NCA-LDAS: Overview and Analysis of Hydrologic Trends for the National Climate Assessment

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ABSTRACT

Terrestrial hydrologic trends over the conterminous United States are estimated for 1980–2015 using the National Climate Assessment Land Data Assimilation System (NCA-LDAS) reanalysis. NCA-LDAS employs the uncoupled Noah version 3.3 land surface model at $0.125^\circ \times 0.125^\circ$ forced with NLDAS-2 meteorology, rescaled Climate Prediction Center precipitation, and assimilated satellite-based soil moisture, snow depth, and irrigation products. Mean annual trends are reported using the nonparametric Mann–Kendall test at $p < 0.1$ significance. Results illustrate the interrelationship between regional gradients in forcing trends and trends in other land energy and water stores and fluxes. Mean precipitation trends range from $+3$ to $+9 \text{ mm yr}^{-1}$ in the upper Great Plains and Northeast to -1 to -9 mm yr^{-1} in the West and South, net radiation flux trends range from $+0.05$ to $+0.20 \text{ W m}^{-2} \text{ yr}^{-1}$ in the East to -0.05 to $-0.20 \text{ W m}^{-2} \text{ yr}^{-1}$ in the West, and U.S.-wide temperature trends average about $+0.03 \text{ K yr}^{-1}$. Trends in soil moisture, snow cover, latent and sensible heat fluxes, and runoff are consistent with forcings, contributing to increasing evaporative fraction trends from west to east. Evaluation of NCA-LDAS trends compared to independent data indicates mixed results. The RMSE of U.S.-wide trends in number of snow cover days improved from 3.13 to 2.89 days yr^{-1} while trend detection increased 11%. Trends in latent heat flux were hardly affected, with RMSE decreasing only from 0.17 to $0.16 \text{ W m}^{-2} \text{ yr}^{-1}$, while trend detection increased 2%. NCA-LDAS runoff trends degraded significantly from 2.6 to 16.1 mm yr^{-1} while trend detection was unaffected. Analysis also indicated that NCA-LDAS exhibits relatively more skill in low precipitation station density areas, suggesting there are limits to the effectiveness of satellite data assimilation in densely gauged regions. Overall, NCA-LDAS demonstrates capability for quantifying physically consistent, U.S. hydrologic climate trends over the satellite era.

1. Introduction and background

Numerous reports confirm that the climate of the conterminous United States (CONUS) has been changing over the past several decades (Melillo et al. 2014; USEPA 2016; USGCRP 2017b), consistent with overall North

American trends (Blunden and Arndt 2013). Analyses of in situ temperature data indicate that current summers are longer and warmer compared to anytime in the past U.S. record and that this trend has been accelerating over the past several decades (USGCRP 2017b). Trends in annual means and extremes have been detected, with minimum temperatures increasing more than maximum temperatures (e.g., Lee et al. 2014; Peterson et al. 2008). Such warming is manifested in most components of the terrestrial hydrologic cycle, linked through land and atmospheric energy and water conservation dynamics. For instance, national trend summaries (USEPA 2016;

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Melillo et al. 2014; USGCRP 2017b) indicate increased annual precipitation P and streamflow throughout the Northeast and upper Midwest, and increasing flooding in rivers near inland cities (Walsh et al. 2014). Heavy precipitation events have increased (Melillo et al. 2014; Zhang et al. 2011), especially in the eastern half of the country. Decreasing snow trends have been identified in the Intermountain West (Harpold et al. 2012) and Southwest while increasing in the North (Kunkel et al. 2009, 2016). Between 1972 and 2015, the extent of North American snow cover decreased on average about $9000 \text{ km}^2 \text{ yr}^{-1}$, largely in spring and summer, and the snow cover season has shortened by about 2 weeks (USEPA 2016).

Assessments of national climate are coordinated by the U.S. Global Change Research Program (USGCRP) through the National Climate Assessment (NCA; USGCRP 2012, 2017a,b; Melillo et al. 2014). The Global Change Research Act of 1990 [Public L. No. 101-606, 104 Stat. 3096-3104 (1990); <https://www.gpo.gov/fdsys/pkg/STATUTE-104/pdf/STATUTE-104-Pg3096.pdf>] calls for an NCA report to be produced on a quadrennial basis. The Third and Fourth NCA had a significant focus on climate impacts in regions of the United States and sectors of the U.S. economy (Melillo et al. 2014; USGCRP 2017b). Chapters reviewed climate change science and discussed adaptation (Bierbaum et al. 2014), mitigation (Jacoby et al. 2014), and decision support (Moss et al. 2014). USGCRP's NCA efforts fall under the "Conduct Sustained Assessment" goal identified in the USGCRP Strategic Plan (USGCRP 2012, 2017b); the focus is to "build sustained assessment capacity that improves the Nation's ability to understand, anticipate, and respond to global change impacts and vulnerabilities."

A specifically identified need of the NCA's Sustained Assessment is to develop consistent trend indicators that track and communicate the causes and effects of climate change, as well as the tools to analyze them (USGCRP 2017a). Successful indicators provide a basic understanding of the physical system, quantify a state that can be tracked over time (USEPA 2016) including its uncertainties, are easily interpreted by technical and nontechnical users (Janetos et al. 2012), and are publicly accessible and documented.

Unfortunately, to date there has been limited capability in providing the above requirements at the nationwide scale. Most trend studies rely on in situ data and are usually focused on a specific region. Studies also differ over the time period of the analyses, or the reference period to which a particular trend is being compared (Melillo et al. 2014; USEPA 2016; USGCRP 2017b; Blunden and Arndt 2013; Lee et al. 2014; Peterson et al. 2008; Walsh et al. 2014), complicating their comparison with other studies. Further lacking is a publicly available, spatially consistent database of the full suite of terrestrial

energy and water related variables with analysis tools. This would facilitate comprehensive indicator analyses over all components of the land water and energy balance, while serving potential users in other related physical, biological, and socioeconomic sciences.

In developing trends, there is also need to optimally merge all relevant data (Dee et al. 2011, 2014) including in situ and remotely sensed data products. For instance, despite a wealth of quality in situ point observations throughout the United States, sparse in situ observations may not capture the complexity and spatial variability of a region. Further, time series observations can possess nonclimatic jumps due to changes in station relocation or instrumentation (Aguilar et al. 2003), making it difficult to separate the natural climate variability from observation inhomogeneity (Kunkel et al. 2007).

Space-based observations offer spatially consistent environmental data records (EDRs), but present their own challenges for trend analysis. For example, optical multispectral sensors that observe land, water, and atmospheric properties, such as the Sentinel-2 mission, have daily to weekly coverage and pixels from 10 to 60 m. Snow water equivalent (SWE) and soil moisture from microwave sensors such as the Advanced Microwave Scanning Radiometers (AMSR-E and AMSR-2) have daily to weekly coverage with 625 km^2 pixels. The Gravity Recovery and Climate Experiment mission sensors (GRACE and GRACE-FO) observe at about $250\,000 \text{ km}^2$ resolution. Of additional concern are time series discontinuities associated with the short record length of individual missions usually designed for a 3–5-yr life cycle, bias between in situ and satellite observations (Dee et al. 2014), and data inhomogeneities associated with replacement and intercalibration between old and new sensors (Su et al. 2016).

