

131 This article also describes the details of the coupled LIS/WRF-Hydro model. The coupled
132 environment is enabled through the use of the Earth System Modeling Framework (ESMF; Hill
133 et al. 2004), which is a high-performance and flexible approach for coupling Earth system
134 models. The ESMF-based design allows for the clear separation of major modeling system
135 components of LIS and WRF-Hydro and allows for their independent development, while
136 maintaining the integrated modeling environment.

137 In section 2 of this paper, we discuss the LIS and WRF-Hydro model structures and the
138 coupling for LIS/WRF-Hydro. Section 3 includes a description of the ASO dataset and the
139 LIS/DA methods. In section 4, we discuss the results from the coupled LIS/WRF-Hydro
140 simulations, impact of the assimilation of ASO data on streamflow, and the added impact of
141 hydrologic routing on land surface states. Section 5 includes a summary and main conclusions of
142 this work.

143 **2 LIS/WRF-Hydro Model Description**

144 2.1 LIS Structure and Configuration

145 LIS is an open source land surface modeling and data assimilation framework that
146 supports modeling over user-specified regional or global domains using an ensemble of LSMs.
147 LIS permits high-resolution LSM simulations and the multivariate and concurrent assimilation of
148 terrestrial remote sensing datasets. The DA subsystem in LIS is an interoperable environment
149 that supports both sequential and non-sequential assimilation approaches such as the Ensemble
150 Kalman Filter (EnKF), particle Filter (pF), and the Ensemble Kalman Smoother (EnKS). These
151 algorithms can be employed with a large suite of observational inputs and LSMs within LIS. In
152 the present study, we take advantage of LIS's data assimilation subsystem within the coupled
153 LIS/WRF-Hydro environment to assimilate NASA ASO SWE estimates over the upper
154 Tuolumne basin (described in Section 3.4 below). The LIS capabilities have been demonstrated
155 for the assimilation of a wide range of remote sensing datasets including soil moisture (e.g.

156 Kumar et al. 2008, 2009; Peters-Lidard. et al. 2011), snow (Liu et al. 2013, Kumar et al. 2014,
157 Liu et al. 2015, Kumar et al. 2015a), skin temperature (Reichle et al. 2010), terrestrial water
158 storage (Kumar et al. 2016), vegetation (Kumar et al. 2019) and albedo (e.g. Kumar et al. 2020).

159 2.2 WRF-Hydro Structure and Configuration

160 The WRF-Hydro model can be coupled to the WRF Advanced Research WRF (WRF-
161 ARW) atmospheric model or executed offline as a stand-alone hydrologic simulation. In this
162 study we are running WRF-Hydro in its “stand-alone” configuration coupled to LIS and not to an
163 atmospheric model. The NOAA National Water Model (NWM) operational hydrologic model is
164 based on the WRF-Hydro model architecture (e.g. Lahmers et al. 2019; 2021), and WRF-Hydro
165 has also been used for research in land-atmosphere interactions (e.g. Arnault et al. 2016). WRF-
166 Hydro (Gochis et al. 2020) can be implemented with either the Noah (Ek et al. 2003) or Noah-
167 MP LSMs (Niu et al. 2011) to resolve vertical soil processes and exchanges with the atmosphere.
168 In addition to the LSM, WRF-Hydro includes horizontal overland and subsurface flow on a high-
169 resolution terrain routing grid. Surface overland flow uses diffusive wave routing (Julien et al.
170 1995; Ogden 1997). Shallow saturated sub-surface flow (i.e. within the 2-m LSM soil column) is
171 also resolved within the high-resolution routing grid of WRF-Hydro using a Boussinesq
172 approximation. In the present study, WRF-Hydro is configured with a 250-m routing grid,
173 similar to the NWM configuration of WRF-Hydro. WRF-Hydro uses a conceptual baseflow
174 model to resolve deep groundwater flow. Water that drains out of the bottom of the LSM soil
175 column is aggregated over the drainage area for a specific reach, then stored and slowly released
176 to the channel using an exponential model based on stored water depth. Our LIS/WRF-Hydro
177 configuration uses the gridded diffusive wave channel flow routing option of WRF-Hydro.

178 WRF-Hydro has been used for both research and operations. The NOAA National
179 Weather Service (NWS) Office of Water Prediction (NWS/OWP) uses WRF-Hydro as the model
180 architecture for the NWM to produce nation-wide streamflow, soil moisture, snow, and ET
181 forecasts (e.g. Gochis et al. 2020). WRF-Hydro has also been tested and modified for a range of
182 local-scale and coupled land-atmosphere studies (e.g. Arnault et al. 2016; Lahmers et al. 2020).

183 2.3 LIS/WRF-Hydro Model Coupling

184 As noted earlier, the integrated LIS/WRF-Hydro system is developed using the
185 standardized software tools and paradigms enabled by ESMF. Prior to coupling of these systems,
186 both LIS and WRF-Hydro were made ESMF compliant, and these updates will carry through
187 subsequent model versions. ESMF includes a superstructure for enveloping model and coupler
188 components and an infrastructure of commonly used utilities, including grid transformations,
189 time management, and data communications. The ESMF design accommodates a wide range of
190 data structures, data discretizations, and component layout and sequencing options. Explicit,
191 semi-implicit, and implicit coupling interactions that involve 2- and 3-dimensional,
192 regional/global, logically rectangular, point cloud and mesh grid types are supported by ESMF.
193 The coupled LIS/WRF-Hydro environment also uses a recent enhancement to ESMF called the
194 National Unified Operational Prediction Capability (NUOPC; Theurich (2014)), which provides
195 coupling protocols for building, initializing, and sequencing models that enable rapid transition
196 and increased interoperability between ESMF-based modeling systems. The interoperability

197 between model components is ensured through the implementation of a NUOPC interface or
198 “cap”, which can be reused across modeling systems.

199 NUOPC provides generic representations of four key modeling system elements: 1) A
200 NUOPC model is a wrapper around the geophysical model code that provides a standard
201 interface to the model data and execution subroutines, 2) a NUOPC driver controls the execution
202 of a set of child components based on a user-defined run sequence, 3) a NUOPC mediator
203 contains custom code for coupling, flux computations, spatial and temporal transforms and other
204 data manipulations and 4) a NUOPC connector that implements standard communication options
205 such as redistribution of data across different numbers of processors and grid remapping using
206 various interpolation methods. The LIS/WRF-Hydro system utilizes NUOPC driver, connector,
207 mediator, and model components to exchange data between an ensemble of coupled land surface
208 and hydrological models. The use of NUOPC standardizes component interfaces and
209 interoperability while preserving model integrity. This software architecture is illustrated in Fig.
210 1, and it enables LIS/WRF-Hydro to run on high performance computing (HPC) environments
211 from a single executable file. LIS/WRF-Hydro in the present study uses Noah-MP version 4.0.1,
212 which is called through the LIS framework. The coupled configuration is as close as possible to
213 WRF-Hydro as a standalone model and has been tested to verify this consistency.

214 Fig. 1 also shows the different software components of LIS/WRF-Hydro. The coupled
215 system adds NUOPC caps to both LIS and WRF-Hydro. These caps enable the models to pass
216 variables to and from a mediator. Thus LIS, which calls the Noah-MP v4.0.1 LSM, and WRF-
217 Hydro are separately called by the main driver at timesteps set by the user. The LIS and WRF-
218 Hydro structures then exchange variables through a LIS/WRF-Hydro mediator. For example,
219 LIS executes first and then passes a set of exchange variables to the mediator. Then the mediator
220 redistributes or interpolates data from the LIS domain to the WRF-Hydro domain. The data are
221 then passed to WRF-Hydro before WRF-Hydro executes, and this same process occurs in reverse
222 when WRF-Hydro feedback variables are returned to LIS. The LIS/WRF-Hydro mediator also
223 supports an ensemble of LIS and WRF-Hydro coupled instances, which enables ensemble DA
224 instances.

225 The DA subsystem within LIS executes the land surface model in an ensemble mode,
226 with small perturbations applied to a select set of model states and meteorological fields. This
227 land surface model ensemble exists entirely within one instance of LIS. At this time a single
228 instance of WRF-Hydro does not support an ensemble of hydrological model instances. In order
229 to avoid coupling an ensemble of land surface model instances to a single hydrological model
230 instance, the LIS/WRF-Hydro system and LIS/WRF-Hydro mediator support running multiple
231 instances of one model in a single executable (i.e. WRF-Hydro). This allows for each member of
232 the LIS ensemble to couple to an individual instance of WRF-Hydro. The LIS/WRF-Hydro
233 mediator redistributes or interpolates data to each hydrological model from the ensemble of land
234 surface model instances. Conversely, data from each WRF-Hydro instance is gathered in the

235 LIS/WRF-Hydro mediator before it is returned to the LIS model. The result is a single
236 executable capable of running an ensemble of coupled model instances.

237 **3 Datasets and Methodology**

238 3.1 NASA Airborne Snow Observatory (ASO) Estimates

239 The NASA ASO SWE dataset is obtained from an observation platform that combines a
240 scanning lidar and an imaging spectrometer to measure snow depth and albedo (Painter et al.
241 2016). ASO data were measured in approximately weekly intervals over the Tuolumne River
242 Basin during the cold season, and the full dataset consists of SWE, depth, and snow albedo. SWE
243 and snow depth are assimilated in the present study; however, albedo is not considered. These
244 variables are assimilated at 00 UTC on the days they are available. SWE is of principal focus of
245 this study, as it is used in our DA system (described in detail in section 3.3). The ASO dataset
246 has a 50-m resolution and its use of high-density Lidar measurements permits it to resolve small-
247 scale variability in snow properties that cannot be resolved by coarser datasets or point estimates.
248 Note that since ASO SWE is derived from snow depth using in situ measurements and model-
249 based assumptions on spatially-distributed snow density, more uncertainty in the derived ASO
250 SWE (compared to snow depth) is likely.

251 ASO has been used in several other recent studies for snow verification and hydrologic
252 modeling. Henn et al. (2016) demonstrated that ASO data, when fused with streamflow for
253 model calibration, was able to reduce the uncertainty of inferred precipitation in a catchment
254 with limited precipitation observations. Cao et al. (2018) used Variable Infiltration Capacity
255 (VIC) LSM combined with ASO to estimate SWE in the Tuolumne basin and used this dataset to
256 validate two satellite based snow products. Oaida et al. (2019) used ASO data to validate a high-
257 resolution SWE dataset based on DA of Moderate Resolution Imaging Spectroradiometer
258 (MODIS) snow data (Painter et al. 2009) into the VIC hydrologic model. This recent work with
259 ASO demonstrates its potential use for hydrologic simulations and possible benefits when
260 integrated with LIS/WRF-Hydro.

261 3.2 Evaluation Datasets

262 For evaluation of LIS and LIS/WRF-Hydro SWE, three reference data products are
263 considered: 1) the University of Arizona (UA; Dawson et al. 2016), 2) the Snow Data
264 Assimilation System (SNODAS; Barrett et al. 2003), and 3) California Cooperative Observing
265 Sensors (California COOP sites; available at <http://cdec.water.ca.gov/>). These grid and point
266 observations are considered over the upper basin study area shown in Fig. 2, which is fully
267 encompassed by the ASO observation area. The University of Arizona dataset is based on
268 gridded upscaled point measurements of snow (~4-km resolution) computed using piecewise
269 linear regression of point measurements and topography (Dawson et al. 2016). The SNODAS
270 dataset uses a snow model that is forced with numerical weather prediction (NWP) data and
271 updated through DA of remote sensing snow observations daily (~1-km resolution). The

272 California COOP sites consist of snow pillow measurements maintained by the state of
273 California.

274 We acknowledge that the SNODAS and University of Arizona gridded datasets have
275 coarser resolution than the ASO model products. Though the two gridded datasets are also
276 developed by incorporating observational data products within a model, evaluation of LIS and
277 LIS/WRF-Hydro compared to these products is still a benchmark for improvement from DA
278 compared to the open-loop simulations, since these datasets are independent of the ASO product.
279 These limitations of the gridded datasets are also the reason why the California COOP sites are
280 also considered where available.

281 Streamflow is validated using USGS streamflow measurements at a single gage above
282 Hetch Hetchy Reservoir. USGS maintains hourly streamflow at sites throughout the CONUS
283 (available online at: <https://waterdata.usgs.gov/nwis/rt>). Details of the gage used in the study area
284 are discussed in section 3.4.

285 3.3 Model Configuration

286 We consider the impacts of physical processes realized through both DA and hydrologic
287 routing by executing four different model simulations for the same Tuolumne basin domain (see
288 next section) as a multi-year case study that includes both wet and dry winters. Atmospheric
289 forcing data sets needed to execute LIS and LIS/WRF-Hydro include incoming shortwave
290 radiation, incoming longwave radiation, specific humidity, air temperature, surface pressure, and
291 near surface wind (both u and v components). The model is forced with atmospheric variables
292 and precipitation from version 2 of the North American Land Data Assimilation
293 System (NLDAS-2) forcing dataset (Xia et al., 2012). We acknowledge that it is possible for the
294 NLDAS-2 product to miss some of the fine-scale precipitation and precipitation variability due
295 to its coarser resolution relative to that of the models and hydrological processes of the region.

296 LIS was executed for WY2014-2017 with WY2012-2013 as spin-up, and LIS was
297 executed both with and without DA (i.e. LIS-Open Loop (OL) and LIS-DA, respectively).
298 Similarly, LIS/WRF-Hydro was also spun-up for WY2012-2013 and analyzed from WY2014-
299 2017 both without and with DA (i.e. LIS/WRF-Hydro OL and LIS/WRF-Hydro DA,
300 respectively). LIS/WRF-Hydro had identical LSM settings to LIS, but also included horizontal
301 surface and sub-surface flow, channel routing, and baseflow as discussed in section 2.2. The
302 descriptions of each model simulation are also included in Table 1.

303 3.4 LIS/WRF-Hydro Domain

304 For the present study, LIS/WRF-Hydro is executed for the full Tuolumne River basin to
305 its outlet with the San Joaquin River (Fig. 2); however, our analysis is above the Hetch Hetchy
306 Reservoir (Fig. 2). The analysis area in the upper basin has no management of the streamflow
307 and is fully encompassed by the ASO dataset. Note that the ASO dataset covers slightly more of
308 the Tuolumne basin than just the upper basin above Hetch Hetchy; however, we limit our
309 analysis area to this domain to make analysis of modeled vs. measured streamflow possible. Fig.
310 2 also shows the high terrain above Hetch Hetchy reservoir. The precipitation climatology (based
311 on the 1980-2009 NLDAS-2 1/8 Degree precipitation climatology (not shown)) consists of

312 amounts on the order of 800-1000 mm/yr over much of the basin. 1981-2010 average
 313 precipitation is of a similar order of magnitude and shown at two National Weather Service
 314 weather stations in Fig. 2. While this demonstrates that NLDAS-2 precipitation is comparable to
 315 observations, we caution that both the NLDAS-2 and station observations likely underestimate
 316 orographic precipitation and are therefore biased towards lower elevations. The upper basin that
 317 is used for analysis has a majority of the deciduous broadleaf forests and needleleaf evergreens,
 318 with a few small areas of shrublands.

