

Investigating the role of antecedent SMAP satellite soil moisture, radar rainfall and MODIS vegetation on runoff production in an agricultural region

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Abstract

Following results by Crow et al. (2017) [Geophys. Res. Lett. 44, 5495–5503] on the impact of antecedent soil moisture on runoff production, we investigate total runoff production during individual rainfall-runoff events in agricultural landscapes as a function of antecedent soil moisture, total rainfall, and vegetation cover for catchments with drainage areas ranging from 80-1000 km^2 in the state of Iowa, USA. For our study, we use Enhanced SMAP soil moisture estimates, the MODIS enhanced vegetation index (EVI), gauge-corrected Stage IV radar rainfall, and USGS streamflow data. We analyze the event runoff ratio as a function of event-scale rainfall, antecedent SMAP soil moisture and soil-moisture-deficit-normalized rainfall for the events in a period from March 31, 2015 to October 31, 2018. Our goal is to confirm the relationships identified by Crow et al. (2017) in heavily managed agricultural landscapes and to refine some of their methodological steps to quantify the role of additional variables controlling runoff production. To this end, we define three different strategies to identify rainfall-runoff events and add a baseflow separation step to better insulate event scale stormflow runoff. We test the effects of antecedent soil moisture, rainfall, and vegetation on the event-scale runoff ratio. The antecedent SMAP soil moisture and event-scale rainfall are found to have significant predictive power in estimating event runoff ratio. Soil moisture deficit-normalized rainfall, introduced as the ratio of event-scale rainfall to available space in top soil before initiation of the event, exhibited a more distinct relationship with runoff

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ratio. The long-term analysis of runoff ratio, rainfall, and MODIS EVI indicated that, in an agricultural region, vegetation plays a significant role in determining event-scale runoff ratios. The methodology and outcome of our study have direct implications on real-time flood forecasting and long-term hydrologic assessments.

Keywords: soil moisture, runoff ratio, satellite, rainfall, hydrology, vegetation

1. Introduction

A recent study by Crow et al. (2017) revealed a significant nonlinear relationship between antecedent soil moisture at the watershed scale and event-scale runoff ratios for 16 basins in the Southern United States. They showed that soil moisture estimations from data assimilation of SMAP (Soil Moisture Active Passive) brightness temperature observations along with meteorological data into CLSM (Catchment Land Surface Model) (Koster et al., 2000) improves representation of prestorm soil moisture conditions for streamflow forecasting.

In this study, we follow-up and further expand the methodology used by Crow et al. (2017) using remote sensing observations of antecedent soil moisture, rainfall, and vegetation to understand the relationships with estimated runoff ratios. Our study is motivated by three issues described as follows.

First, the accuracy of satellite-based soil moisture retrievals depends on biomass or vegetation water content (e.g. Jackson and Schmugge (1991), Njoku and Entekhabi (1996), Calvet et al. (2011)). The study region in Crow et al. (2017) had low vegetation water content. We assess the validity and significance of the relationship between antecedent SMAP satellite soil moisture and event-scale runoff ratio found by Crow et al. (2017) in a different region, dominated by cropland, such as Iowa.

Second, in contrast to antecedent soil moisture, Crow et al. (2017) were not able to find a significant relationship between event total rainfall and event-scale runoff ratio. We test if event total rainfall has a significant predictive power for estimating event runoff ratio and we examine the dependence of these relationships on storm event definition and/or baseflow separation.

Finally, apart from antecedent soil moisture and rainfall, previous studies have shown that vegetation is another significant factor in controlling runoff

27 production (e.g. Kozak et al. (2007), Elhakeem and Papanicolaou (2009)). The
28 effect of vegetation can become more prominent in heavily agricultural regions.
29 We test this aspect by analyzing annual cycles of runoff ratio, event total rainfall,
30 and vegetation.

31 For addressing the objectives of our study, we use SMAP satellite soil mois-
32 ture and radar rainfall to investigate the role of antecedent soil moisture and
33 the event total rainfall on event runoff ratio by introducing three different types
34 of rainfall-runoff event definition. We estimate runoff ratio before and after
35 baseflow separation in basins that are less than 1000 km^2 in the state of Iowa,
36 USA. For more practical flood forecasting purposes, we introduce soil moisture
37 deficit-normalized rainfall to evaluate the potential added-value of using both
38 SMAP satellite soil moisture and S-band radar rainfall data. Furthermore, we
39 explore the long-term annual variation of runoff ratio and we try to explain
40 its potential controls by event total rainfall and MODIS (Moderate Resolution
41 Imaging Spectroradiometer) vegetation index.