Over the past decade, land reanalysis through satellite data assimilation has improved the estimation of gridded hydrologic time series, including variables not routinely measured, mainly by constraining stores and fluxes (Boni et al. 2001; Reichle et al. 2002). To date, most studies have focused on univariate satellite assimilation addressing soil moisture (Galantowicz et al. 1999; De Lannoy et al. 2015), surface temperature T (Reichle et al. 2010), runoff R (Chen et al. 2014; Brocca et al. 2012), terrestrial water storage (Zaitchik et al. 2008; Forman and Reichle 2013; Giroto et al. 2016), evapotranspiration or latent heat flux (ET; Park and Choi 2015; Peters-Lidard et al. 2011), snow cover and water equivalent (Slater and Clark 2006; Zaitchik and Rodell 2009), and vegetation (Barbu et al. 2014; Sawada and Koike 2014; Sawada et al. 2015). Land data assimilation systems (LDASs) have further enabled regional to global reanalysis by imbedding simulations within sophisticated

FIG. 1. The long-term vision of NCA-LDAS is to optimally combine the full suite of all relevant past and future satellite EDRs to provide a high-quality climatology of U.S. terrestrial hydrology. Satellite EDRs would include soil moisture, snow, land surface temperature, water surface elevation, vegetation, irrigation intensity, and terrestrial water storage.

modeling environments. Examples include the North American LDAS (NLDAS-2; Mitchell et al. 2004; Xia et al. 2012a,b), the Global LDAS (GLDAS; Rodell et al. 2004), and the Famine Early Warning Systems Network LDAS (FLDAS; McNally et al. 2017), which runs within the NASA Land Information System (LIS; Kumar et al. 2006). Other examples include LDAS-Monde (Albergel et al. 2017) and the Coupled Land and Vegetation DAS (CLVDAS; Sawada and Koike 2014; Sawada et al. 2015).

Although there has been considerable discussion on the value of satellite data assimilation within atmospheric models for climate analysis (Bengtsson et al. 2004; Dee et al. 2011; Albergel et al. 2013; Thorne and Vose 2010; Grotjahn and Huynh 2018; Simmons et al. 2010; Dorigo et al. 2012), there have been comparatively few trend studies using land data assimilation (Giroto et al. 2017; Khaki et al. 2018; Khaki and Awange 2019). Giroto et al. (2017) reported mixed results from GRACE assimilation within the Catchment model due to unmodeled processes, while Khaki and Awange (2019) reported improved groundwater trends by assimilating GRACE and satellite soil moisture within the World Wide Water Resources Assessment model. Both studies identified the need for improved modeling of groundwater withdrawals.

NCA-LDAS was recently developed as a particular instance of LIS that includes a first-of-its-kind assimilation of multisensor Earth observations of soil moisture, snow cover and depth, and irrigation simulation over the continental United States. (Kumar et al. 2018).

The long-term vision, shown in Fig. 1, is to optimally combine the full suite of past and future Earth observations of all relevant land EDRs observations to provide high-quality, publicly available data products and analyses that support the USGCRP's goals for sustained climate assessment (Jasinski et al. 2014, 2015).

NCA-LDAS's current products (<https://ldas.gsfc.nasa.gov/NCA-LDAS>) demonstrated high skills for soil moisture, snow depth, R , and ET when compared to eight other land surface models (Kumar et al. 2018). NCA-LDAS's time series of 42 land products thus offers one of the most compelling databases for constructing consistent, gridded national hydrologic trends. Example trends of the principal terrestrial components described herein demonstrate NCA-LDAS's flexibility as an enabling tool for investigating terrestrial hydrologic climate science and decision support.

2. Approach

a. Model setup summary

NCA-LDAS, summarized in Table 1 and Fig. 2, employs the uncoupled Noah version 3.3 (Ek et al. 2003) at $0.125^\circ \times 0.125^\circ$ spatial resolution over the continental United States, with a 36-yr (1979–2015) record of NLDAS-2 forcings and satellite-based products. The precipitation field is derived from gauge-only Climate Prediction Center (CPC) analysis of daily precipitation

TABLE 1. Basic characteristics of NCA-LDAS.

Latitude extent	25°–53°N
Longitude extent	125°–67°W
Spatial resolution	1/8°
Temporal resolution	Daily
Time step	15 min
Dimension	224 (lat) × 464 (lon)
Gridbox center points	Lower left: 25.0626°N, 124.9375°W; upper right: 52.9375°N, 67.0625°W
Land surface model	Noah version 3.3
Format	NetCDF-4
Forcing data	NLDAS Phase-2

(Higgins et al. 2000; Chen et al. 2008), with orographic adjustment (Daly et al. 1994). The meteorology forcing fields including surface temperature, radiation, wind, and humidity are derived primarily from the North American Regional Reanalysis (Mesinger et al. 2006). The current NCA-LDAS version 2.0 simultaneously ingests satellite-based EDRs of soil moisture, snow depth and cover, and irrigation intensity. Assimilation employs a 1D ensemble Kalman filter (Reichle et al. 2002) with concurrent, sequential assimilation of satellite EDRs, while irrigation is simulated using a demand-driven approach based on a MODIS classification scheme (Ozdogan et al. 2010; Kumar et al. 2018). Specific satellite platforms and corresponding EDRs assimilated into NCA-LDAS are listed in Table 2.

b. Trend development and assessment

Mean annual trend indicators of the principal terrestrial water cycle components for October 1979–September 2015 (or water years 1980–2015) were computed using NCA-LDAS. Trends were constructed from NCA-LDAS daily data products and mapped for each grid cell in the domain. Analyses focused on monotonic trends in annual mean and standard deviation, and annual high and low multiday averages using the nonparametric Mann–Kendall test (Mann 1945; Kendall 1975; Helsel and Hirsch 2002). For ease of comparison, the results were mapped at a common 10% significance level ($p < 0.10$) except where noted. Gridcell values that did not pass the significance test were left blank. Trends were qualitatively compared to other published values, and also statistically evaluated for each NCA region with independent data for three land components [ET, number of snow-covered days (SCD), and R] using root-mean-square error (RMSE), or,

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (\text{Trend}_{\text{EVAL},i} - \text{Trend}_{\text{NCA-LDAS},i})^2}{n}},$$

where $\text{Trend}_{\text{NCA-LDAS},i}$ is the estimated significant NCA-LDAS trend value of grid cell i , $\text{Trend}_{\text{EVAL},i}$ is the corresponding significant independent evaluation data

FIG. 2. Schematic of NCA-LDAS version 2.0. Built within LIS, NCA-LDAS adds the capability to assess trend indicators for any of the 42 input and output variables.

TABLE 2. Satellite datasets that are assimilated in NCA-LDAS.

Name	Variable/data	Platform(s)	Years
ESA CCI	Surface soil moisture	Various	1979–2002
LPRM (AMSR-E)	Surface soil moisture	<i>Aqua</i>	2002–11
SMOPS (ASCAT)	Surface soil moisture	<i>MetOp-A/B</i>	2007–15
SMOPS (SMOS)	Surface soil moisture	SMOS	2010–15
SMAP (NSIDC)	Surface soil moisture	SMAP	2015
SMM/I	Snow depth	Various	1987–2002
AMSR-E	Snow depth	<i>Aqua</i>	2002–11
AMSR2	Snow depth	<i>GCOM-W1</i>	2012–15
IMS	Snow-covered area	Various	1997–2015
MODIS	Snow-covered area	<i>Terra</i>	2000–15
MODIS	Irrigated area	<i>Terra</i>	1979–2015

trend in cell i , and n is the total number of significant gridcell pairs. If either the NCA_LDAS or EVAL trend value was not significant for a given cell, the pair was not included in the RMSE calculation.