319 The 1-km LSM grid for the full model used in the present study was derived using Land
 320 surface Data Toolkit (LDT; Arsenault et al. 2018), which is the preprocessing environment for
 321 LIS. The 250-m WRF-Hydro routing grid, channel grid, and the baseflow basin model grid was
 322 derived using version 5.1.1 of the WRF-Hydro GIS Pre-Processing tools (Gochis and Sampson
 323 2019) based on the Hydrosheds (Available online at:
 324 https://www.hydrosheds.org/images/inpages/HydroSHEDS_TechDoc_v1_2.pdf) digital
 325 elevation model (DEM) dataset. The baseflow basin model grids, as described above, were
 326 derived using the default ‘FullDom LINKID local basins’ method of the WRF-Hydro processing
 327 tools (Gochis and Sampson 2019), where groundwater basins are derived for specific channel
 328 reaches (computed from the routing grid). All model parameters are default values based on
 329 Noah-MP and WRF-Hydro parameter lookup tables, and no model calibration was performed.

330 3.5 LIS-DA Methods

331 In the present study, we use a one-dimensional ensemble Kalman Filter (EnKF) (e.g.
 332 Reichle et al. 2002;) for the assimilation of the ASO SWE (Fig. 1). As noted in prior studies
 333 (Houtekamer and Mitchell. 1998; Reichle et al. 2002; Zhou et al. 2006; Pan and Wood, 2006;
 334 Kumar et al. 2008; Hain et al. 2012) EnKF allows for the flexible characterization of model
 335 errors with an ensemble and the handling of non-linear model dynamics and temporal
 336 observational discontinuities. Alternative DA approaches such as the Particle Smoothing
 337 Approach (e.g. Margulis et al. 2019) offer advantages over EnKF because they can produce
 338 analysis results with coarser temporal resolution without discontinuities at assimilation
 339 timesteps. These methods are not feasible in the present study as they require a larger ensemble
 340 and have a higher latency window between observations, which is not ideal for hydrologic
 341 forecasting applications. The EnKF approach works in a sequential manner by alternating
 342 between a model forecast step and an analysis update step.

343 The forecast step (i.e. running the LSM) is performed first, wherein the analysis state
 344 from timestep $k-1$ is projected forward from $(\hat{\mathbf{x}}_{k-1}^+)$ to the LSM state at k ($\hat{\mathbf{x}}_k^-$). This is followed
 345 by the analysis step where the increments are computed as:

$$346 \quad \hat{\mathbf{x}}_k^+ = \hat{\mathbf{x}}_k^- + \mathbf{K}_k(\hat{\mathbf{y}}_k - \mathbf{H}_k\hat{\mathbf{x}}_k^-)$$

347 where the observation state ($\hat{\mathbf{y}}_k$) is combined with the a priori state ($\hat{\mathbf{x}}_k^-$) to generate the a
 348 posteriori state ($\hat{\mathbf{x}}_k^+$). \mathbf{H}_k represents the observation operator that relates the model states to the
 349 observation, and \mathbf{K}_k is the Kalman gain that acts as the weighting factor that determines the
 350 influence of forecast innovations ($\hat{\mathbf{y}}_k - \mathbf{H}_k\hat{\mathbf{x}}_k^-$) in the analysis update. The Kalman gain is

351 diagnosed as a function of the model error covariance (\mathbf{P}_k) and the observational error
 352 covariance (\mathbf{R}_k).

$$353 \quad \mathbf{K}_k = \frac{\mathbf{P}_k \mathbf{H}_k^T}{\mathbf{H}_k \mathbf{P}_k \mathbf{H}_k^T + \mathbf{R}_k}$$

354 Consistent with prior snow studies (e.g. Liu et al. 2015), we use a 20-member ensemble in the
 355 present study.

356 It should be noted that the ensemble assimilation systems are limited when the model
 357 spread is insufficient to represent the underlying uncertainty. For example, if the observation
 358 represents a non-zero snow value when the model simulation is near zero, developing a reliable
 359 ensemble spread to represent the model uncertainty is difficult. These issues are common to all
 360 ensemble data assimilation systems as discussed in Kumar et al. (2017) and are not limited to
 361 EnKF assimilation.

362 Noah-MP snow states are computed using a full energy-balance (e.g. accounting of
 363 radiative, thermal and liquid mass transport fluxes), multilayer snow model (up to 3 layers) that
 364 accounts for changes in snow volume caused by melt and snowfall, as well as changes to density
 365 caused by compaction. No explicit accounting for impurities such as dust, black carbon, forest
 366 litter or aerosol deposition is made. The snow energy balance is used to estimate snowmelt,
 367 sublimation, evaporation and temperature. The top most layer of the snowpack is thinnest and
 368 used to compute sensible and latent fluxes as well as radiative exchanges with the atmosphere
 369 (Niu et al. 2011). The model state vector in the assimilation consists of the total SWE and snow
 370 depth variables. After every data assimilation update, the total SWE is used to update the
 371 multilayer snowpack states of Noah-MP. A 20-member ensemble with small perturbations
 372 applied to a select set of meteorological forcing variables and the model state vector is used in
 373 the present study. The details of the perturbation parameters are shown in Table 2. These settings
 374 were recommended by prior experiments (Su et al. 2010; Peters-Lidard et al. 2011) and have
 375 been used widely for snow assimilation in recent work (e.g. Liu et al. 2013; Kumar et al. 2014;
 376 Kumar et al. 2015b; Liu et al. 2015). While strictly speaking, EnKF assumes a linear system with
 377 mutually and serially uncorrected associated Gaussian errors (Nerini et al. 2019), such conditions
 378 are seldom met in real applications such as the example in this manuscript. The perturbation
 379 settings used here are developed from prior studies that ensure a reasonable compromise between
 380 the assimilation improvements and possible suboptimal filter performance due to the deviations
 381 from Gaussian assumptions (e.g. Crow et al. 2006; Kumar et al. 2008; Reichle et al. 2008; De
 382 Lannoy et al. 2012). Perturbation frequencies for forcing, model state, and observations are set to
 383 1-hour, 3-hours, and 6-hours, respectively. As noted in Liu et al. (2013), perturbations to
 384 meteorology forcing, which include cross correlation in space and time are intended to simulate
 385 model uncertainty for DA. Time correlation uses a first-order regressive model (time-order of 3-
 386 hours) as in Liu et al. (2013). In order to avoid the addition of spurious skill in the model

387 ensemble from perturbations, a bias correction approach following Ryu et al. (2009) is
388 employed.

389 **4 Results**

390 4.1 Impacts of ASO DA on LIS and LIS/WRF-Hydro SWE

391 In this section, we evaluate the impacts of SWE DA in a fully coupled hydrological
392 environment on both direct (SWE) and downstream (ET and soil moisture) variables. The results
393 in Table 3 show that the assimilation of ASO SWE results in reduced errors in the snow states in
394 the model. Relative to the respective OL integrations, the LIS-DA and LIS/WRF-Hydro DA
395 simulations have statistically significant reduced RMSE and bias estimates when validated
396 against the University of Arizona dataset based on a Chi-Square Distribution and a student's t-
397 test (95% confidence intervals for each value are shown), respectively. In particular, the model
398 integrations without assimilation have large negative biases in SWE, but these biases are reduced
399 in both the LIS-DA and LIS/WRF-Hydro-DA simulations compared to the SNODAS and UA
400 datasets. The DA simulations do have slightly worse correlation coefficients (95% confidence
401 intervals are computed using a Fisher transform), likely due to removal of snow in the lower
402 basin (which we will show in later figures). Reductions of negative bias are well pronounced
403 compared to the independent SNODAS and University of Arizona (on the order of ~15%).

404 The spatial impact of these results (averaged over the full WY2014-2017 analysis period)
405 is presented in Fig. 3, which shows model SWE from the LIS/WRF-Hydro-OL and LIS/WRF-
406 Hydro-DA simulations as well as the reference products (SNODAS and University of Arizona).
407 This figure only shows the upper basin, where ASO snow data are available and that are
408 upstream of the Hetch Hetchy reservoir (Fig. 2). Fig. 3d shows that LIS/WRF-Hydro in the OL
409 configuration has a less spatially variable distribution of SWE across the domain compared to the
410 DA solution (Fig. 3e), which has more SWE in the high elevation headwater reaches. Both
411 solutions have less snow compared to the two evaluation products (Fig. 3a,b); however, the DA
412 solution increases the amount of model SWE by as much as 60% in some locations in the higher
413 elevations of the ASO domain (Fig. 3f). Lower elevation SWE in the DA solution is decreased.
414 Fig. 3c shows the magnitude of these snow increases as well as their relative distribution across
415 the basin. The SWE in the DA solution is more realistic than the OL solution when compared to
416 the independent SNODAS and University of Arizona observations. These improvements in the
417 model SWE are visible despite the tendency for both evaluation datasets to underestimate SWE
418 variations as a function of elevation (discussed in detail in section 3.2).

419 The LIS/WRF-Hydro solutions are also compared in Fig. 4 at three California
420 Cooperative Snow Measurement Sites (Fig. 4a). The DAN site (Fig. 4b) has the most complete
421 data, and the bias at this site is clearly reduced from DA. A delay in snowmelt in WY2017 from
422 the DA solution increases RMSE here (Table 3), despite improvements at other times.
423 Observation data at the SLI (Fig. 4c) and TUM (Fig. 4d) sites are less complete; however, Fig. 4
424 shows the added value of DA, particularly for reducing bias. At these sites, RMSE significantly
425 improves from DA (Table 3), and bias improves at the SLI site. Analysis of Fig. 4 and the skill

426 scores from Table 3 show the added value of DA compared to snow observations, in addition to
427 the improvements from the University of Arizona and SNODAS sites.

428 The impacts of DA can be better understood in Fig. 5, which shows the timeseries of the
429 basin average SWE for LIS/WRF-Hydro-OL and LIS/WRF-Hydro-DA for the Tuolumne basin
430 above Hetch Hetchy reservoir as well as all of the observation-based data products. WY2014-
431 2015 were associated with drier than average precipitation due to an ongoing drought, while
432 WY2016-2017 both experienced Atmospheric River events and were associated with wetter
433 conditions. This figure shows that DA generally reduces the low bias of the LIS/WRF-Hydro-OL
434 simulation in both wet and dry years. Changes to the SWE bias are also not uniform in time. For
435 example, LIS/WRF-Hydro-OL has less low bias in WY2014 (Fig. 5b) and WY2015 (Fig. 5b),
436 both dry years, and LIS/WRF-Hydro-DA is associated with fewer changes to LIS/WRF-Hydro
437 SWE. Meanwhile, low bias in WY2016 (Fig. 5c) and WY2017 (Fig. 5d) (both wet years) is more
438 noticeable, and LIS/WRF-Hydro with DA experiences a greater correction. These changes in
439 SWE subsequently impact the streamflow in later timesteps, and the location of SWE changes
440 also impact hydrologic response, both of which are shown in later figures.

441 Figure 5 also shows that DA causes the model to exhibit some discontinuities in the SWE
442 timeseries. The discontinuities in Figure 5 are a result of the infrequent set of observations and
443 the fact that we are using a sequential data assimilation method. The magnitude of the
444 corrections introduced by DA is dependent on the differences between the observations and the
445 prior model state (before the analysis), which is why the corrections look more dramatic in some
446 years.

447 Changes to SWE model skill for the full WY2014-2017 analysis period, including RMSE
448 and correlation coefficient for LIS/WRF-Hydro-OL and LIS/WRF-Hydro-DA are shown in Fig.
449 6. In this figure, correlation and RMSE differences shown in the panels are based on the
450 quantities computed from the timeseries of the model variables compared to the observations at
451 each grid point. This figure includes statistical significance to RMSE changes (based on a Chi-
452 Squared Distribution) and correlation changes (based on a Fisher transform). DA reduces RMSE,
453 primarily due to decreases in negative bias, across the northern areas of the basin compared to
454 both SNODAS (Fig. 6a) and UA SWE (Fig. 6c) products. RMSE changes are less consistent in
455 the lower basin, as removal of excess valley snow has a more mixed impact. Even as RMSE is
456 improved over much of the basin due to improvements from bias (particularly in the northern
457 headwaters), there are also areas with increased RMSE (i.e. more error), and these are
458 statistically significant. These increases to RMSE follow decreased correlation coefficients in
459 some of the lower reaches where there is less snow after DA (Fig. 3b,d). The likely reason for
460 this reduced model skill is the reduction of SWE in the lower basin may be responsible for
461 reducing the correlation coefficient for SWE in this area due to snow becoming less frequent and
462 therefore more variable. Reductions to model SWE after DA also increase negative bias further
463 upstream to the East, which lead to increased RMSE values. Thus, while DA mostly improves
464 SWE skill, this is not true everywhere in the domain.

465 Fig. 7 shows the impacts of DA on other surface variables in the LIS/WRF-Hydro
466 simulations for the melt season (when surface runoff and streamflow are high). This includes the
467 months of April through July during the full WY2014-2017 period. This figure shows that the
468 northern basin, where DA increases snow, is also associated with increased soil moisture, while

469 soil moisture is reduced slightly downstream (Fig. 7a,c). This is consistent with the changes to
470 SWE demonstrated in Fig. 3c,f. While the percent change to snow is large throughout the domain
471 (~50% or greater in some areas; Fig. 3f), this corresponds to only minor and often spatially
472 variable changes in ET, even during the melting season (Fig. 7b,d). These results demonstrate
473 that SWE DA does impact other surface variables, and this is particularly noticeable for soil
474 moisture. While lateral flow routing is more physically consistent with hydrologic systems, the
475 addition of this component does make ET changes from SWE DA more spatially variable.

476 4.2 Impacts of DA on Streamflow

477 In this section, we consider the impacts of physical changes realized through ASO SWE
478 DA on streamflow. The only USGS gauge in the upper Tuolumne basin is USGS 11274790, and
479 this is upstream of the Hetch Hetchy reservoir (Fig. 2), which significantly alters the hydrologic
480 response downstream for water management. Since this model configuration does not include the
481 reservoir or streamflow extractions/diversions in the lower basin, model streamflow estimates at
482 this gauge are considered “natural” flows and expected to approximate the gage observations in
483 the upper basin only. In this basin, default model parameters are used in WRF-Hydro, so the
484 impacts of calibration are not considered here. Streamflow from the upper basin is shown in Fig.
485 8. Overall, the model hydrologic response reasonably follows the observations, despite the model
486 having a slightly over-active diurnal cycle (where runoff tends to follow snowmelt during the
487 primary melt season due to the diurnal temperature cycle).