42 We begin with description of the study basins, methods and data used for
43 this study. Then, we present our main findings from data analysis with interpre-
44 tations, followed by discussion of results and their relevance to previous studies.
45 We conclude with the main implications that can be drawn from our study for
46 hydrologic applications and flood forecasting.

47 **2. Study region and Methodology**

48 *2.1. Study basins*

49 In this study, we consider basins located in Iowa that are not affected by up-
50 stream flow regulation and have drainage areas in a range from 80 to 1000 km^2 .
51 Iowa is located at U.S. Cornbelt with a warm and humid climate. USGS (United
52 States Geological Survey) stream gage locations of the 38 basins considered in
53 this study are shown in Fig. 1.

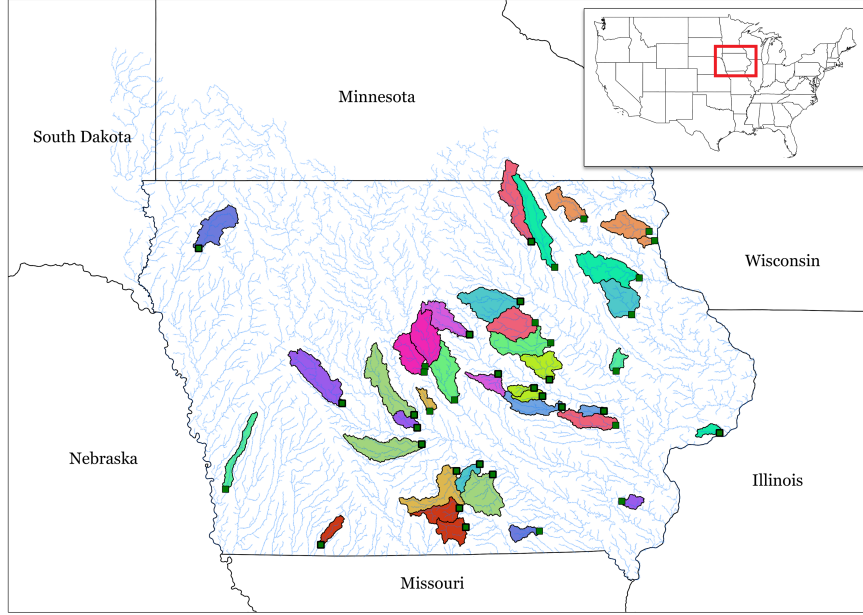


Figure 1: Location and outlet (green square) of the basins in Iowa used in this study.

54 The selection of basins with drainage areas less than 1000 km^2 is mainly
 55 based on three reasons: (1) streamflow for larger basins exhibit longer memory
 56 than basins with smaller drainage areas (Hirpa et al., 2010). Therefore, attribut-
 57 ing streamflow to a specific rainfall event becomes more challenging due to the
 58 merging effect of two consecutive rainfall responses in streamflow measured at
 59 the outlet of larger basins; (2) the calculation of runoff ratio from streamflow
 60 becomes more prone to errors because larger basins are less sensitive to rain-
 61 fall intermittency (Ayalew et al., 2015); (3) finally, due to spatial variability of
 62 rainfall and soil moisture, the spatial average of these two quantities may not
 63 be representative for the basins with larger drainage areas.

64 2.2. Data

65 For this study, we use radar rainfall, SMAP satellite soil moisture and
 66 streamflow. We obtain these three datasets for April 1, 2015 to October 31,
 67 2018 for 38 basins shown in Fig. 1. To avoid the probable impacts of frozen sur-
 68 face on estimation of soil moisture from SMAP, we exclude January, February,
 69 March, November and December months.