3. U.S. terrestrial hydrology trend indicators

a. Data assimilation impact versus precipitation station density

Prior to computation of the indicators, an analysis was conducted to determine how well NCA-LDAS improves forecasts as a function of CPC precipitation station density. Precipitation is arguably the most important forcing in land surface models. Despite high-quality gauge observations, sparse sampling can impact the quality of the daily gridcell estimate (Wilson et al. 1979; St-Hilaire et al. 2003; Krajewski et al. 2003; Villarini et al. 2008). CPC gridbox precipitation is estimated from the four reporting gauges that are closest to the center of the cell using optimal interpolation. While there are typically about 8000 daily reporting stations over the continental United States (Chen et al. 2008), station density is not equally distributed as shown in Fig. 3a (from Higgins et al. 2000). Average daily gauge density for the NCA-LDAS grid cell is about 0.16 gauges per cell, although the actual daily reporting density can be as low as zero. Lowest densities generally occur in the Southwest and Midwest.

The analysis was conducted by stratifying soil moisture, snow depth, and streamflow skill as a function of the station density. Skill was estimated in terms of anomaly correlation, RMSE, and the Nash–Sutcliffe efficiency (NSE) normalized information contribution (NIC; Kumar et al. 2009) as compared to the open-loop (OL) or case without assimilation, as reported in Kumar et al. (2018). While the number of stations reporting can vary over time, only the average station density was used in the analyses. The range of station densities varied for each variable due to the availability

of in situ data. Results are shown in Figs. 3b–d for soil moisture, snow depth, and streamflow, respectively. For soil moisture, anomaly correlations of NCA-LDAS compared to in situ data are generally higher than for the OL for all densities in the range of 0.0–1.0, except 0.8. Streamflow comparisons using NIC indicate that improvement is generally better where station density is lower than 0.8 but about the same for larger densities. In the case of snow depth, the RMSE is lower for NCA-LDAS compared to OL for all densities 0.8 or lower, but mixed for larger densities. These results suggest overall that NCA-LDAS improves skill and value when precipitation station density is low. They further suggest that there are possible limits to the effectiveness of data assimilation in regions with dense gauge networks.

b. Precipitation

Given that NCA-LDAS is not dynamically coupled to an atmospheric model, trends were first derived for the P , net radiation (R_{net}), and T forcing variables to understand their variability. For mean annual P , the trend is shown in Fig. 4a for NCA-LDAS's full output, and also in Fig. 4b for only $p < 0.10$ significance. The results reveal that significance testing eliminates most of the coverage in Fig. 4b, indicating that less than about one-third of the United States exhibits a nonzero P trend for $p < 0.10$. Significant regions indicate increasing trends of $3\text{--}9\text{ mm yr}^{-1}$ for most of the Northeast stretching down into Ohio, Indiana, Illinois, and also in North Dakota and Montana. Decreasing trends of a similar magnitude are shown in Minnesota, while decreasing trends from -1 to -9 mm yr^{-1} are exhibited throughout the West and Southwest including Arizona, New Mexico, Nevada, southern Colorado, and California. Decreasing trends of up to -10 mm yr^{-1} were computed for Oregon and Washington.

The above patterns and magnitudes from the NCA-LDAS trends are generally consistent with other published sources including the National Centers for

FIG. 3. (a) Typical CPC reporting stations for a single day (Higgins et al. 2000). Impact of CPC precipitation station density on NCA-LDAS evaluation for (b) soil moisture, (c) Nash–Sutcliffe efficiency normalized information contribution, and (d) snow depth, where station density is the number of reporting gauges per NCA-LDAS 0.25° grid cell.

Environmental Information (<https://www.ncdc.noaa.gov/temp-and-precip/us-trends>), and the USGCRP Fourth Assessment annual precipitation change, computed as the difference between the average annual present-day period (1986–2015) and the average annual baseline period (1901–60) [see NOAA/NCEI Fig. 7.1, p. 209, in Easterling et al. (2017); analysis based on Peterson et al. (2013)]. However, exact comparison is problematic as each analysis employs a different precipitation database [CPC versus Global Historical Climatology Network (GHCN)-Daily station data], different significance ($p = 0.1$ versus 0.05), and reporting analysis (trends in mm yr^{-1} versus change in percent); the NCA-LDAS time period does not extend prior to 1979; and the USGCRP does not report significance. Despite these differences, the NCA-LDAS, NCEI, and USGCRP show an increase in P of about 5%–10% in the Northeast and Midwest and from -5% to -10% in the Southwest over a 30-yr period. The one exception is the Northwest where NCA-LDAS shows decreasing trends while NOAA/NCEI change is increasing.

Several indicators representing precipitation variability also were developed. Figures 5a and 5b indicate trends in the annual mean number of days of heavy ($>10\text{ mm}$) and very heavy precipitation ($>20\text{ mm}$) at $p < 0.10$, respectively, as described by Zhang et al. (2011). Trends in heavy precipitation range from about $+1$ to over $+4$ days decade $^{-1}$ in the eastern United States with the greatest amounts in the northeast to -1 to -4 days decade $^{-1}$ in the southwestern and western states. Trends in very heavy precipitation cover a greater percentage of area but show slightly fewer number of days. Also plotted in Figs. 5c and 5d are the annual trends in precipitation variance and in annual 5-day high precipitation, respectively. Trends in precipitation variance somewhat mirror those of heavy and very heavy precipitation; all three of which have a similar pattern with some regional differences. Indicators capturing the more extreme precipitation trends, including very heavy precipitation, variance, and 5-day high, show increased trends along the Atlantic coast.

FIG. 4. NCA-LDAS trends in annual precipitation for water years 1980–2015 for (a) full model results and (b) only for $p < 0.10$.

When comparing the annual and extreme trends, several features are noted. First, areas of increasing heavy precipitation and precipitation variance coincide with the regions of increasing annual P , as seen in the upper Great Plains, the Ohio River basin, and the Northeast. Perhaps more noteworthy is that the area covered by the extreme indicators exhibiting increasing trends (Figs. 5a–d) is much larger than that of the annual P trend in Fig. 4b. The coverage of heavy precipitation also extends farther into the southern United States. Western U.S. areas of decreasing annual trends in P also show decreasing trends in extremes. These results suggest that while in many parts of the United States there is no significant trend in annual mean P as determined by the Mann–Kendall test, the distribution of the annual P is changing, with more intense individual rainfall events. More extreme P is evident along the U.S. Gulf and Atlantic Coasts, extending from Texas to Maine. These findings show overall good consistency with previous assessments (USEPA 2016; Melillo et al. 2014; Karl et al. 2009).

c. Temperature

The NCA-LDAS mean annual T trend is shown in Fig. 6a. Most of the trends computed over the northern Great Plains, northern Rockies and Intermountain West,

and northwestern United States do not pass the significance test. The results show that for the period 1979–2015, the trend in annual mean T for most of the United States has been increasing at a CONUS-wide average of about $0.28 \text{ K decade}^{-1}$, while regionally ranging from -0.1 to $+1.0 \text{ K decade}^{-1}$. The largest increases of 0.25 – $0.50 \text{ K decade}^{-1}$ occur in the northern Midwest in upper Michigan and northern Wisconsin. The T trends in the Southeast show a smaller increase of only 0.1 – $0.25 \text{ K decade}^{-1}$, with only slight changes along the Atlantic and Gulf Coasts, except for Florida that exhibits negligible significant trend. Parts of the Southwest including Arizona, New Mexico, and California also show an increasing trend of 0.1 – $0.5 \text{ K decade}^{-1}$. These NCA-LDAS results are generally consistent with NOAA/NCEI changes between average present-day temperatures (1986–2016) and reference period averages (1901–60; Melillo et al. 2014), although NOAA shows a decreasing average T change in Alabama and Mississippi (Hausfather et al. 2016; Rohde et al. 2013) that is not supported by NCA-LDAS. NCEI national trends (<https://www.ncdc.noaa.gov/temp-and-precip/us-trends>), reported at $p < 0.05$, are also consistent with NCA-LDAS with no significant trends reported in the Northwest and northern Great Plains. The NCDC results also exhibit mostly increasing trends throughout the western United States, although their significance levels were not reported.

d. Net radiation

The trend in annual Rnet is often not reported, but it is nonetheless an important energy forcing as it impacts on trends in ET and other components of the land surface energy and water balance. Global Rnet trends over the past several decades have been analyzed with respect to trends in aerosols, cloud cover, and surface albedo. Analyses based on International Satellite Cloud Climatology Project data (Wild 2012; Wild et al. 2008) indicate nonlinear trends since the 1950s ranging from -1.0 to over $+2.0 \text{ W m}^{-2} \text{ decade}^{-1}$ (e.g., Cohen and Stanhill 2016).