488 For WY2014 (Fig. 8a) and WY2015 (Fig. 8b), when the basin was drier, SWE DA
489 eliminates some slight low streamflow bias during those dry years, even as water was removed
490 from the snowpack at times during those same years (Fig. 5a,b). As we will show in later figures,
491 this is due to the redistribution of SWE from DA that can be visualized in Fig. 3. Similarly, snow
492 DA substantially decreases wet bias for streamflow during WY2016 (Fig. 8c), and to a lesser
493 extent WY2017 (Fig. 8d), which were both wetter than the earlier years in the simulation (Fig.
494 5c,d). Table 4 shows streamflow skill for both the OL and DA simulations as bias, correlation,
495 RMSE, Nash-Sutcliffe Efficiency (NSE), and Kling-Gupta Efficiency (KGE; Gupta et al. 2009).
496 These quantities are improved from DA. Note that KGE equally weights correlation, bias, and
497 standard deviation errors, while NSE tends to weight correlation higher (e.g. Gupta et al. 2009).
498 This suggests that the changes to snow in the model, which had only nominal changes to SWE in
499 dry years and reduced the low SWE bias in wet years are also able to ameliorate some
500 streamflow biases. During WY2015, LIS/WRF-Hydro with DA is able to capture runoff early in
501 the season that the OL simulation does not resolve. Note that DA only was used for SWE (not
502 streamflow or other hydrologic variables); however, these results show added value from snow
503 DA in LIS in a hydrologic simulation.

504 The physical processes that lead to the redistribution of streamflow due to DA are
505 considered in Figs. 9 and 10. In Fig. 9, it is obvious that most lateral flow (i.e. surface runoff and
506 shallow saturated flow that reaches the WRF-Hydro channel network) originates in the high
507 elevations, where the snowpack is the greatest. Close analysis of this figure also reveals that
508 much of the flow entering the channel network originates at a few points while inflow in
509 surrounding channel grid points is less. This would be expected in a basin dominated by snow
510 hydrology, and is especially true in the years with greater snowpack (i.e. WY2016-2017).
511 However, Fig. 10 also demonstrates that changes to this runoff entering the channels from DA

512 tend to vary in wet and dry years. During dry years (i.e. WY2014-2015), runoff is added to
513 upstream reaches in the northern part of the basin, where SWE is generally the highest (i.e. Fig.
514 3), and this is consistent with the reduction of low streamflow bias during these same years (i.e.
515 Fig. 8) from added SWE in these areas. Meanwhile, during the wet years, while some runoff is
516 again added in the high elevation reaches, runoff is also reduced in the lower reaches, consistent
517 with Fig. 3 where SWE is reduced in these areas. This reduction of snowpack in the lower basin
518 (above Hetch Hetchy reservoir) is the reason why the high streamflow bias in the OL simulation
519 is reduced in the DA simulation during WY2016-2017. Thus, the spatial redistribution of SWE
520 from DA, where SWE increases in the high elevations but decreases further down seems to be
521 important for correcting some of the model streamflow errors, such that low flow bias during dry
522 years and high flow bias during wet years are partially corrected by these spatial changes that are
523 realized through DA. While the increase in SWE and decrease of streamflow during wet years
524 may seem counter-intuitive, it is consistent with the impact of SWE redistribution on the model
525 hydrologic response.

526 Fig. 10 also shows that DA affects at least some snowmelt and runoff outside of the
527 analysis area above Hetch Hetchy. This is because the ASO domain is slightly larger than our
528 analysis domain. ASO DA does not affect other parts of the basin, as the 1-D EnKF only affects
529 model variables where ASO data are available.

530 4.3 Impacts of hydrologic routing on land surface states

531 The coupled LIS/WRF-Hydro system not only enables the translation of improved land
532 surface states through LIS from data assimilation to streamflow, but also allows the simulation of
533 the impact of hydrologic routing on land surface states. In this section, we consider the impacts
534 of that lateral redistribution of water from WRF-Hydro on soil moisture and ET. For example,
535 surface flow recycled from routing that is otherwise removed from the LSM would influence the
536 soil moisture states (e.g. Lahmers et al. 2020). The influence of the two-way feedbacks simulated
537 by the coupled LIS/WRF-Hydro environment is examined by contrasting the LIS/WRF-Hydro
538 simulations with LIS-only simulations in supplemental material, Figs. 11-12, and in Table 5.

539 A figure equivalent to Fig. 8 is included in Supplemental material, and it considers the
540 impacts of hydrologic model routing by plotting WRF-Hydro channel flow compared to LIS-
541 only surface and sub-surface runoff (the LIS surface runoff variable is not used when coupled to
542 WRF-Hydro terrain routing schemes since explicit routing is included). In this figure, the
543 LIS/WRF-Hydro OL and DA streamflow is plotted with solid red and dark blue lines,
544 respectively (as in Figure 8). LIS OL and DA aggregated surface and sub-surface runoff (over
545 the same basin) are plotted with dashed orange and purple lines, respectively. Observed
546 streamflow is plotted with a solid black line. 24-hour averages are used in this figure as the LIS-
547 only runoff is written daily in our configuration. The LIS-only runoff follows a similar trajectory
548 to LIS/WRF-Hydro, but tends to miss the timing of some peaks captured by LIS/WRF-Hydro
549 and USGS streamflow. LIS-only simulations tend to have runoff peaks that are too fast and
550 flashier compared to the observations and LIS/WRF-Hydro solution. This is especially true
551 earlier in the water year, when runoff is driven by rainfall rather than snowmelt. This is likely
552 due to WRF-Hydro aggregating some runoff and routing it downstream, which is slower and
553 more consistent with actual hydrologic response. In some cases late in the season, LIS-only
554 runoff (surface and sub-surface) also has a longer recession, which may indicate increased

555 reliance on sub-surface flow. Thus, this figure shows the added value of LIS/WRF-Hydro
556 surface runoff.

557 The addition of lateral terrain routing tends to influence the hydrologic response, as
558 shown in soil moisture for both the OL (Fig. 11a) and DA (Fig. 11c) simulations. Fig. 11b,d
559 shows a vectorized version of the LIS/WRF-Hydro routing grid in the analysis domain. This
560 figure shows that soil moisture changes from routing are relatively constant across much of the
561 model domain, but increases tend to be more pronounced near channel grid cells. As DA reduced
562 SWE and soil moisture further downstream but increased both variables upstream (i.e. Fig. 3 and
563 Fig. 7, respectively), the effects of routing are slightly more noticeable downstream when DA is
564 used because lateral terrain routing increases soil moisture downstream in areas where DA would
565 otherwise reduce it. Meanwhile, increases in soil moisture also lead to increased ET near the
566 channel network in LIS/WRF-Hydro (Fig. 12b,d). Basin ET averages are also shown in Fig
567 12a,c.

568 The driving force for these changes is increased surface flow at high elevations, as
569 infiltration excess produced from Noah-MP that would otherwise be removed from the system as
570 a sink is allowed to flow down-gradient through WRF-Hydro. Table 5 also shows that soil
571 moisture and ET increase the most at lower elevations, which is expected since increased surface
572 runoff results in more infiltration further downstream in the basin. This occurs to a lesser extent
573 at higher elevations.

574 **5 Summary and Implications**

575 This article presents the development of the coupled LIS/WRF-Hydro system, which is
576 aimed at exploiting and connecting the land surface DA capabilities of NASA LIS and the
577 hydrological modeling capabilities of WRF-Hydro. The coupled environment is facilitated using
578 the constructs of the ESMF, enabling a flexible and interoperable environment that integrates the
579 two large modeling systems. The application of the coupled LIS/WRF-Hydro system is
580 demonstrated over the Tuolumne basin in California, where remotely sensed SWE estimates
581 from the NASA ASO dataset are employed for DA. The ASO SWE estimates are assimilated
582 within LIS to improve the representation of snow states within the land surface model, and the
583 coupled LIS/WRF-Hydro environment is used to examine the corresponding impacts on
584 streamflow from snow DA. The ASO estimates are available over a subset of the entire modeled
585 domain. For this work, we use EnKF DA due to its ability to run with fewer ensembles and its
586 shorter latency window, which is ideal for a streamflow forecasting proof of concept. This would
587 not preclude the use of other DA methods such as particle smoothing (e.g. Margulis et al. 2019)
588 for future work if the computational challenge of its larger ensemble size could be overcome.

589 Over areas where ASO coverage exist, the ASO SWE DA leads to reduced SWE biases
590 (Table 3) in the LIS/WRF-Hydro simulations. Further, these benefits also extend to the
591 hydrologic model simulation through the improvements to model runoff. For example,
592 streamflow bias at USGS gauge 11274790 (above Hetch Hetchy Reservoir) is reduced from 16%
593 to less than 10% with DA. The benefits of snow DA for streamflow are better understood when
594 considering the impacts of DA on surface runoff entering channels (i.e. Fig. 10), as removal of

595 snow at low elevations tends to reduce high bias during wet years, while added snow at high
596 elevations tends to reduce negative bias during dry years.

597 Model improvements via reductions of model streamflow biases above Hetch Hetchy
598 reservoir from ASO DA (too dry in dry years and too wet in wet years) should be significant for
599 water management in the western US and other semi-arid environments with growing
600 populations. We also note that negative SWE bias is reduced across much of the high-elevation
601 northern area of the study region, while excess SWE in the valleys and at generally lower
602 elevations is removed. At high elevations, especially to the North, SWE is increased by over
603 60% in some areas, while it is reduced by ~25% in lower elevations (Fig. 3). This redistribution
604 of SWE with additional SWE in the headwaters and reduced SWE downstream improves the
605 hydrologic response, where the former reduces negative bias during dry years and the latter
606 reduces excessive positive bias of streamflow above Hetch Hetchy Reservoir during wet years.
607 If SWE DA in hydrologic models can improve forecasts of streamflow entering reservoirs, this
608 modeling framework (applied in a real-time quasi-operational simulation) could potentially be
609 significant for dam operations and seasonal water forecasts.

610 Addressing the impacts of SWE DA on streamflow for this application would not be
611 possible without the integrated capabilities of LIS coupled to WRF-Hydro. Though prior studies
612 have examined the use of remote sensing snow measurements on land surface characterization,
613 only a few studies have focused their impact on the integrated land and hydrological response
614 (e.g. Caleb and Moradkhani, 2011, Liu et al. 2015, Huang et al. 2017). The results described here
615 therefore provide the systematic process level quantification of the impact of ASO SWE DA on
616 various land surface and hydrologic processes. As future remote sensing estimates of snow are
617 being developed, quantitative assessment of their anticipated utility for hydrologic process
618 improvements is important to quantify. The methodology and the results of this study using the
619 coupled LIS/WRF-Hydro system serve as an important benchmark in this regard.

620 The evaluations presented in this study also indicate that the systematic errors in the snow
621 and streamflow estimates are significant sources of uncertainty in the model simulations. These
622 errors may be due to uncertainties in model forcing, physics schemes within the model structure,
623 and adjustable parameters. To further improve the accuracy of model simulations (including
624 those with DA), calibration (e.g. Gupta et al. 2009; Samaniego et al. 2010) of land surface and
625 hydrologic parameters that control surface water partitioning, snow, and flow routing parameters
626 could be beneficial. The calibration approaches must also consider inconsistencies between
627 model streamflow and surface variables, as Lahmers et al. (2019) demonstrated that calibration
628 to surface flow degraded soil moisture in some southwest US catchments. Both LIS and WRF-
629 Hydro include significant parameter estimation capabilities, which could be exploited to
630 potentially ameliorate these issues through the refinement of relevant model parameters.

631 Another finding of this analysis is the coupled LIS/WRF-Hydro system simulates the
632 redistribution of soil moisture from the feedback of the hydrologic model into the land surface
633 model. Over the simulation domain, this feedback leads to increases in soil moisture and ET in
634 areas near the channel network. ET and soil moisture near the channel network can increase by
635 over 10% in some locations (Figs. 11-12). These findings are similar to the results from Lahmers
636 et al. (2020), who showed that soil moisture increases in WRF-Hydro compared to control
637 simulations without surface hydrology in a semi-arid environment, especially in areas with low

638 soil conductivity. This addition of physical processes representing surface hydrology can
639 therefore impact land-atmosphere interactions in some environments (e.g. Lahmers et al. 2020),
640 and is thus relevant to future work.

641 The combination of DA and hydrologic routing in the coupled LIS/WRF-Hydro
642 modeling system opens up new possibilities for the analysis of surface processes on atmospheric
643 coupling (e.g. Santanello et al. 2018). The snow DA example demonstrated here is a “weakly-
644 coupled” DA instance where the assimilation is performed within the offline land surface model
645 and the impacts on streamflow are demonstrated (indirectly) through the mediator between LIS
646 and WRF-Hydro. The development of the coupled system also paves the way for strongly
647 coupled DA environments where cross-model DA updates are used. For example, the
648 assimilation of streamflow observations within WRF-Hydro could be employed with the land
649 surface moisture variables (in LIS) updated in a DA instance. Such a strongly coupled DA
650 environment could be accomplished with an additional mediator designed specifically for DA
651 related exchanges. Similarly, the addition of hydrologic routing and its impacts on soil moisture
652 could influence surface fluxes, as was shown in previous literature (e.g. Maxwell et al. 2011;
653 Arnault et al. 2016; Lahmers et al. 2020). Thus, this new coupled modeling system has the
654 potential to combine both of these abilities to improve our understanding of land surface
655 processes and variables on atmospheric processes that govern NWP and climate prediction.

656 **Acknowledgements:**

657 This work was supported by NASA Modeling, Analysis, and Prediction (MAP) Federal Grant
658 Number: NNH15ZDA001N-MAP and by the NASA Postdoctoral Program (NPP).

659 **Open Data Statement:**

660 The LIS/WRF-Hydro model is available online as the NASA-Land-Coupler:
661 <https://github.com/NASA-LIS/NASA-Land-Coupler.git>. The version of LIS/WRF-Hydro used
662 for this manuscript is tagged online at: [https://github.com/NASA-LIS/NASA-Land-
663 Coupler/tree/96017ce6dbf4783efa4e22a6d9b2d7b40ef10960/src](https://github.com/NASA-LIS/NASA-Land-Coupler/tree/96017ce6dbf4783efa4e22a6d9b2d7b40ef10960/src). Archived plotting scripts and
664 post-processed data are available for download at: <https://doi.org/10.5281/zenodo.6330018>. ASO
665 snow data are available online at: <https://nsidc.org/data/aso>. California Department of Water
666 Resources Data are available at: <https://cdec.water.ca.gov/snow/current/snow/>. SNODAS data
667 are available at: <https://nsidc.org/data/g02158>, and University of Arizona SWE data are available
668 at: <https://nsidc.org/data/nsidc-0719/versions/1>. NLDAS-2 forcing data are available at:
669 [https://disc.sci.gsfc.nasa.gov/datasets/NLDAS_NOAH0125_H_002/summary?keywords=NLDA
670 S](https://disc.sci.gsfc.nasa.gov/datasets/NLDAS_NOAH0125_H_002/summary?keywords=NLDA). USGS streamflow data were downloaded using the USGS data retrieval tools (available at:
671 <https://owi.usgs.gov/R/training-curriculum/usgs-packages/dataRetrieval-readNWIS/>) with data
672 stored at: <https://waterservices.usgs.gov/>.

673 **References**

674 Anderson, E.A., (1973) National Weather Service River Forecast System – Snow Accumulation
675 and Ablation Model, NOAA Technical Memorandum: NWS Hydro-17, US National Weather
676 Service.

677

- 678 Arnault, J., Wagner, S., Rummeler, T., Fersch, B., Bliefernicht, J., Andresen, S., and Kunstmann,
679 H., (2016), Role of Runoff–Infiltration Partitioning and Resolved Overland Flow on Land–
680 Atmosphere Feedbacks: A Case Study with the WRF-Hydro Coupled Modeling System for West
681 Africa. *J. Hydrometeor.*, 17, 1489–1516.
- 682
683 Arsenault, K.R., Kumar, S.V., Geiger, J.V., Wang, S., Kemp, E., Mocko, D.M., Beaudoin,
684 H.K., Getirana, A., Navari, M., Li, B., Jacob, J., Wegiel, J., and Peters-Lidard, C.D., (2018), The
685 Land surface Data Toolkit (LDT v7.2) – a data fusion environment for land data assimilation
686 systems. *Geosci. Model Dev.*, 11, 3605-3621, [doi:10.5194/gmd-11-3605-2018](https://doi.org/10.5194/gmd-11-3605-2018)
687
- 688 Barbu, A. L., Calvet, J.-C., Mahfouf, J.-F. and Lafont, S., (2014), Integrating ASCAT surface
689 soil moisture and GEOV1 leaf area index into the SURFEX modelling platform: A land data
690 assimilation application over France. *Hydrol. Earth Syst. Sci.*, 18, 173–192,
691 <https://doi.org/10.5194/hess-18-173-2014>.
- 692
693 Barrett, A. (2003), National Operational Hydrologic Remote Sensing Center SNOW Data
694 Assimilation System (SNODAS) Products at NSIDC. NSIDC Special Report 11. Boulder, CO,
695 USA: National Snow and Ice Data Center. Digital media.
- 696
697 Caleb, D., and Moradkhani, H., (2011), Radiance data assimilation for operational snow and
698 streamflow forecasting. *Advances in Water Resources* 34(3) 351-364.
- 699
700 Cao, Q., Painter, T. H., Curriet, W. R., Lundquist, J. D., and Lettenmaier, D. P., (2018),
701 Estimation of Precipitation over the OLYMPEX Domain during Winter 2015/16, *J.*
702 *Hydrometeor.*, 19, 143-160, doi: 10.1175/JHM-D-17-0076.1.
- 703
704 Clark, M. P., Fan, Y., Lawrence, D. M., Adam, J. C., Bolster, D., Gochis, D. J., Hooper, R.
705 P., Kumar, M., Leung, L. R., Mackay, D. S., Maxwell, R. M., Shen, C., Swenson, S. C.,
706 and Zeng, X. (2015), Improving the representation of hydrologic processes in Earth System
707 Models, *Water Resour. Res.*, 51, 5929–5956, doi:[10.1002/2015WR017096](https://doi.org/10.1002/2015WR017096).
- 708
709 Clark, M. P., Bierkens, M. F. P., Samaniego, L., Woods, R. A., Uijlenhoet, R., Bennett, K. E.,
710 Pauwels, V. R. N., Cai, X., Wood, A. W., and Peters-Lidard, C. D. (2017), The evolution of
711 process-based hydrologic models: historical challenges and the collective quest for physical
712 realism, *Hydrol. Earth Syst. Sci.*, 21, 3427–3440, doi:<https://doi.org/10.5194/hess-21-3427-2017>,
713 2017.
- 714
715 Crow, W. T., and Van Loon, E. (2006), Impact of Incorrect Model Error Assumptions on the
716 Sequential Assimilation of Remotely Sensed Surface Soil Moisture, *Journal of*
717 *Hydrometeorology*, 7(3), 421-432, doi: <https://doi.org/10.1175/JHM499.1>
- 718
719 Dawson, N., Broxton, P., Zeng, X., Leuthold, M., Barlage, M., & Holbrook, P., (2016), An
720 Evaluation of Snow Initializations in NCEP Global and Regional Forecasting Models, *Journal of*
721 *Hydrometeorology*, 17(6), 1885-1901. Retrieved Feb 5, 2021,
722 from https://journals.ametsoc.org/view/journals/hydr/17/6/jhm-d-15-0227_1.xml
723

- 724 de Lannoy, G. J. M., Reichle, R. H., Arsenault, K. R., Houser, P. R., Kumar, S., Verhoest, N. E.
725 C., and Pauwels, V. R. N., (2012), Multiscale assimilation of Advanced Microwave Scanning
726 Radiometer–EOS snow water equivalent and Moderate Resolution Imaging Spectroradiometer
727 snow cover fraction observations in northern Colorado. *Water Resour. Res.*, 48, W01522,
728 <https://doi.org/10.1029/2011WR010588>.
729
- 730 Ek, M. B., Mitchell, K. E., Lin, Y., Rogers, E., Grunmann, P., Koren, V., Gayno, G.,
731 and Tarpley, J. D. (2003), Implementation of Noah land surface model advances in the National
732 Centers for Environmental Prediction operational mesoscale Eta model, *J. Geophys. Res.*, 108,
733 8851, doi:[10.1029/2002JD003296](https://doi.org/10.1029/2002JD003296), D22.
734
- 735 Gupta, H. V., Kling, H., Yilmaz K., and Martinez, G., (2009), Decomposition of the mean
736 squared error and NSE performance criteria: Implications for improving hydrological modeling.
737 *J. Hydrol.*, **377**, 80-91.
738
- 739 Gochis, D.J., Barlage M., Cabell, R., Casali, M., Dugger, A., FitzGerald, K., McAllister, M.,
740 McCreight, J., RafieeiNasab, A., Read, L., Sampson, K., Yates, D., Zhang, Y., 2020: The WRF-
741 Hydro(R) modeling system technical description, (Version 5.1.1). NCAR Technical Note. 107
742 pages. Available online
743 at: <https://ral.ucar.edu/sites/default/files/public/WRFHydroV511TechnicalDescription.pdf>.
744 Source Code doi:[10.5281/zenodo.3625238](https://doi.org/10.5281/zenodo.3625238)
745
- 746 Hain, C. R., Crow, W. T., Anderson, M. C., and Mecikalski, J. R. (2012), An ensemble
747 Kalman filter dual assimilation of thermal infrared and microwave satellite observations of soil
748 moisture into the Noah land surface model, *Water Resour. Res.*, **48**, W11517,
749 doi:[10.1029/2011WR011268](https://doi.org/10.1029/2011WR011268).
750
- 751 Hamman, J. J., Nijssen, B., Bohn, T. J., Gergel, D. R., and Mao, Y., 2018: The Variable
752 Infiltration Capacity model version 5 (VIC-5): infrastructure improvements for new applications
753 and reproducibility, *Geosci. Model Dev.*, **11**, 3481–3496, [https://doi.org/10.5194/gmd-11-3481-](https://doi.org/10.5194/gmd-11-3481-2018)
754 2018
755
- 756 Henn, B., M. P. Clark, D. Kavetski, B. McGurk, T. H. Painter, and J. D. Lundquist (2016),
757 Combining snow, streamflow, and precipitation gauge observations to infer basin-mean
758 precipitation, *Water Resour. Res.*, 52, 8700–8723, doi:10.1002/2015WR018564.
759
- 760 Hill, C., DeLuca, C., Balaji, V., Suarez, M., and da Silva, A., (2004), Architecture of the Earth
761 System Modeling Framework. *IEEE Comput. Sci. Eng.*, 6(1), 18-28.
762
- 763 Houtekamer, P. L., and Mitchell, H. L., (1998), Data Assimilation Using an Ensemble Kalman
764 Filter Technique, *Monthly Weather Review*, **126**(3), 796-811, doi:[https://doi.org/10.1175/1520-](https://doi.org/10.1175/1520-0493(1998)126%3C0796:DAUAEK%3E2.0.CO;2)
765 0493(1998)126%3C0796:DAUAEK%3E2.0.CO;2
766
- 767 Huang, C, et al. (2017), Evaluation of snow data assimilation using the ensemble Kalman filter
768 for seasonal streamflow prediction in the western United States. *Hydrology and Earth System*
769 *Sciences* **21.1** 635-650.

- 770
771 Julien, P. Y., Saghafian, B., and Ogden, F. L., (1995), Raster-based hydrological modeling of
772 spatially-varied surface runoff. *J. Amer. Water Resour. Assoc.*, **31**, 523–
773 536, <https://doi.org/10.1111/j.1752-1688.1995.tb04039.x>.
774
- 775 Kumar, S.V., and coauthors, (2006), Land Information System - An Interoperable Framework for
776 High Resolution Land Surface Modeling. *Environ. Modell. Softw.*, 21, 1402-1415.
777
- 778 Kumar, S.V., Reichle, R.H., Peters-Lidard, C.D., Koster, R.D., Zhan, X., Crow, W.T., Eylander,
779 J.B., and Houser, P. R., (2008), A Land Surface Data Assimilation Framework using the Land
780 Information System: Description and Applications, *Advances in Water Resources*, 31, 1419-
781 1432, DOI:10.1016/j.advwatres.2008.01.013
782
- 783 Kumar, S., Reichle, R., Koster, R., Crow, W., and Peters-Lidard, C., 2009: Role of subsurface
784 physics in the assimilation of surface soil moisture observations, *Journal of Hydrometeorology*,
785 **10**, 1534–1547, doi:10.1175/2009JHM1134.1.
786
- 787 Kumar, S.V., and Coauthors, (2014), Assimilation of remotely sensed soil moisture and snow
788 depth retrievals for drought estimation. *J. Hydrometeor.*, 15, 2446–2469,
789 <https://doi.org/10.1175/JHM-D-13-0132.1>.
790
- 791 Kumar, S.V., Peters-Lidard, C.D., Arsenault, K.R., Getirana, A., Mocko, D., and Liu, Y.,
792 (2015a), Quantifying the added value of snow cover area observations in passive microwave
793 snow depth assimilation. *J. Hydrometeor.*, **16** (4): 1736–1741, doi:[https://doi.org/10.1175/JHM-](https://doi.org/10.1175/JHM-D-15-0021.1)
794 [D-15-0021.1](https://doi.org/10.1175/JHM-D-15-0021.1)
795
- 796 Kumar, S. V., Peters-Lidard, C. D., Santanello, J. A., Reichle, R. H., Draper, C. S., Koster, R. D.,
797 Nearing, G., and Jasinski, M. F., (2015b), Evaluating the utility of satellite soil moisture
798 retrievals over irrigated areas and the ability of land data assimilation methods to correct for
799 unmodeled processes, *Hydrol. Earth Syst. Sci.*, **19**, 4463–4478, doi:[https://doi.org/10.5194/hess-](https://doi.org/10.5194/hess-19-4463-2015)
800 [19-4463-2015](https://doi.org/10.5194/hess-19-4463-2015).
801
- 802 Kumar, S.V., Zaitchik, B.F., Peters-Lidard, C.D., Rodell, M., Reichle, R., Li, B., Jasinski, M.,
803 Mocko, D., Getirana, A., Lannoy, G.D.M., Cosh, M., Hain, C.R., Anderson, M. (2016),
804 Assimilation of gridded GRACE terrestrial water storage estimates in the North American Land
805 Data Assimilation System (NLDAS), *J. Hydrometeor.*, **17**(7), doi: 10.1175/JHM-D-15-0157.1.
806
- 807 Kumar, S. V., Dong, J., Peters-Lidard, C. D., Mocko, D., and Gómez, B., (2017), Role of forcing
808 uncertainty and background model error characterization in snow data assimilation, *Hydrol.*
809 *Earth Syst. Sci.*, 21, 2637–2647, <https://doi.org/10.5194/hess-21-2637-2017>.
810
- 811 Kumar, S.V., Jasinski, M., Mocko, D.M., Rodell, M., Borak, J., Li, B., Kato Beaudoin, H., and
812 Peters-Lidard, C.D., (2019a), NCA-LDAS land analysis: Development and performance of a
813 multisensor, multivariate land data assimilation system for the National Climate Assessment. *J.*
814 *Hydrometeor.*, 20, 1571-1593, [doi:10.1175/JHM-D-17-0125.1](https://doi.org/10.1175/JHM-D-17-0125.1)
815

- 816 Kumar, S.V., Mocko, D.M., Wang, S., Peters-Lidard, C.D., and Borak, J., (2019b), Assimilation
817 of remotely sensed Leaf Area Index into the Noah-MP land surface model: Impacts on water and
818 carbon fluxes and states over the Continental U.S. *J. Hydrometeor.*, 20, 1359-
819 1377, [doi:10.1175/JHM-D-18-0237.1](https://doi.org/10.1175/JHM-D-18-0237.1)
820
- 821 Kumar, S.V., Holmes, T.R., Bindlish, R., de Jeu, R., and Peters-Lidard, C.D. (2020),
822 Assimilation of vegetation optical depth retrievals from passive microwave radiometry. *Hydrol.*
823 *Earth Syst. Sci.*, 24, 1-20, [10.5194/hess-2020-36](https://doi.org/10.5194/hess-2020-36).
824
- 825 Lahmers, T. M., Gupta, H., Castro, C. L., Gochis, D. J., Yates, D., Dugger, A., Goodrich, D., and
826 Hazenberg, P., (2019), Enhancing the Structure of the WRF-Hydro Hydrologic Model for
827 Semiarid Environments. *J. Hydrometeor.*, 20, 691–714, [https://doi.org/10.1175/JHM-D-18-](https://doi.org/10.1175/JHM-D-18-0064.1)
828 [0064.1](https://doi.org/10.1175/JHM-D-18-0064.1).
829
- 830 Lahmers, T. M., Castro, C. L., and Hazenberg, P., (2020), Effects of Lateral Flow on the
831 Convective Environment in a Coupled Hydrometeorological Modeling System in a Semiarid
832 Environment. *J. Hydrometeor.*, 21, 615–642, <https://doi.org/10.1175/JHM-D-19-0100.1>
833
- 834 Lahmers T. M., P. Hazenberg, H. V. Gupta, C. L. Castro, D. J. Gochis, A. L. Dugger, D. N.
835 Yates, L. K. Read, L. Karsten, Y-H. Wang: Evaluation of NOAA National Water Model
836 Parameter Calibration in Semi-Arid Environments Prone to Channel Infiltration, *J. Hydrometeor.*,
837 *in press*, doi:10.1175/JHM-D-20-0198.1
838
- 839 Lettenmaier, D. P., Alsdorf, D., Dozier, J., Huffman, G. J., Pan, M., and Wood, E.
840 F. (2015), Inroads of remote sensing into hydrologic science during the WRR era, *Water*
841 *Resour. Res.*, 51, 7309–7342, doi:[10.1002/2015WR017616](https://doi.org/10.1002/2015WR017616).
842
- 843 Liu, Y., Peters-Lidard, C.D., Kumar, S.V., Foster, J.L., Shaw, M., and Tian, Y., (2013),
844 Assimilating satellite-based snow depth and snow cover products for improving snow
845 predictions in Alaska. *Advances in Water Resources*, 54, 208-227.
846
- 847 Liu, Y., Peters-Lidard, C.D., Kumar, S.V., Arsenault, K., and Mocko, D., (2015), Blending
848 satellite based snow depth products with in-situ observations for streamflow predictions in the
849 upper Colorado river basin, *Water Resources Research*, doi:
850 <https://doi.org/10.1002/2014WR016606>
851
- 852 Margulis, S. A., Fang, Y., Li, D., Lettenmaier, D. P., & Andreadis, K. (2019), The Utility of
853 Infrequent Snow Depth Images for Deriving Continuous Space-Time Estimates of Seasonal
854 Snow Water Equivalent. *Geophysical Research Letters*, 46(10), 5331-
855 5340. <https://doi.org/10.1029/2019GL082507>
856
- 857 Maxwell, R. M., Lundquist, J. K., Mirocha, J. D., Smith S. G., Woodward, C. S., and A. F. B.
858 Tompson, A. F. B. (2011) Development of a Coupled Groundwater–Atmosphere Model. *Mon.*
859 *Wea. Rev.*, **139**, 96–116.
860