The NCA-LDAS indicator for annual trend in Rnet is shown in Fig. 6b. Results indicate a strong regional pattern with a distinct east–west trend gradient stretching across the United States. A positive annual Rnet trend from about $+0.05$ to $0.20 \text{ W m}^{-2} \text{ yr}^{-1}$ is estimated throughout most of the eastern half of the United States, with the greatest magnitude in the Southeast, ranging up to $0.25 \text{ W m}^{-2} \text{ yr}^{-1}$. The Rnet trend gradient decreases to the West, with a low from -0.05 to $-0.20 \text{ W m}^{-2} \text{ yr}^{-1}$ in the West and Southwest. A unique north–south swath through the Great Plains, where the Rnet transitions from positive to negative, exhibits no significant trend.

FIG. 5. Trends in (a) mean annual number of days of heavy precipitation (>10 mm), (b) mean annual number of days of very heavy precipitation (>20 mm), (c) variance in annual daily precipitation, and (d) 5-day high precipitation for water years 1980–2015, $p < 0.10$.

A notable sharp decrease in R_{net} in Wyoming is likely due to a disproportionately greater number of precipitation stations in the mountainous areas compared to lower elevations. A slight increase in R_{net} is also shown in the Northwest, especially the coastal region of Oregon and Washington. The above trends in the East are consistent with published results using a combination of satellite data, reanalysis, modeling, and GEWEX/SRB analyses (Cohen and Stanhill 2016; Ma et al. 2017; Niu et al. 2011) except for NCA-LDAS western decreasing trends that are not supported.

e. Soil moisture

The indicator for NCA-LDAS annual soil moisture trends, shown in Fig. 7, was computed based on the total column moisture content within the four NCA-LDAS soil layers. The results show consistency with annual P trends where significance is reported. That is, there are positive soil moisture trends in the Northeast and upper Great Plains and northern Rocky Mountains averaging up to 3 mm yr^{-1} . Decreasing trends in soil moisture

cover most of the remaining United States, especially the Northwest, Southwest and upper Midwest, ranging from -1 to -9 mm yr^{-1} . Decreasing trends down to -3 mm yr^{-1} appear in Louisiana and Florida. The overall NCA-LDAS U.S. drying trend in the West and Southwest is generally consistent with trends developed from the merged global microwave-based surface soil moisture dataset of the European Space Agency (ESA) Climate Change Initiative (CCI) (Feng and Zhang 2015; Dorigo et al. 2012; Liu et al. 2012). NCA-LDAS also shows drying across the South and Southeast, while the soil moisture products derived mainly from passive and active microwave sensors are inconsistent in this region.

f. Latent heat flux

The NCA-LDAS indicator for mean annual ET for 1980–2015 is shown in Fig. 8a. Results show increasing trends throughout the eastern half of the United States and upper Midwest, with greatest magnitude in the South stretching from eastern Texas to northern Florida.

FIG. 6. Trends in mean annual (a) surface temperature and (b) net radiation for 1980–2015, $p < 0.10$.

The positive annual trends in the East are similar in distribution as Rnet trends previously shown in Fig. 6b. There is also additional positive response to the increased P (Fig. 4b) and Rnet throughout most of the northern United States. Notable exceptions are southeast Texas, which exhibits a negative trend in ET compared to Rnet, while Florida exhibits mixed increasing and decreasing trends. Overall, from a climate standpoint, the East and North behave as energy-limited systems.

In stark contrast to the eastern United States, negative trends in ET extend throughout most of the West and Southwest. Trends ranging from -0.05 to $-0.25 \text{ W m}^{-2} \text{ yr}^{-1}$ are exhibited in nearly the same regions as the negative P (Fig. 4b), Rnet (Fig. 6b), and soil moisture trends (Fig. 7). The strong decreasing ET trend with similar negative trends in soil moisture and P indicate a climatically moisture-limited system. These results are consistent with previous NLDAS-2 analyses over the Missouri basin, California, and Mexico (Parr et al. 2016) that showed a strong positive correlation between ET, P , and soil moisture, and a negative correlation with Rnet. However, NCA-LDAS trends differ to the Parr study by also exhibiting ET trends in the same direction as Rnet and T , where

FIG. 7. NCA-LDAS indicator for the trend in mean annual soil moisture for the period 1980–2015, $p < 0.10$.

additional factors including soil moisture, land cover type, aerosols, and cloud cover come into play.

The NCA-LDAS ET trends were statistically evaluated against the FLUXNET_MTE multitree ensemble (Jung et al. 2009) data product trends using RMSE. FLUXNET-MTE provides monthly, $0.5^\circ \times 0.5^\circ$ gridded ET, independently derived from upscaling eddy covariance measurements from the FLUXNET global network (Baldocchi et al. 2001). While not ground truth, it has been successfully used for benchmarking gridded surface fluxes (e.g., Bonan et al. 2011; Alemohammad et al. 2017). The analysis was conducted only for the period of overlap of the NCA-LDAS and FLUXNET-MTE data products, or 1983–2008, where grid cells from both datasets exhibited significance, as shown in Figs. 8b and 8c. Visual inspection indicates generally good agreement between the NCA-LDAS and FLUXNET trends throughout the United States, except in the upper Midwest states of Illinois, Wisconsin, Iowa, and Minnesota, where the trends are opposed. Statistical results, aggregated to each NCA region, are shown in Table 3. They indicate RMSE errors ranging from $0.05 \text{ W m}^{-2} \text{ yr}^{-1}$ in the Northeast to $0.21 \text{ W m}^{-2} \text{ yr}^{-1}$ in the Midwest, with a CONUS-wide error of $0.16 \text{ W m}^{-2} \text{ yr}^{-1}$.

g. Sensible heat and evaporative fraction

Trends were also developed for 1980–2015 for the mean summer, or June–August (JJA), ET, the sensible heat flux H , and mean evaporative fraction (EF), shown in Figs. 9a–c, respectively. Overall, for this period, H trends are from about one-third to one-fourth the magnitude of the ET trends. There are decreasing trends from the upper Great Plains to the Intermountain West, and increasing trends in the Southeast and Northwest.

Trends in the mean JJA EF, where EF is the ratio of ET to total available energy flux or $\text{EF} = \text{ET}/(H + \text{ET})$,

FIG. 8. Trend in mean annual ET, $p < 0.10$, for (a) entire NCA-LDAS simulation period 1980–2015, (b) NCA-LDAS simulation period 1983–2008 that overlaps with FLUXNET-MTE, and (c) FLUXNET-MTE period 1983–2008.

are also computed, demonstrating low but positive values throughout the entire East, then extending with increasing EF trend gradient toward the upper Great Plains. The NCA-LDAS estimated trends for the significant grid cells are greatest in the upper Great Plains and upper Midwest about $0.03 \text{ EF decade}^{-1}$ or 10.8% over the 36-yr period. For these regions, EF trends favor the production of ET, or an increase in ET. Trends become negative moving into the Southwest decreasing down to $0.04 \text{ EF decade}^{-1}$ or -14% in some regions. The implication is that the Southwest is trending to increasingly drier conditions, while the upper Great Plains are trending toward more temperate conditions.

TABLE 3. RMSE comparison of NCA-LDAS (DA) and open loop (OL), each evaluated against independent data (FLUXNET-MTE for ET; CMC for SCD; HUC8 for runoff).

	ET ($\text{W m}^{-2} \text{ yr}^{-1}$)	SCD (days yr^{-1})	Runoff (mm yr^{-1})
Northeast			
OL	0.05	1.59	2.11
DA	0.05	1.15	2.70
Southeast			
OL	0.125	—	3.36
DA	0.14	—	3.17
Midwest			
OL	0.21	—	1.72
DA	0.21	—	2.42
Great Plains			
OL	0.15	3.71	2.20
DA	0.16	3.85	12.33
Northwest			
OL	0.15	2.28	7.55
DA	0.11	2.04	9.00
Southwest			
OL	0.20	4.05	2.243
DA	0.15	3.49	22.184
CONUS			
OL	0.17	3.13	2.55
DA	0.16	2.89	16.05

h. Snow-covered days

Several studies and reports have indicated that the number of annual SCD is decreasing in the United States and North America (USEPA 2016; Rutgers University Global Snow Lab 2016; Mote and Sharp 2016). An NCA-LDAS indicator that depicts the trend in annual SCD is shown in Figs. 10a for the full 1980–2015 period. Results indicate decreasing trends ($p < 0.1$) across nearly the entire the United States ranging from 0 to over 2 days yr^{-1} , with the largest decrease occurring in the West and Intermountain West. The mean annual CONUS-wide trend is $-1.2 \text{ days yr}^{-1}$, over twice published values (Hori et al. 2017; USEPA 2016; Knowles 2015; Burakowski et al. 2008), although there is high uncertainty due to varying methods and data records. Possible reasons for this discrepancy are discussed in section 4a.

Also plotted in Figs. 10b and 10c are a comparison of annual SCD trends estimated from both NCA-LDAS and the gridded CMC snow depth product (Brown et al. 2010; Brown and Brasnett 2015), respectively, but only the period for which the CMC data are available or 1999–2015. During these more recent 15 years, both figures indicate a strong decrease in SCD of more than 2 days yr^{-1} especially in the central and northern Rocky Mountains. There is also some agreement that during 1999–2015 the number of SCD has actually increased

FIG. 9. Trends in JJA for the period 1980–2015, $p < 0.10$, for (a) mean latent heat flux, (b) mean sensible heat flux, and (c) mean EF per decade.

slightly in the central United States. However, area covered by significant trends for this abbreviated period is only about one-third of the United States, most likely due to the statistical effect of comparing the shorter available 16-yr record.

Two analyses were carried out to evaluate NCA-LDAS trends. First, the NCA-LDAS SCD indicator was compared to earlier analyses by Harpold et al. (2012) over nine watersheds covering a majority of the Intermountain West region shown in Fig. 10a. They analyzed trends in snow cover duration using SNOTEL data collected between 1984 and 2009, applying the regional Mann–Kendall test at $p < 0.05$. Their results

FIG. 10. Trends in number of snow-covered days for (a) NCA-LDAS period 1980–2015, (b) NCA-LDAS period 1999–2015, and (c) CMC snow cover period 1999–2015.

for each basin, shown in Fig. 11, yielded significant negative trends ranging from 0.3 days yr^{-1} in the upper Colorado to 0.9 days yr^{-1} in southeast Utah. Also plotted on the same graph are the NCA-LDAS SCD trends of only the model grid cells covering each watershed, adjusted for the same period and $p < 0.05$ value as the Harpold analysis. Results show very good agreement in negative trend direction in 10 out of 13 basins analyzed, especially the Upper Colorado. Of the three remaining watersheds, no comparison could be made as significance was met in neither the NCA-LDAS nor Harpold analyses. NCA-LDAS trends generally exhibited greater magnitude compared to Harpold's study by a factor of about 2. Potential reasons for this bias are discussed in section 4a.

Second, similar to the above ET analyses, the RMSE was evaluated for NCA-LDAS SCD trends, compared

FIG. 11. Evaluation of trend in number of days with snow on ground in intermountain west (blue bars), compared to Harpold et al. 2012 (green markers) for 1984–2009 with $p < 0.05$.

to the trends of an independent dataset, in this case the CMC snow cover product or the overlapping period 1999–2015. Only those grid cells possessing a significant trend in all three data products were used in the computation ($p < 0.10$) as shown in Figs. 10b and 10c. Analyses were conducted for each NCA region and for CONUS shown in Table 3. They indicate RMSE errors ranging from 1.15 days in the Northeast to 2.51 days in the Midwest, with a CONUS-wide error of 2.9 days.

i. Snow water equivalent

Trends in annual CONUS-wide SWE based solely on observations are difficult to estimate as the quantities available from station data are primarily snow depth, precipitation, and temperature. Satellite-based SWE can be unreliable in complex terrain, forested areas, and in deep snow (Luo et al. 2016) although regional evaluations exist (e.g., Mote and Sharp 2016). This is due in large part to lack of knowledge of snow density, which needs to be estimated from snowfall and temperature (Knowles 2015; Sturm et al. 2010). By merging both in situ snow data and satellite snow observations, NCA-LDAS is able to provide an estimate of CONUS-wide SWE at the gridcell resolution.

An indicator consisting of mean SWE for the snow season months of October–June at $p < 0.1$ was developed as shown in Fig. 12a. Results show a clearly defined region of decreasing trends in SWE over much

of the southern and western United States. Trends in the south are negative, but not hydrologically relevant. Increasing trends in SWE are identified in parts of the Northeast and in the northern to central Rocky Mountains.

The NCA-LDAS mean SWE indicator can be qualitatively compared to the trend in the National Operational Hydrologic Remote Sensing Center (NOHRSC) Snow Data Assimilation System (SNODAS) data product for 2004–15, which became available in 2003 (NOHRSC 2004; Barrett 2003). Recognizing the limitations of trend estimation over such a short period, the two databases compare favorably as shown in Figs. 12b and 12c, respectively. The significant areas are predominantly the West and Northwest where the estimated SWE annual trend ranges to -0.5 mm yr^{-1} . Computed significant trends for NCA-LDAS are also evident in the northern Rockies, upper Midwest, and Northeast.

j. Runoff

The trend in annual R arises from the integrated interactions and trends of other terrestrial storage and fluxes components. Figure 13a shows the mean annual trend in total R , estimated as the sum of the NCA-LDAS surface and subsurface R variables. Mean annual R is consistent with increasing mean annual P trends (Fig. 4b), with increased R in the Northeast, Midwest, and upper Great Plains. Decreasing trends in R are observed

FIG. 12. Trends in mean October–June SWE with 7-day smoothing, $p < 0.10$, for (a) full NCA-LDAS period, 1980–2015, (b) NCA-LDAS 2004–15, and (c) same trend analyses for SNODAS data 2004–15.

throughout the Northwest, Southwest, and sporadically in the Southeast, also similar to the mean annual P trend. One notable exception is the region of the central and southern Great Plains, where a positive trend in R is observed. For Nebraska and Kansas, this can be explained mostly by the increase trend in P shown in Fig. 4b, although for Texas, the increased streamflow is also consistent with the reduced ET trend previously shown in Fig. 8a. Evaluating the NCA-LDAS R trend is difficult due to the lack of observed natural streamflow, unimpacted by anthropogenic impoundments and withdrawals. As a surrogate, the statistical comparisons of NCA-LDAS annual R trends were conducted, each against trends estimated from the monthly USGS Hydrologic Unit Code 8 (HUC8; 4 km) R product

(<https://waterwatch.usgs.gov/>) shown in Fig. 13b. HUC8 R , estimated by merging historical streamflow data, stream gauge drainage areas, and watershed boundaries, has been successfully used in previous grid-based evaluations (Xia et al. 2016; Velpuri et al. 2013). Results are shown in Table 3. They indicate RMSE errors ranging from 2.42 mm in the Midwest to 22.2 mm in the Southwest, with a CONUS-wide RMSE error of 16.1 mm.