- 861 Nerini, D., Foresti, L., Leuenberger, D., Robert, S., and Germann, U. (2019), A Reduced-Space
862 Ensemble Kalman Filter Approach for Flow-Dependent Integration of Radar Extrapolation
863 Nowcasts and NWP Precipitation Ensembles, *Monthly Weather Review*, **147**(3), doi:
864 10.1175/MWR-D-18-0258.1
- 865
866 Nielsen, S.A., Hansen, E., (1973) Numerical simulation of the rainfall runoff process on a
867 daily basis. *Nordic Hydrol.* 4, 171–190.
- 868
869 Niu G. Y., and coauthors, (2011), The community Noah land surface model with
870 multiparameterization options (Noah-MP): 1. Model description and evaluation with local-scale
871 measurements. *J. Geophys. Res.*, **116**.
- 872
873 Ogden, F. L., (1997), CASC2D Reference Manual. Dept. of Civil and Environmental
874 Engineering U-37, University of Connecticut, 106 pp.
- 875
876 Oaida, C. M., and coauthors, (2019), A High-Resolution Data Assimilation Framework for Snow
877 Water Equivalent Estimation across the Western United States and Validation with the Airborne
878 Snow Observatory, *J. Hydrometeorol.*, 20, 357-378, doi: 10.1175/JHM-D-18-0009.1.
- 879
880 Pan, M., & Wood, E. F., (2006), Data Assimilation for Estimating the Terrestrial Water Budget
881 Using a Constrained Ensemble Kalman Filter, *Journal of Hydrometeorology*, 7(3), 534-547, doi:
882 <https://doi.org/10.1175/JHM495.1>
- 883
884 Painter, T. H., Rittger, K., McKenzie, C., Slaughter, P., Davis, R. E., and Dozier, J., (2009),
885 Retrieval of subpixel snow-covered area, grain size, and albedo from MODIS. *Remote Sens.*
886 *Environ.*, **113**, 868–879, <https://doi.org/10.1016/j.rse.2009.01.001>.
- 887
888 Painter, T. H., Berisford, D. F., Boardman, J. W., Bormann, K. J., Deems, J. S., Gehrke, F.,
889 Hedrick, A., Joyce, M., Laidlaw, R., Marks, D., Mattmann, C., McGurk, B., Ramirez, P.,
890 Richardson, M., Skiles, S. M., Seidel, F. C., and Winstral, A., (2016), The Airborne Snow
891 Observatory: Fusion of scanning lidar, imaging spectrometer, and physically-based modeling for
892 mapping snow water equivalent and snow albedo, *Remote Sensing of Environment*, **184**, 139-
893 152, <https://doi.org/10.1016/j.rse.2016.06.018>.
- 894
895 Peters-Lidard , C.D., and coauthors, (2007), High-performance Earth system modeling with
896 NASA/GSFC's Land Information System. *Innov. Syst. Softw. Eng.*, 3(3), 157-165.
- 897
898 Peters-Lidard, C.D., Kumar, S.V., Mocko, D., and Tian, Y., (2011), Estimating
899 evapotranspiration with land data assimilation systems, *Hydrological Processes*, 25(26), 3979-
900 3992.
- 901
902 Peters-Lidard, C. D., Clark, M., Samaniego, L., Verhoest, N. E. C., van Emmerik, T., Uijlenhoet,
903 R., Achieng, K., Franz, T. E., and Woods, R. (2017), Scaling, similarity, and the fourth paradigm
904 for hydrology, *Hydrol. Earth Syst. Sci.*, 21, 3701–3713, [https://doi.org/10.5194/hess-21-3701-](https://doi.org/10.5194/hess-21-3701-2017)
905 2017, 2017.
- 906

- 907 Pitman, A.J. (2003), The evolution of, and revolution in, land surface schemes designed for
908 climate models. *Int. J. Climatol.*, 23: 479-510. doi:[10.1002/joc.893](https://doi.org/10.1002/joc.893)
909
- 910 Regan, R.S., Markstrom, S.L., LaFontaine, J.H., (2020), PRMS version 5.1.0: Precipitation-
911 Runoff Modeling System (PRMS): U.S. Geological Survey Software Release, 05/01/2020.
912
- 913 Reichle, R. H., McLaughlin, D. B., & Entekhabi, D. (2002), Hydrologic Data Assimilation with
914 the Ensemble Kalman Filter, *Monthly Weather Review*, 130(1), 103-114.
915
- 916 Reichle, R., Koster, R. D., Liu, P., Mahanama, S. P. P., Njoku, E. G., and Owe, M. (2007),
917 Comparison and assimilation of global soil moisture retrievals from the Advanced Microwave
918 Scanning Radiometer for the Earth Observing System (AMSR-E) and the Scanning Multichannel
919 Microwave Radiometer (SMMR). *J. Geophys. Res.*, 112, D09108,
920 <https://doi.org/10.1029/2006JD008033>.
921
- 922 Reichle, R. H., W. T. Crow, and C. L. Keppenne (2008), An adaptive ensemble Kalman filter for
923 soil moisture data assimilation, *Water Resour. Res.*, **44**, W03423, doi:10.1029/2007WR006357.
924
- 925 Reichle, R.H., Kumar, S.V., Mahanama, S.P.P., Koster R.D., and Liu, Q., (2010), Assimilation
926 of satellite-derived skin temperature observations into land surface models, *J. Hydrometeor.*,
927 **11**(5) 1103-1122 doi: 10.1175/2010JHM1262.1.
928
- 929 Ryu, D., W. T. Crow, X. Zhan, and T. J. Jackson (2009), Correcting unintended perturbation
930 biases in hydrologic data assimilation, *Journal of Hydrometeorology*, 10(3), 734–750.
931
- 932 Samaniego, L., Kumar, R., and Attinger, S., (2010), Multiscale parameter regionalization of a
933 grid-based hydrologic model at the mesoscale, *Water Resour. Res.*, **46**, W05523,
934 doi:10.1029/2008WR007327.
935
- 936 Sampson, K., and Gochis, D.J., (2020), WRF Hydro GIS Pre-Processing Tools, Version 5.1.1
937 Documentation, 45 pages. Available online at:
938 [https://github.com/NCAR/wrf_hydro_argis_preprocessor/releases/download/v5.1.1/WRFHydro](https://github.com/NCAR/wrf_hydro_argis_preprocessor/releases/download/v5.1.1/WRFHydro_GIS_Preprocessor_v5_1_1.pdf)
939 [_GIS_Preprocessor_v5_1_1.pdf](https://github.com/NCAR/wrf_hydro_argis_preprocessor/releases/download/v5.1.1/WRFHydro_GIS_Preprocessor_v5_1_1.pdf)
940
- 941 Santanello, J.A., and coauthors, (2018), Land–Atmosphere Interactions: The LoCo
942 Perspective. *Bull. Amer. Meteor. Soc.*, 99, 1253–1272.
943
- 944 Su H, Yang Z-L, Dickinson RE, Wilson CR, and Niu G-Y, (2011), Multisensor snow data
945 assimilation at the continental scale: the value of gravity recovery and climate experiment
946 terrestrial water storage information. *Journal of Geophysical Research*, **115**(D10), 1–14.
947 doi:<http://dx.doi.org/10.1029/2009JD013035>.
948
- 949 Sun N, M Wigmosta, T Zhou, J Lundquist, S Dickerson-Lange, and N Cristea. (2018),
950 Evaluating the Functionality and Streamflow Impacts of Explicitly Modelling Forest–Snow
951 Interactions and Canopy Gaps in a Distributed Hydrologic Model. *Hydrological*
952 *Processes* **32**(13):2128-2140. DOI: 10.1002/hyp.13150

953
954
955
956
957
958
959
960
961
962
963
964
965
966
967
968

Theurich, (2014), NUOPC Layer Reference, ESMF v7.0.0*. Available online at:
<https://www.earthsystemcog.org/projects/nuopc/refmans>

Xia, Y., et al. (2012), Continental-scale water and energy flux analysis and validation for the North American Land Data Assimilation System project phase 2 (NLDAS-2): 1. Intercomparison and application of model products, *J. Geophys. Res.*, 117, D03109, doi:[10.1029/2011JD016048](https://doi.org/10.1029/2011JD016048).

Zaitchik, B. F., Rodell, M., (2009), Forward-looking assimilation of MODIS-derived snow-covered area into a land surface model. *J. Hydrometeor.*, 10, 130–148,
<https://doi.org/10.1175/2008JHM1042.1>.

Zhou, Y, McLaughlin, D., and Entekhabi, D, (2006), Assessing the Performance of the Ensemble Kalman Filter for Land Surface Data Assimilation, *Monthly Weather Review*, **134**(8), 2128-2142, doi:<https://doi.org/10.1175/MWR3153.1>

969 **Table 1:** LIS and LIS/WRF-Hydro simulation descriptions.

Simulation Name	Description
LIS-OL	LIS Noah-MP v4.0.1 model run without assimilation
LIS-DA	LIS Noah-MP v4.0.1 with ASO SWE DA
LIS/WRF-Hydro-OL	LIS Noah-MP v4.0.1 coupled to WRF-Hydro, including surface routing, sub-surface flow, baseflow, and channel routing without assimilation
LIS/WRF-Hydro-DA	LIS Noah-MP v4.0.1 coupled to WRF-Hydro, including surface routing, sub-surface flow, baseflow, and channel routing with ASO SWE DA

970

971

972 **Table 2:** Parameters for meteorological forcing and model state variables for EnKF
 973 configuration.

974

Variable	Perturbation Type	Std. Dev.	Cross Correlation across variables			
			SW corr	LW corr	PCP corr	T corr
Meteorological Forcing						
Downward Shortwave (SW)	Multiplicative	0.2	1	-0.3	-0.5	0.3
Downward Longwave (LW)	Additive	30	-0.3	1	0.5	0.6
Precipitation (PCP)	Multiplicative	0.5	-0.5	0.5	1	-0.1
Near surface Air Temperature (T)	Additive	0.5	0.3	0.6	-0.1	1
Noah LSM snow states			SWE	snod		
SWE	Multiplicative	0.01	1	0.9		
Snow depth (snod)	Multiplicative	0.01	0.9	1		

975 **Table 3:** LIS and LIS/WRF-Hydro skill scores compared to University of Arizona and SNODAS
 976 data on the top two panels and the California COOP sites on the bottom three panels. For gridded
 977 datasets, skill is computed in the basin area above Hetch Hetchy Reservoir. Confidence intervals
 978 for RMSE and Bias are based on a Chi-Square Distribution and a student's T-test, respectively,
 979 for the timeseries of area averaged errors. Intervals are computed for correlation coefficient use a
 980 Fisher transform.

UA	LIS-OL	LIS-DA	LIS/WRF-Hydro OL	LIS/WRF-Hydro DA
RMSE	108.6 (104.9 – 112.7)	90.9 (87.8 – 94.4)	108.6 (104.8 – 112.7)	91.0 (87.8 – 94.4)
Bias (mm)	-46.9 ±5.0	-32.5 ±4.4	-46.8 ±5.0	-32.5 ±4.4
R (-)	0.988 (0.987 – 0.990)	0.980 (0.978 – 0.982)	0.988 (0.987 – 0.989)	0.980 (0.978 – 0.982)
SNODAS				
RMSE	129.3 (124.8 - 134.1)	99.6 (96.1 - 103.3)	129.3 (124.7 - 134.1)	99.6 (96.1 - 103.4)
Bias (mm)	-49.0 ±6.1	-34.6 ±4.8	-48.9 ±6.1	-34.6 ±4.8
R(-)	0.980 (0.978 – 0.982)	0.981 (0.979 – 0.983)	0.980 (0.978 – 0.982)	0.981 (0.979 – 0.983)
DAN CA Coop.				
RMSE	94.6 (91.3 – 98.2)	169.3 (163.4 – 175.7)	94.6 (91.3 – 98.2)	169.4 (163.4 – 175.7)
Bias (mm)	-31.1 ± 4.6	4.6 ± 8.7	-31.1 ± 4.6	4.6 ± 8.7
R(-)	0.972 (0.969 - 0.974)	0.893 (0.882 – 0.903)	0.972 (0.969 – 0.974)	0.893 (0.882 - 0.903)
SLI CA Coop.				
RMSE	413.6 (399.1 – 429.1)	281.8 (271.9 – 292.4)	413.7 (399.3 – 429.3)	281.9 (272.0 – 292.5)
Bias (mm)	-238.3 ± 29.8	-179.5 ± 19.1	-238.3 ± 29.8	-179.6 ± 19.1
R(-)	0.993 (0.993 - 0.994)	0.978 (0.976 - 0.980)	0.993 (0.993 - 0.994)	0.978 (0.976 - 0.980)
TUM CA Coop.				
RMSE	107.1 (103.3 – 111.1)	74.7 (77.5 – 72.1)	107.2 (103.4 – 111.2)	74.71 (77.5 – 72.1)

Bias (mm)	-2.8 ± 7.8	-11.3 ± 5.4	-2.8 ± 7.8	-11.3 ± -5.4
	0.960	0.982	0.960	0.982
R(-)	(0.955 – 0.963)	(0.980 – 0.984)	(0.955 – 0.963)	(0.980 – 0.984)

982 **Table 4:** Streamflow skill scores at USGS gauge 11274790 for the control and DA ensemble
983 mean LIS/WRF-Hydro simulations.