An additional indicator that highlights how the R distribution has changed is the trend in annual variance of daily R that is shown in Fig. 14a. The results are consistent with the annual precipitation extreme indicators shown in Figs. 5a–d. Overall, results indicate increasing variance in annual runoff in the eastern half of the United States, except along the southern Appalachian Mountains. Decreasing trends are predominant in the western states, with mixed trends for the Rocky Mountain region. The results are generally consistent with the precipitation variance plot shown in Fig. 5c.

Two other indicators related to extreme runoff are the maximum and minimum runoff events in a year. Figures 14b and 14c depict trends in annual 7-day low and 3-day high total runoff, respectively (USEPA 2016). Trends in annual low flows are not significant at $p < 0.1$ in much of the United States. Positive trends are evident along the East coast, while negative trends are observed in Florida and along the Gulf Coast. The lack of any significant trend in the West may be associated with the low end constraint of zero discharge. Increased trends in annual 3-day high flows, however, are significant across much of the Great Plains, upper Midwest, and in the East, except for the Appalachians. Results indicate positive trends in annual low and high flows along the East Coast, except for Florida, where low flows are decreasing and high flows are increasing. The NCA-LDAS trend patterns demonstrate consistency with those previously reported by Peterson et al. (2013) and Georgakakos et al. (2014).

k. Reference period using Thiel–Sen estimator

The above results were presented in terms of absolute units that, while useful for scientific analyses, may be less apparent for certain users. To more readily show the trend over the period of analysis, absolute changes are often compared to an earlier reference period (Melillo et al. 2014). Here the intercept of the Thiel–Sen estimator (Sen 1968) is employed that avoids having to decide which reference period is most appropriate. The Thiel–Sen estimator (Sen 1968) is based on a least squares fit over the median that minimizes the impact of outliers. Use of the intercept as the reference database effectively bases the trend on the entire 36-yr period, and avoids having to choose an

FIG. 13. Mean annual runoff trends for period 1980–2015 at $p < 0.10$ for (a) NCA-LDAS and (b) USGS HUC8.

arbitrary single year or average number of years that might be anomalous. It further averts having to compare to years prior to 1979 that are outside the simulation period.

Figures 15a and 15b show two examples, the percent change in mean annual precipitation and latent heat flux over NCA-LDAS's entire 36-yr satellite period, respectively. These are similar to Figs. 4b and 8a, except that each grid cell has been normalized by the Theil–Sen intercept and multiplied by 100 to be expressed as a percent. Only significant trends are reported. The images more clearly highlight the change over the 1980–2015 satellite era. For instance, annual P in the Southwest has decreased from 0.9% to 1.2% yr^{-1} compared to the median trend of that region, while the upper Great Plains have experienced an increase in P of about that same magnitude. Portions of the Northeast and Midwest have experienced an increase in P of about 0.6%–0.9% yr^{-1} . Similarly, the Southwest has experienced a decrease in ET of 0.9%–1.2% yr^{-1} , while the eastern half of the United States shows increases in ET throughout, ranging up to 0.6% yr^{-1} along the eastern states, and up to 0.9% yr^{-1} percent in the upper Great Plains, Midwest, and South.

4. Discussion

a. Assessment of NCA-LDAS trends

Overall, the NCA-LDAS mean annual hydrology trends demonstrate good consistency between the forcing variables and other land surface components. For instance, increasing trends in P and heavy precipitation in the northern Great Plains, Midwest, and Northeast, are reflected in increased trends in R and flooding in the Upper Missouri and Ohio Rivers, and major northeast rivers (e.g., Connecticut, Hudson, Susquehanna), respectively, consistent with Peterson et al. (2013). Large positive trends in R_{net} throughout the eastern United States and negative trends throughout the Southwest are largely reflected by corresponding trends in ET and EF in those same respective regions. Decreasing P further decreases ET in the moisture limited Southwest. The decreasing trend in SCD throughout the United States is impacted by severe decreasing trends in P in the Southwest and increasing T and R_{net} in the East.

Table 3 summarizes the NCA-LDAS RMSE for ET, SCD, and R for each NCA region. For instance, the RMSE for mean annual ET trend ranged from a low of $0.05 \text{ W m}^{-2} \text{ yr}^{-1}$ in the Northeast to a high of $0.21 \text{ W m}^{-2} \text{ yr}^{-1}$ in the Midwest. This range is in fact about the same magnitude as the domain-wide ET trend from Fig. 8a that ranged ± 0.05 – $0.25 \text{ W m}^{-2} \text{ yr}^{-1}$ and yields an overall 36-yr change of ± 1.8 – 9.0 W m^{-2} . These two measures arise from two separate sources; RMSE a comparison with independent data, and Mann–Kendall trend from an analysis of time series variability without comparison to ground truth. Similarly, the NCA-LDAS mean annual SCD trend RMSE ranged from a low of $1.15 \text{ days yr}^{-1}$ in the Northeast to a high of $3.85 \text{ days yr}^{-1}$ in the Great Plains. The domain wide SCD trend range of ± 0.4 – 2.0 days yr^{-1} shown in Fig. 10a yields an overall 36-yr change of ± 14.4 – 72.0 days . For R , the RMSE was about 3 mm yr^{-1} for the Northeast, Southeast and Midwest. For these regions, the R trends range from 3 to 12 mm yr^{-1} or 108–432 mm over 36 years. For the Great Plains and Southwest regions, a high RMSE of 12.3–22.0 mm is observed.

At the regional level, the ET trends from NCA-LDAS and FLUXNET showed good agreement over the overlapping 1983–2008 period. One major exception was the upper Midwest states of Illinois, Wisconsin, Iowa, and Minnesota, where Figs. 8a and 8b exhibited contrasting trends for NCA-LDAS and FLUXNET, respectively. While many factors contribute to ET, the difference is most likely due to NCA-LDAS's use of monthly climatological vegetation parameters, including greenness fraction, that preclude land cover change trends.

FIG. 14. Trend in NCA-LDAS over 1980–2015 for (a) variance in annual streamflow, (b) annual 7-day low streamflow, and (c) annual 3-day high streamflow (USEPA 2016).

Recent analyses of the AVHRR based normalized difference vegetation index (NDVI) by Scheftic et al. (2014) for 1982–2008 show a positive trend in duration of growing season throughout much of the United States, except in the Midwest Corn Belt that exhibits a negative trend. They attribute the decreasing growing season to the expansion of agriculture that has a shorter growing period compared to natural vegetation.

The SCD trends compared favorably in direction with Harpold's analyses in 10 of 13 basins of the intermountain west region as shown in Fig. 11. These basins represent about half of the entire U.S. Rocky Mountains. Despite the excellent statistics, the NCA-LDAS trends were about twice as large as Harpold's trends. The mean annual nationwide average of 1.2 days yr^{-1} was also as high. Possible reasons for this are inaccurate calibration of the 0.125° grid cell values over complex terrain, diminished satellite sensitivity at high snow depth due to microwave sensor saturation (Luo et al. 2016), and elevation bias of the SNOTEL stations. There also may be underestimation of the in situ analysis due to unequal distribution of the station locations, most of which are in nonmountainous areas.

The R trend errors are reasonable except in the Great Plains and Southwest. This is attributed to the large impact of the NCA-LDAS irrigation scheme which

occurs without any consideration of irrigation source, be it groundwater or streamflow. As implemented, NCA-LDAS adds substantial “forcing,” unaccounted in the modeled water balance. For example, NCA-LDAS irrigation simulation in several states shown in Fig. 16, such as California's Central Valley ($\sim 300 \text{ mm yr}^{-1}$), Nebraska (100 mm yr^{-1}), and northwest Texas (100 mm yr^{-1}), represent 50%, 17%, and 14% of average annual P , respectively. California, whose irrigation withdrawals are greater than all other Southwest NCA regions combined, takes about one-third of its supply from groundwater (Maupin et al. 2014). In the Great Plains, the groundwater withdrawals in Kansas, Nebraska, and Texas are about 80%, 60%, and 31%, respectively, of total irrigation. For other areas such as Texas that rely also on surface water withdrawals from lakes and rivers, streamflow is greatly reduced.

Further, the current analysis illustrates that trends computed over a shorter record tend to produce less significant coverage. This is particularly evident in the ET analyses in Figs. 8a and 8b, where the period of analyses is reduced from 36 to 24 years, the SCD analyses in Figs. 10a and 10b, where the period of analysis is reduced from 36 to 17 years, and in the SWE analyses in Figs. 12a and 12b, where the period of analysis changed from 36 to 12 years.

FIG. 15. Percent change in (a) mean annual precipitation, and (b) mean annual latent heat flux, over the period 1980–2015, expressed with respect to intercept of the Theil–Sen Estimator for $p < 0.1$.

b. Effect of multivariate assimilation on RMSE and trend detection

The effect of NCA-LDAS data assimilation is examined two ways. First, a comparison is made between the RMSE evaluations of the NCA-LDAS for ET, SCD, and R against independent data, to OL evaluations using the same approach, as shown in Table 3. For ET, when compared against independent FLUXNET-MTE data, NCA-LDAS showed mixed results. NCA-LDAS RMSE for ET, when compared to OL, showed only slight improvement in the Northwest and Southwest; no impact in the Northeast and Midwest; and slight degradations for Great Plains and Southeast. NCA-LDAS also exhibited only very slight improvement in CONUS-wide (RMSE from 0.17 to $0.16 \text{ W m}^{-2} \text{ yr}^{-1}$). NCA-LDAS SCD trends provided a more robust result. When evaluated against CMC data, NCA-LDAS RMSE demonstrated improvement in 3 of 4 reporting regions. For CONUS, NCA-LDAS reduced RMSE from 3.13 to

$2.89 \text{ days yr}^{-1}$. Comparison was not possible for the Southeast and Midwest due to insufficient significant CMC record. For streamflow the NCA-LDAS RMSE degraded in 4 of 5 regions. These degradations were greatest in the Great Plains and Southwest where the irrigation scheme (Kumar et al. 2018; Ozdogan et al. 2010) was applied the most, as shown in Fig. 16, affecting the natural water balance.

Second, the impact of multivariate assimilation was evaluated with respect to “trend detection” based on the change in significant trend area between NCA-LDAS and OL. Table 4 indicates that trend detection slightly improved for ET in 4 of 6 NCA regions. For SCD, NCA-LDAS had a large effect as significant area increased in all areas ranging from 9% to 13%. For R , trend detection was unaltered. CONUS-wide, the NCA-LDAS-OL significant areas for ET, SCD, and R increased by 2%, 11%, and 0%, respectively. While not indicating an improvement in trend accuracy, the positive changes imply a decrease in uncertainty for those grid cells, and arguably a measure of the impact of data assimilation.

While the overall effect of satellite assimilation is small, several factors contribute to the impact of NCA-LDAS on model trends and improved significant area. First, land surface energy and water balance processes constitute an integrated nonlinear system. Although bias is removed from the two assimilated state variables [satellite soil moisture (SM) and snow depth (SD)], it is still theoretically possible that small differences can arise between NCA-LDAS and OL modeled land variables due to their nonlinear linkages with the above two state variables, leading to small differences between the OL and NCA-LDAS trends. Second, since the model forcing time series (P , incoming radiation, wind speed, atmospheric water vapor deficits) as well as the prescribed vegetation and soil type parameters are not altered, any difference between the original and corrected states during assimilation will have a corresponding effect on other processes such as ET, R , infiltration, that are link to those states. For instance, SM is assimilated only at the surface soil layer (top 5 cm), but its impact is propagated by infiltration physics into the deeper subsurface soil layers. Also, ET is a nonlinear function not only of root zone soil moisture, but also the model forcings that affect moisture transport through the root zone. At the same time, nonlinear R generation is occurring related to SM and snowmelt. That is, a unit of rainfall on dry soil may provide no R , while the same amount rain or snowmelt on saturated soil will completely run off. Other contributing factors include the influence of the snow cover area satellite (SCA) constraint within the NCA-LDAS scheme can also impact on trend detection. Another factor is that the SD observations are assimilated only if the Interactive

FIG. 16. NCA-LDAS mean assimilated irrigation intensity over the period 1980–2015 (from Kumar et al. 2018).

Multisensor Snow and Ice Mapping System (IMS) and the MODIS SCA observations both indicate nonzero snow values. Consequently, the nonlinear relationship with modeled flux and store variables can theoretically induce some impact of NCA-LDAS on trends. Finally, since data assimilation systems including EnKF are designed to correct the random error in the model background, while not altering the trend direction, the reduced variance in the time series can promote an improvement in trend “detection” as manifested in the increased significant area shown in Table 4 at $p < 0.1$ used in this study. For NCA-LDAS, this can be attributed to both the theoretical reduction in random error associated with the snow depth bias reduction within EnKF, as well as the implementation of the IMS/MODIS snow cover detection algorithm. Finally, unlike the OL, NCA-LDAS employs a demand-driven, sprinkler irrigation scheme that affects soil moisture content (Ozdogan et al. 2010). Although not data assimilation per se, the implementation in NCA-LDAS affects ET and R which can further lead to divergence of the trend as the irrigation scheme is not at all included in the OL.

5. Conclusions

There is pressing need to develop consistent trend indicators to facilitate scientific understanding of national climate change. Land reanalysis has evolved as an effective tool to achieve this goal, by merging disparate datasets of multiscale, multisensor, in situ and satellite data within a data assimilation modeling environment.

NCA-LDAS has shown high skill when compared to other land surface models, offering a compelling database for constructing regional-scale national hydrologic trends.

Analyses of annual mean hydrologic trends using NCA-LDAS demonstrate the interrelationship between regional gradients in forcing trends, and trends in other land energy and water stores and fluxes. Mean annual

TABLE 4. Comparison of percent significant area ($p < 0.1$) of trends in ET, SCD, and runoff for NCA-LDAS (DA) and open loop (OL), and their differences (DA – OL).