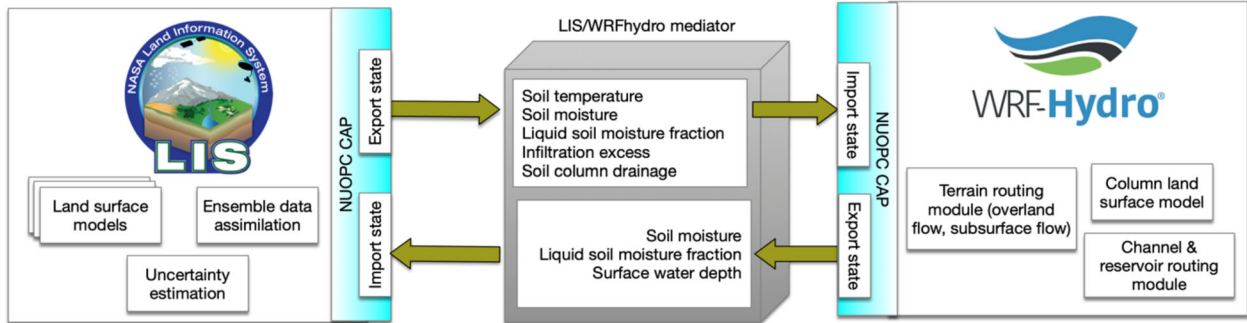
LIS/WRF-Hydro OL Simulation					
Gage	KGE	NSE	Bias	R	RMSE
11274790	0.04	-0.65	15.86	0.80	21.99
LIS/WRF-Hydro DA Simulation					
Gage	KGE	NSE	Bias	R	RMSE
11274790	0.44	0.14	9.48	0.80	15.88

984

985 **Table 5: Average percent increase to ET and soil moisture between LIS/WRF-Hydro and**
986 **LIS (LIS/WRF-Hydro – LIS) for elevation ranges across the upper basin model analysis**
987 **domain (Fig. 2). Analysis is for simulations with DA.**

Elevation Range (m)	ET (%-Increase)	0-10 cm Soil Vol. Water (%-Increase)
1400-1800	8.83	4.80
1800-2200	11.63	4.62
2200-2600	8.47	3.13
2600-3000	8.53	2.91
3000-3400	8.61	2.28
3400-3800	5.17	2.33

988
989



990

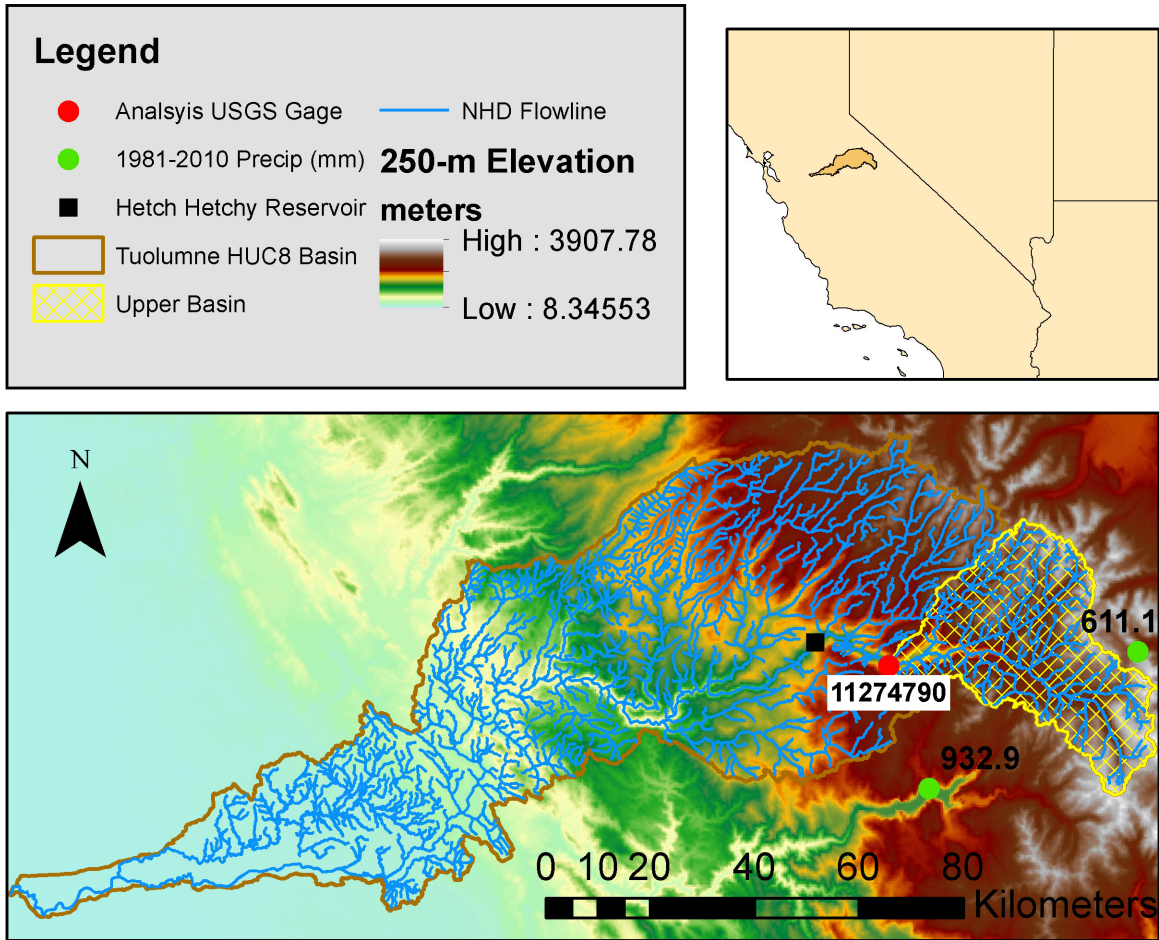
991

992

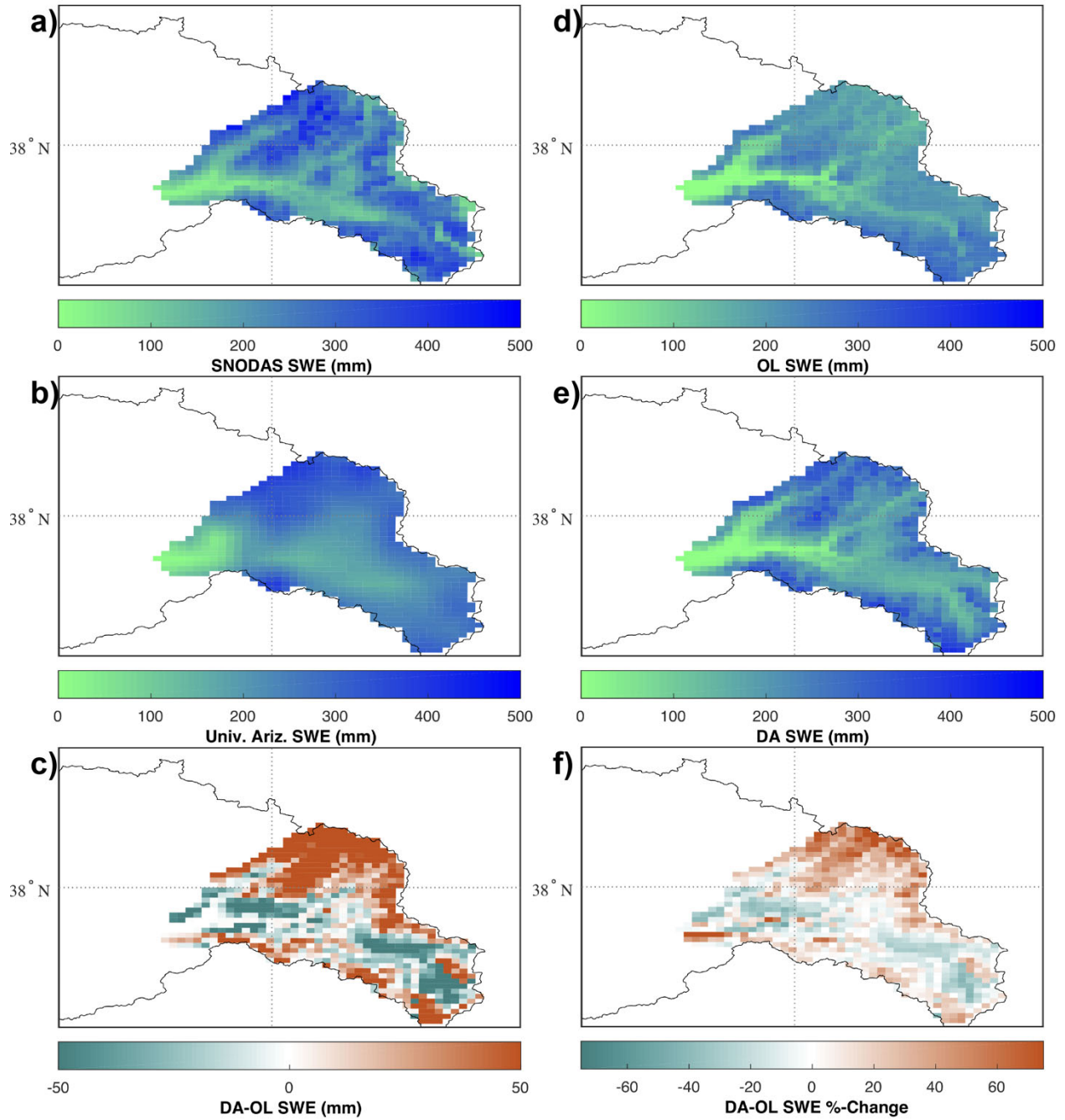
993

994

Figure 1: Conceptual illustration of the LIS/WRF-Hydro system. LIS and WRF-Hydro share data through a mediator in the center right of the image that exchanges model variables through the LIS and WRF-Hydro NUOPEC caps.

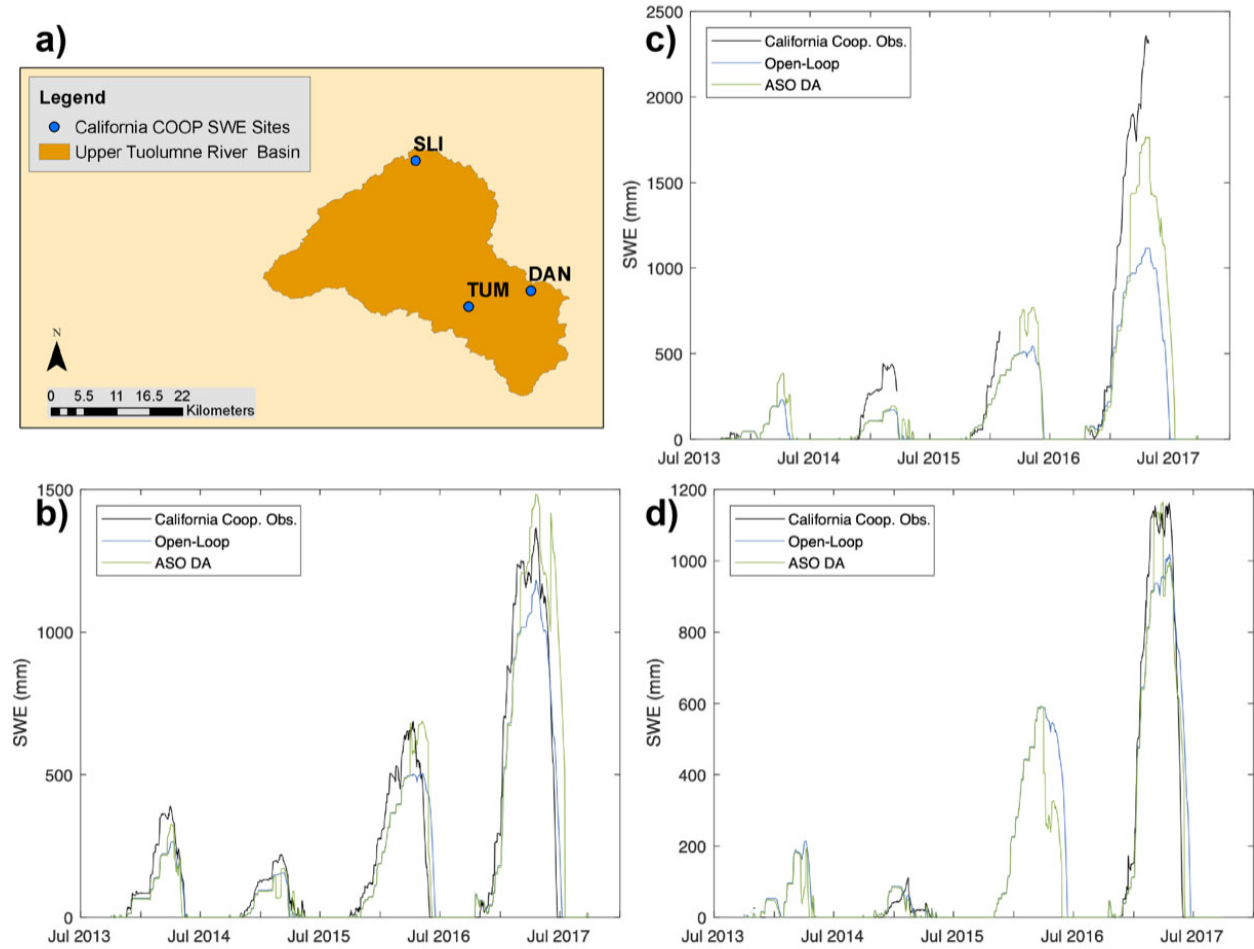


995
 996 **Figure 2:** The Tuolumne test basin is shown relative to the Contiguous US (CONUS) (top). The
 997 full basin with National Hydrography Dataset (NHD) flowlines is shown in the bottom panel. The
 998 Upper Tuolumne Basin analysis area with the analysis USGS Gage, Hetch Hetchy Reservoir,
 999 elevation from the 250-m grid, and two precipitation observations are also shown.
 1000