NCA region		ET	SCD	Runoff
Northeast	OL	88	76	34
	DA	88	88	40
	DA – OL	0	12	6
Southeast	OL	76	59	8
	DA	78	72	8
	DA – OL	2	13	0
Midwest	OL	77	78	16
	DA	78	90	16
	DA – OL	1	12	0
Great Plains	OL	38	58	35
	DA	35	67	32
	DA – OL	–3	9	–3
Northwest	OL	42	61	23
	DA	47	72	23
	DA – OL	5	11	0
Southwest	OL	58	71	43
	DA	66	84	44
	DA – OL	8	13	1
CONUS	OL	58	66	28
	DA	60	77	28
	DA – OL	2	11	0

precipitation trends range from +3 to +9 mm yr⁻¹ in the upper Great Plains and Northeast to -1 to -9 mm yr⁻¹ in the West and South; net radiation flux trends range from +0.05 to +0.20 W m⁻² yr⁻¹ in the East to -0.05 to -0.20 W m⁻² yr⁻¹ in the West; U.S.-wide temperature trends average about +0.03 K yr⁻¹.

Trends in the response water balance components, including annual mean soil moisture, snow cover, latent and sensible heat fluxes and runoff are consistent with forcings. For instance, increasing trends in P and heavy precipitation in the northern Great Plains, Midwest, and Northeast, are reflected, respectively, in increased trends in R in the Upper Missouri and Ohio Rivers, as well as major northeast rivers, consistent with previous reports. Large positive trends in R_{net} and P throughout the eastern United States and negative trends throughout the Southwest are largely reflected by corresponding trends in ET , and an increasing evaporative fraction trend from west to east. The decreasing trend in SCD throughout the United States is impacted by severe decreasing trends in P in the Southwest, increasing R_{net} in the East, and elevated T throughout the United States.

Evaluation of NCA-LDAS trends compared to independent data at the regional scale indicates mixed results. The RMSE of CONUS-wide trends in number of snow cover days improved from 3.13 to 2.89 days yr⁻¹ while trend detection increased 11%; Trends in latent heat flux were hardly affected, RMSE decreasing only from 0.17 to 0.16 W m⁻² yr⁻¹, while trend detection increased 2%; NCA-LDAS runoff trends degraded significantly from 2.6 to 16.1 mm yr⁻¹ while trend detection was unaffected.

The implication for the current analyses is that the West and Southwest are trending to increasingly drier conditions under a climatically moisture-limited system, while the East and North behave as energy-limited systems, trending toward more temperate conditions. Regions of sparse significant forcing trends often result in reduced significant trends in other hydrologic components, as evidenced by the central Great Plains.

At the regional level, the ET trends from NCA-LDAS and FLUXNET demonstrated good agreement for the overlapping 1983–2008 period. One major exception was the upper Midwest states where NCA-LDAS's use of monthly climatological vegetation parameters for this area is not consistent with the decreasing growing season due to the expansion of agriculture.

The SCD trends compared favorably in direction with Harpold's analyses using in situ data in 10 of the 13 basins of the intermountain west region as shown in Fig. 11. These basins represent about half of the entire U.S. Intermountain West. Despite the excellent statistics, the NCA-LDAS trends were about twice as

TABLE 5. NCA-LDAS variables available on GES-DISC.

Short name	Long name	Unit
Swnet	Net shortwave radiation flux	W m ⁻²
Lwnet	Net longwave radiation flux	W m ⁻²
Qle	Latent heat net flux	W m ⁻²
Qh	Sensible heat net flux	W m ⁻²
Qg	Heat flux	W m ⁻²
Snowf	Snow precipitation rate	kg m ⁻² s ⁻¹
Rainf	Rain precipitation rate	kg m ⁻² s ⁻¹
Evap	Evapotranspiration	kg m ⁻² s ⁻¹
Qs	Storm surface runoff	kg m ⁻² s ⁻¹
Qsb	Baseflow-groundwater runoff	kg m ⁻² s ⁻¹
Qsm	Snowmelt	kg m ⁻² s ⁻¹
RadT	Average radiative temperature	K
SWE	Snow depth water equivalent	kg m ⁻²
SnowDepth	Snow depth	m
SnowFrac	Snow covered fraction	Fraction
SoilMoist0_10cm	Soil moisture (0–10 cm)	m ³ m ⁻³
SoilMoist10_40cm	Soil moisture (10–40 cm)	m ³ m ⁻³
SoilMoist40_100cm	Soil moisture (40–100 cm)	m ³ m ⁻³
SoilMoist100_200cm	Soil moisture (100–200 cm)	m ³ m ⁻³
SoilTemp0_10cm	Soil temperature (0–10 cm)	K
SoilTemp10_40cm	Soil temperature (10–40 cm)	K
SoilTemp40_100cm	Soil temperature (40–100 cm)	K
SoilTemp100_200cm	Soil temperature (100–200 cm)	K
PotEvap	Potential evaporation rate	kg m ⁻² s ⁻¹
ECanop	Canopy water evaporation rate	kg m ⁻² s ⁻¹
TVeg	Transpiration rate	kg m ⁻² s ⁻¹
ESoil	Direct evaporation from bare soil	kg m ⁻² s ⁻¹
SubSnow	Snow sublimation rate	kg m ⁻² s ⁻¹
CanopInt	Plant canopy surface water	kg m ⁻²
Streamflow	Streamflow	m ³ s ⁻¹
FloodedFrac	Flooded fraction	Fraction
FloodedArea	Flooded area	m ²
IrrigatedWater	Irrigated water rate	kg m ⁻² s ⁻¹
Wind_f	Wind speed	m s ⁻¹
Rainf_f	Total precipitation rate	kg m ⁻² s ⁻¹
Tair_f	Temperature	K
Tair_f_min	Daily minimum temperature	K
Tair_f_max	Daily maximum temperature	K
Qair_f	Specific humidity	kg kg ⁻¹
Psurf_f	Pressure	Pa
SWdown_f	Downward shortwave radiation	W m ⁻²
LWdown_f	Downward longwave radiation flux	W m ⁻²

large as Harpold's trends while the mean annual nationwide average of 1.2 days yr⁻¹ was also high. Possible reasons for this may be inaccurate calibration of the 0.125° grid cells over this complex terrain; diminished satellite sensitivity at high snow depth, and non-representative distribution of the station locations, most of which appear in nonmountainous areas. The R trend errors are reasonable except in the Great Plains and

Southwest where the impact of NCA-LDAS irrigation is high. As currently implemented, NCA-LDAS adds substantial “forcing,” unaccounted in the modeled water balance that needs to be addressed in future NCA-LDAS versions.

Precipitation station density analysis showed that satellite data assimilation improves skill for soil moisture, streamflow, and snow depth when precipitation station density is low, while providing mixed results for higher precipitation station densities. This suggests that there are possible limits to the effectiveness of data assimilation in regions with dense gauge networks.

Use of the Theil–Sen estimator as a reference level offers an effective normalizing method for comparing trends over a given period, and avoids having to choose an arbitrary single year or average number of years that might be anomalous. For satellite-based reanalysis, it further averts having to compare to databases that are outside the simulation period.

The overall results demonstrate NCA-LDAS’s capability as an effective enabling tool for merging diverse satellite data products that can quantify physically consistent terrestrial climate trends for scientific understanding and decision support. Data products are produced not only for the principal hydrology components, but for a total of 42 variables as shown in Table 5, and available for formulation of other indicators.

NCA-LDAS’s long-term goal is to optimally combine the full suite of past and future Earth observations of all relevant land EDRs. Future work will include observations associated with terrestrial water storage, vegetation and altimetry. At the same time, the results herein implicitly illustrate that employing the highest quality forcing dataset is still of paramount importance to producing good hydrologic indicators. This notion provides impetus for improving capability both in the accuracy and resolution of current satellite state observations, and also for expanding space observations to include other fluxes such as surface winds, H , and ET.

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