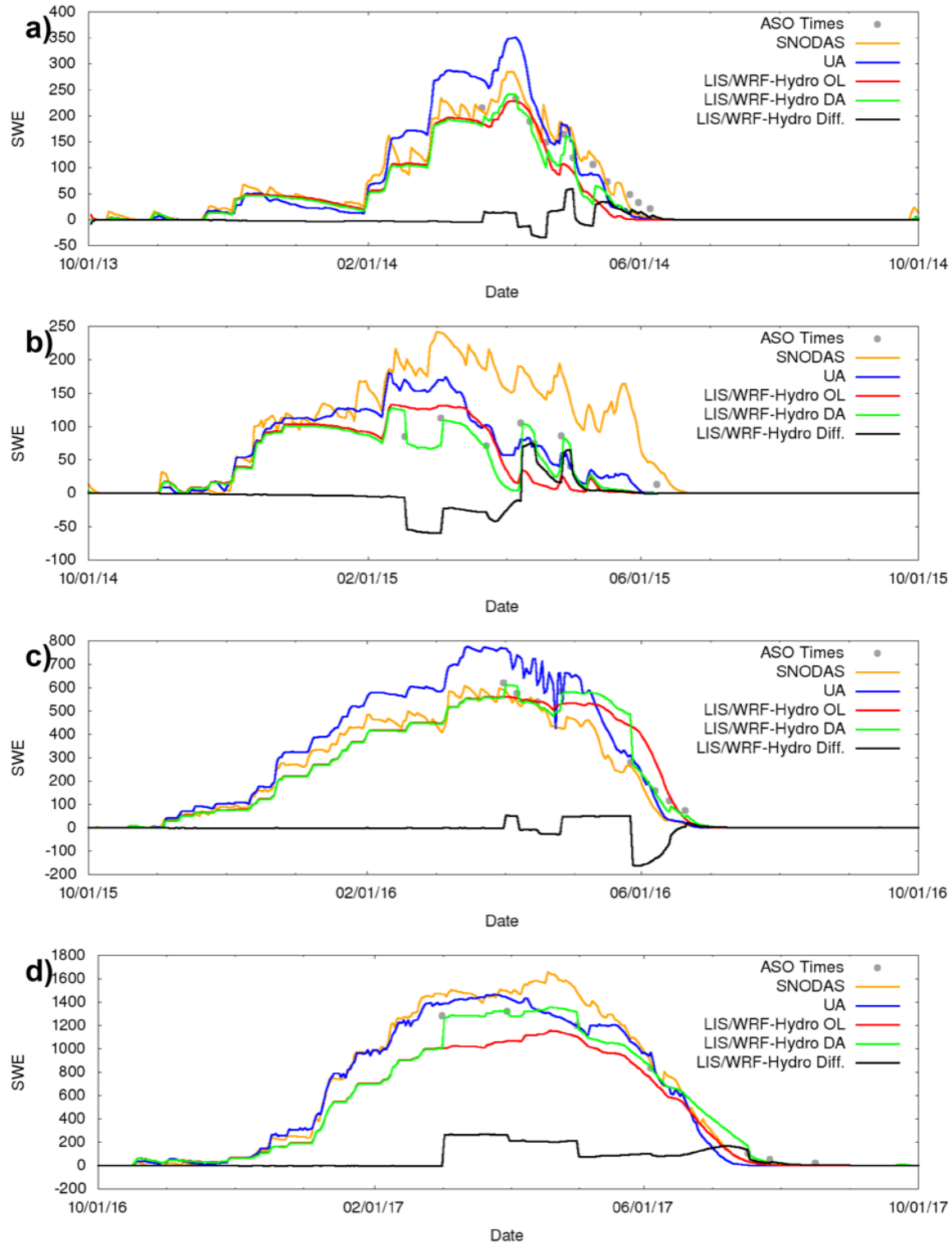
1001
 1002 **Figure 3:** Mean SWE (in mm) for SNODAS, (a), University of Arizona (b), LIS/WRF-Hydro
 1003 DA vs. OL (c), LIS/WRF-Hydro OL (d), LIS/WRF-Hydro DA (e) and LIS/WRF-Hydro DA vs.
 1004 OL percent change (f).

1005



1006
1007
1008

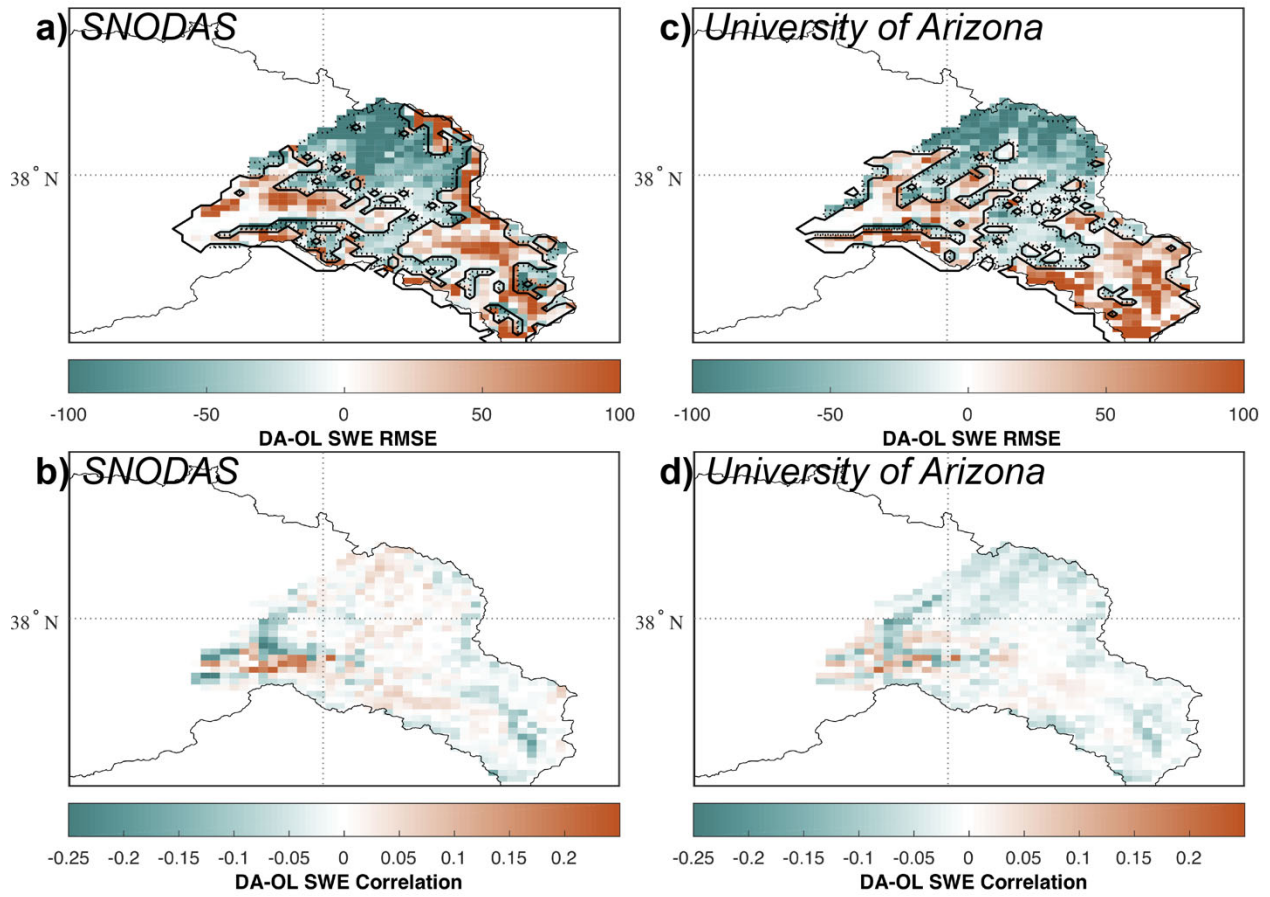
Figure 4: California Cooperative SWE sites (a) and LIS/WRF-Hydro OL and LIS/WRF-Hydro DA SWE v. California Cooperative Site SWE. Sites include DAN (b), SLI, (c), and TUM (d).



1009
 1010 **Figure 5:** Timeseries of modeled (LIS/WRF-Hydro) and observed basin-averaged SWE. Data
 1011 for WY2014 (top) to WY2017 (bottom).

1012

1013



1014

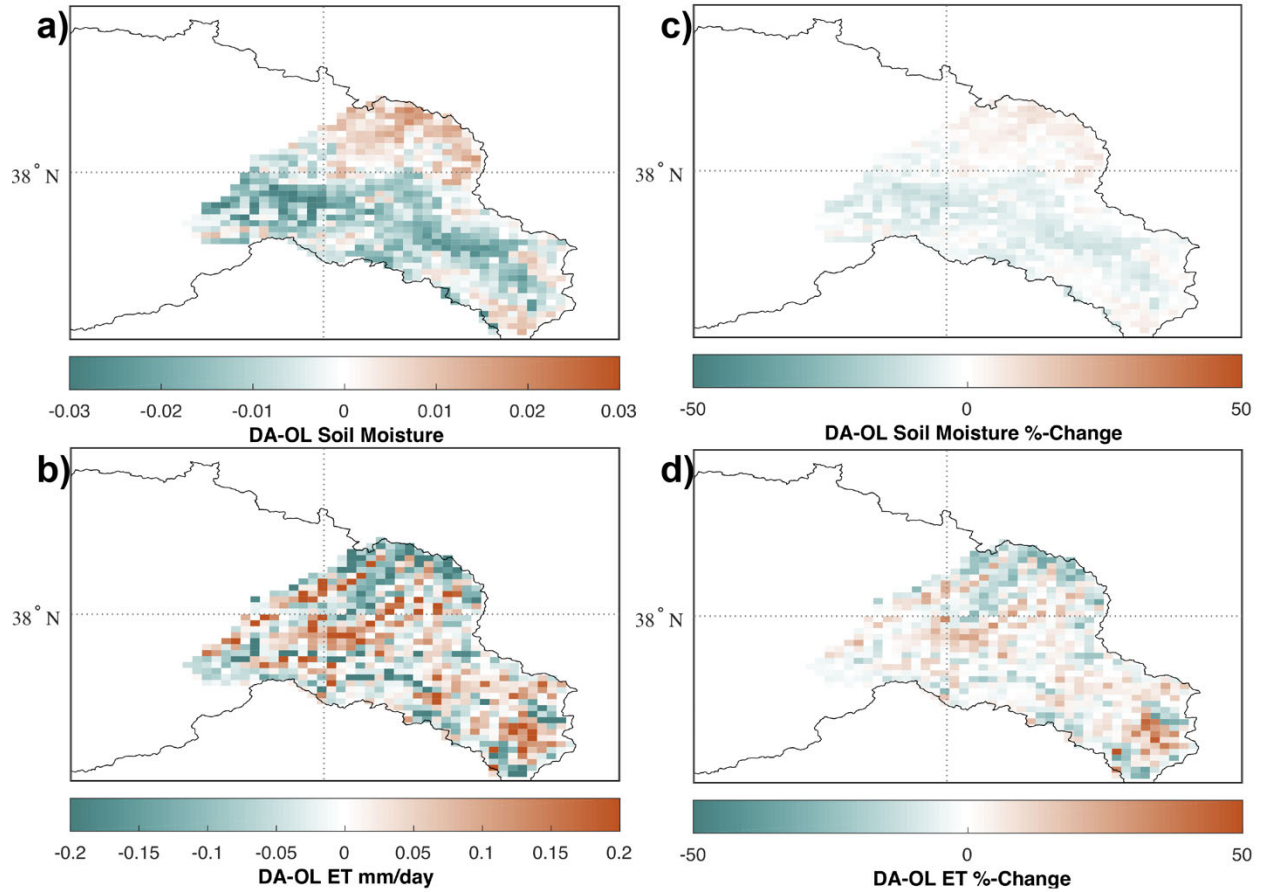
1015

1016

1017

Figure 6: Change in RMSE (mm) (top) and Correlation (bottom) from DA compared to SNODAS (left) and University of Arizona observations (right) for the LIS/WRF-Hydro simulations.

1018



1019

1020

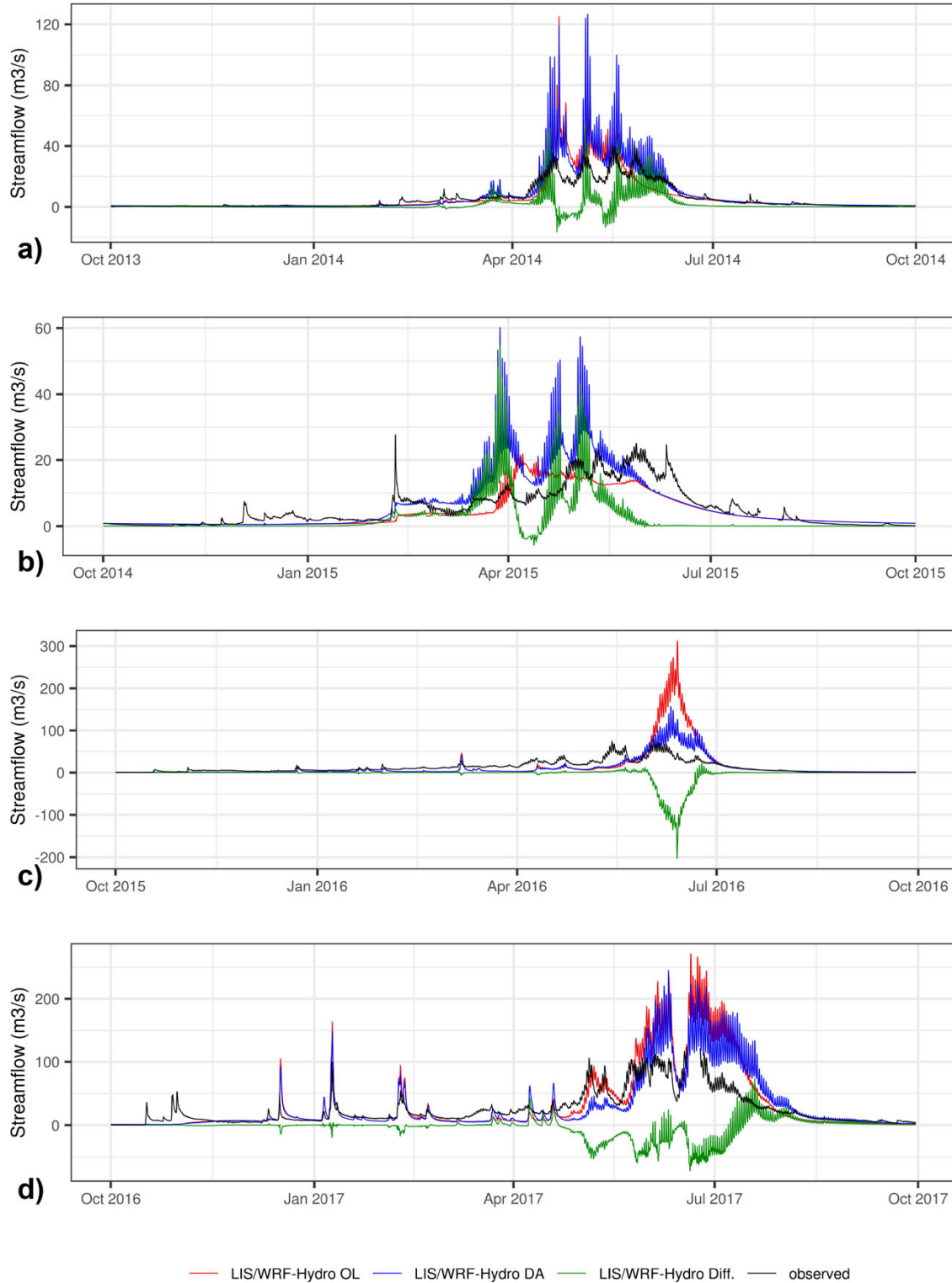
1021

1022

Figure 7: Change in Noah-MP 0-10 cm soil volumetric water content (top) and ET (bottom) from ASO DA for LIS/WRF-Hydro (left) and for LIS/WRF-Hydro as a percent change (right) during the snowmelt season (April – July).

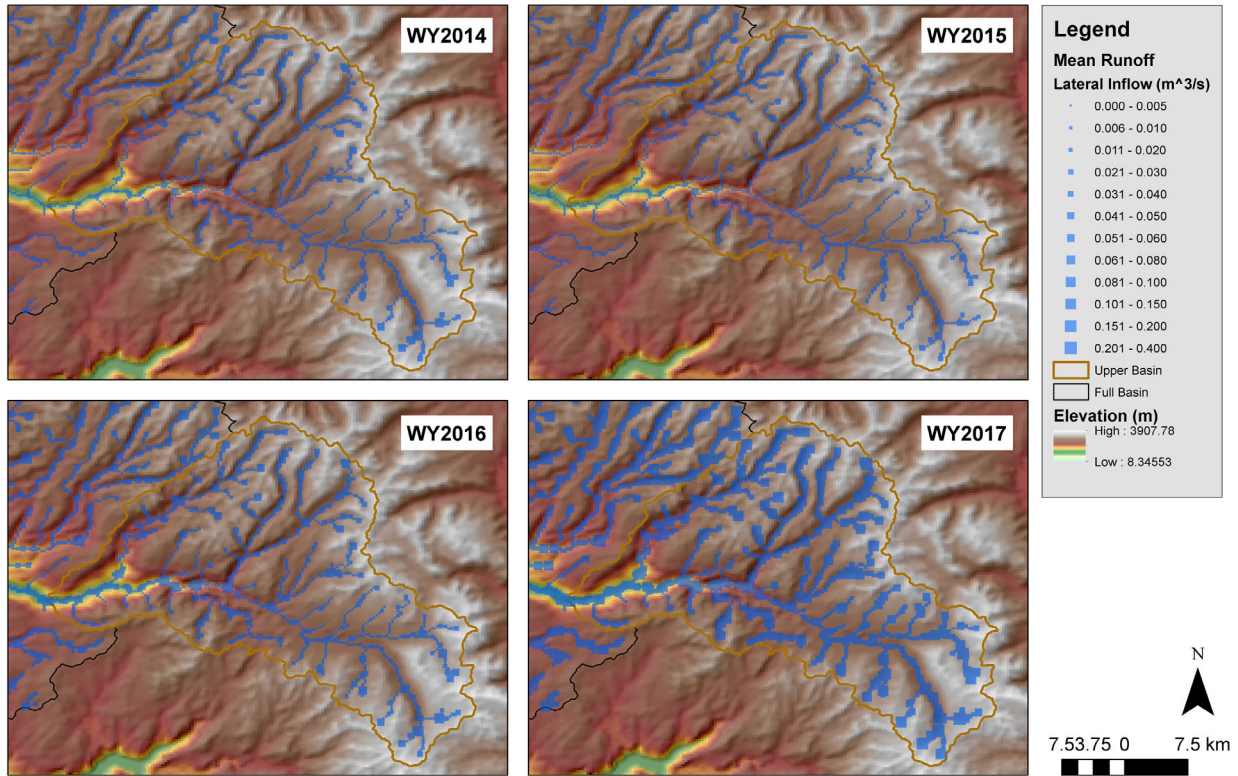
1023

1024



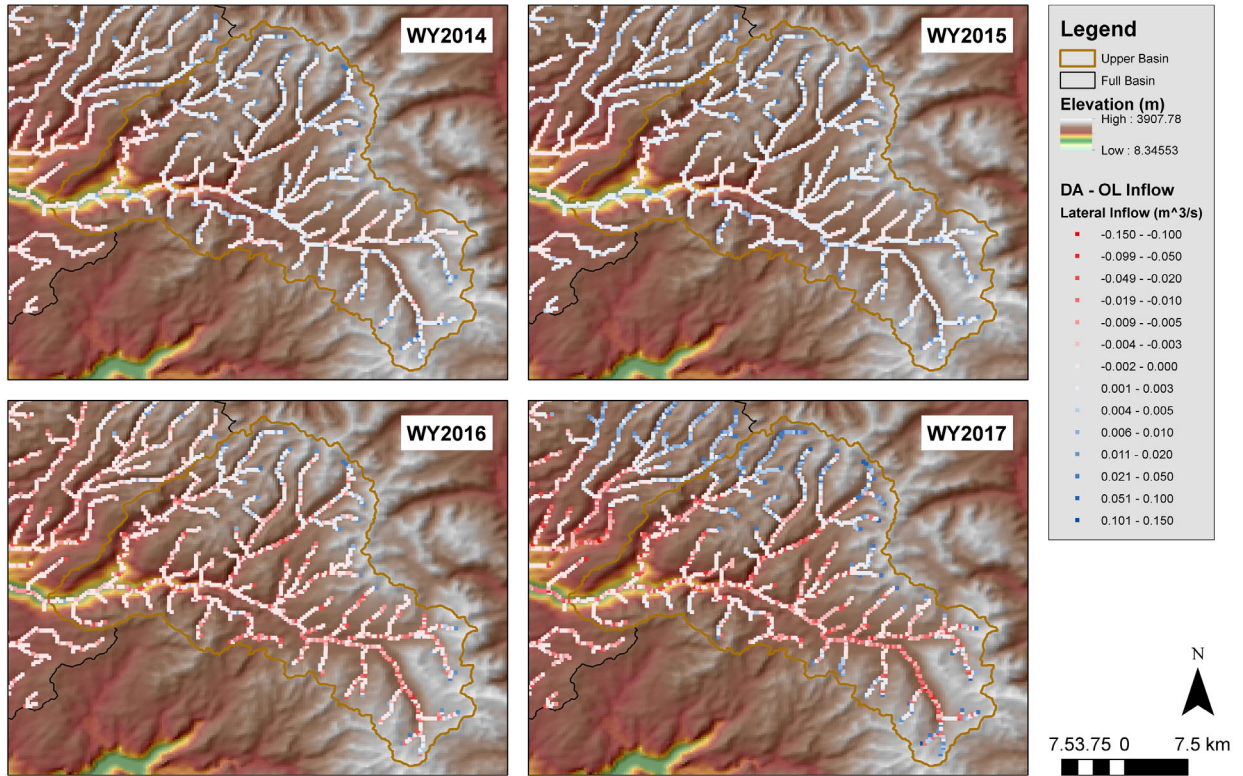
1025
1026
1027
1028

Figure 8: Hydrographs from LIS/WRF-Hydro OL (red), ASO DA ensemble mean (dark blue), LIS/WRF-Hydro DA minus OL (green), and observations (black) at USGS gauge 11274790 for WY2014 through WY2017 (top to bottom).



1029
1030
1031
1032
1033

Figure 9: Upper Tuolumne Basin mean annual lateral flow (m^3s^{-1}) into stream channels for WY2014 (top left), WY2015 (top right), WY2016 (bottom left), and WY2017 (bottom right) from the LIS/WRF-Hydro DA simulation.



1034

1035

1036

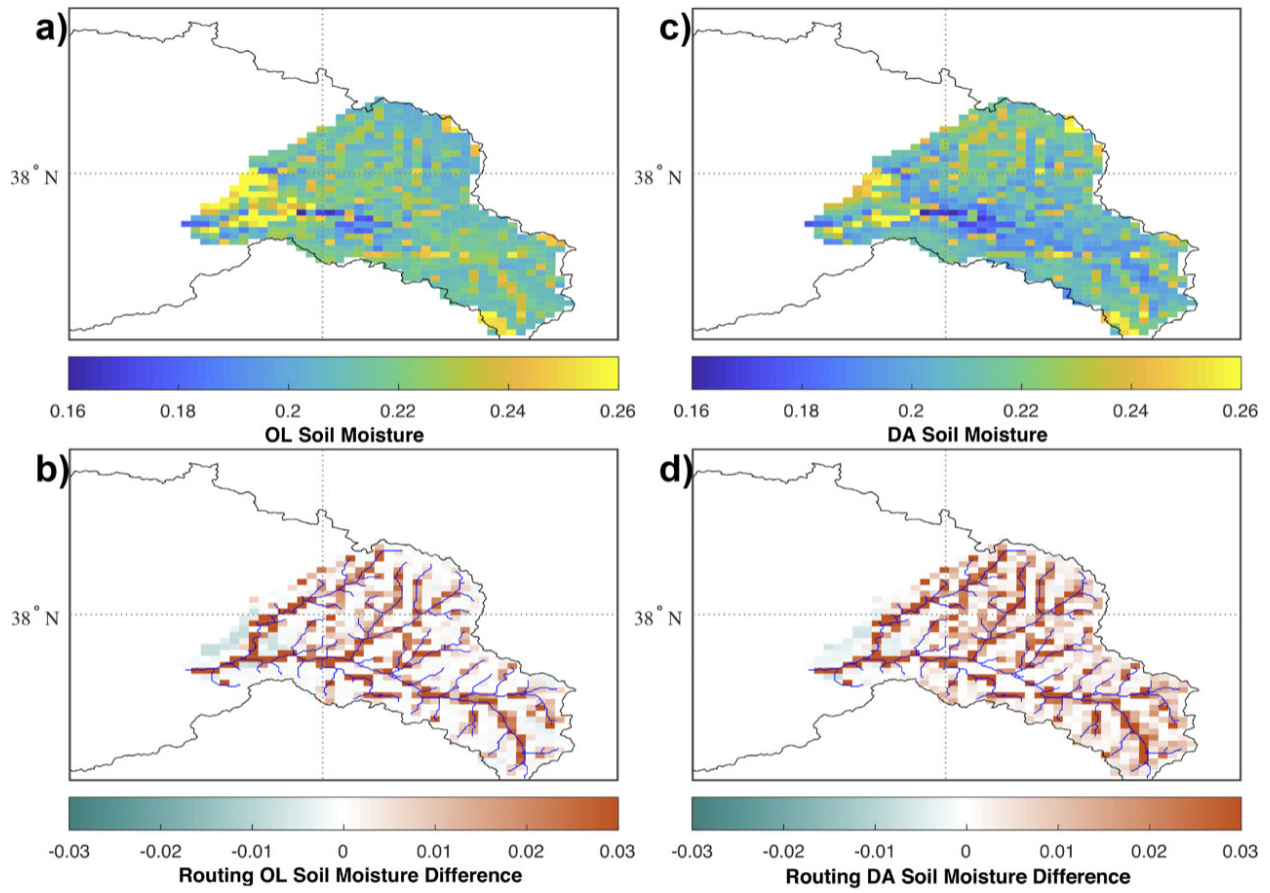
1037

Figure 10: Upper Tuolumne Basin DA minus OL change to mean annual lateral flow (m^3s^{-1}) into stream channels for WY2014 (top left), WY2015 (top right), WY2016 (bottom left), and WY2017 (bottom right).

1038

1039

1040



1041

1042

1043

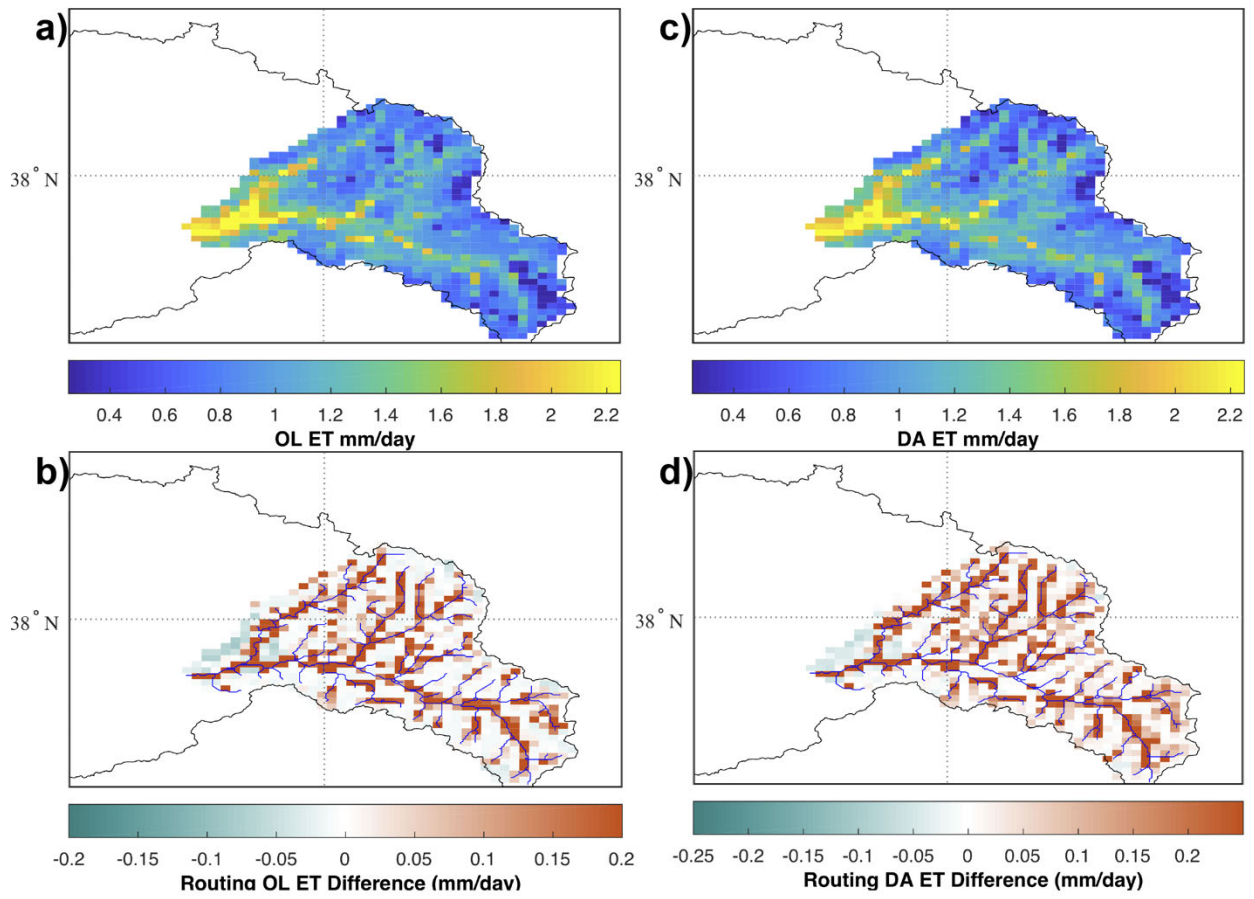
1044

Figure 11: Average soil volumetric water content for LIS/WRF-Hydro (top) and change in soil moisture in LIS/WRF-Hydro compared to LIS (bottom) for the OL (left) and DA (right) simulations.

1045

1046

1047



1048

1049 **Figure 12:** Average ET (mm/day) for LIS/WRF-Hydro (top) and change in ET in LIS/WRF-
 1050 Hydro compared to LIS (bottom) for the OL (left) and DA (right) simulations.