70 Furthermore, for understanding the runoff ratio variability over time, we
71 obtain radar rainfall, streamflow and basin-averaged MODIS EVI for Jan 1,
72 2002 to Dec 31, 2018. Specific details of each dataset is provided as follows,

73 Soil moisture: We use Enhanced SMAP Level 3 Version 2 (L3_P_E) soil
74 moisture generated by using Backus-Gilbert optimum interpolation method
75 (Chaubell et al., 2016). Enhanced SMAP L3 soil moisture is based on Single
76 Channel Algorithm (O’neill et al., 2016) and brightness temperature correspond-
77 ing to Vertical Polarization (SCA-VPOL). Enhanced SMAP data is provided on
78 EASE-Grid version 2 (Brodzik et al., 2012) with resolution of 9 km in space.
79 We obtain SMAP soil moisture data for March 31, 2015 to October 31, 2018.
80 Descending and ascending orbits of SMAP correspond to approximately 6 AM
81 and 6 PM local time of the satellite footprint, respectively. For our study, at any
82 timestamp, SMAP data should cover at least 60 percent of the basin’s drainage
83 area to be considered as a representative average antecedent soil moisture of the
84 basin.

85 Radar rainfall: We use rain gauge bias-corrected Stage IV hourly rainfall (Lin
86 and Mitchell, 2005) that is distributed by National Centers for Environmental
87 Prediction (NCEP) and posted on a grid with approximate spatial resolution
88 of 4 km (Reed and Maidment, 1999). We calculate daily total rainfall volume
89 for each basin by temporal summation of hourly rainfall volume for each basin
90 and then we normalize it by basin drainage area for finding the basin-averaged
91 rainfall depth.

92 Streamflow: We obtain daily mean streamflow provided by U.S. Geological
93 Survey on National Water Information System (U.S. Geological Survey, 2016).

94 Enhanced Vegetation Index (EVI): We use MODIS satellite EVI (MCD43A4
95 version 6) dataset (Schaaf and Wang, 2015) which is daily product driven by
96 using 16-day retrieval algorithm with an approximate spatial resolution of 500
97 (m). We calculate basin-averaged MODIS EVI for each rainfall-runoff event.
98 For this purpose, we use Google Earth Engine (Gorelick et al., 2017) which is a
99 cloud-based platform for planetary geospatial analysis.

100 2.3. Methods

101 For understanding the dependence of runoff ratio on definition of rainfall-
102 runoff event, we consider three different methods to define a runoff event,

103 whereas for each method, we calculate the event total runoff with and with-
 104 out base flow separation.

105 Event-scale runoff ratio (RC) is defined as

$$RC = \frac{V_Q}{V_P} \quad (1)$$

106 whereas V_Q (m^3) is total volume of streamflow and V_P (m^3) is total precipitation
 107 volume over a given basin for the duration of a rainfall-runoff event.

108 2.3.1. Baseflow separation

109 Streamflow, during a rainfall-runoff event, is composed of stormflow and
 110 baseflow. Stormflow, which is due to surface runoff, is defined as

$$Q_s = Q - Q_b \quad (2)$$

111 where Q (m^3/s) is daily mean streamflow and Q_b (m^3/s) is daily mean baseflow
 112 at the outlet of the basin. For estimation of baseflow (Q_b), we use the local
 113 minimum method of HYSEP, which is a tool developed by USGS for hydrograph
 114 separation (Sloto and Crouse, 1996). In HYSEP, the duration of surface runoff
 115 for calculation of stormflow is defined by an empirical relationship given as

$$N = 0.8A^{0.2} \quad (3)$$

116 where N is the number of days after which surface runoff ceases and A (km^2)
 117 is the drainage area of the basin.

118 We calculate runoff ratio using streamflow and stormflow to understand the
 119 effect of baseflow separation on the relationship of antecedent soil moisture,
 120 event total rainfall and deficit-normalized rainfall with runoff ratio. We use
 121 three types of rainfall-runoff event definition whereas we discuss the details of
 122 each method in following sections (Sections 2.3.2-2.3.4).

123 2.3.2. Method 1 – Constant event duration (M1)

124 For this event definition, we follow the rainfall-runoff event definition by
 125 Crow et al. (2017) that used a constant duration. They defined the event as
 126 a 6-day period following a triggering threshold rainfall depth. They selected
 127 rainfall-runoff events based on the threshold rainfall depth. They used two
 128 criteria for selecting a rainfall-runoff event: (1) an event should not have more

129 than one basin-averaged rainfall equal or greater than threshold depth (P_{th})
 130 during the storm event; (2) the rainfall of the day prior to initiation of a storm
 131 event should not exceed the threshold depth.

132 We calculate daily average SMAP soil moisture of the basin. Then, we
 133 select the antecedent soil moisture of the event as the minimum of the daily
 134 average SMAP soil moisture for a two-day period prior to the initiation of
 135 event. Crow et al. (2017) found that using different event durations does not
 136 effect significance of the relationship between antecedent soil moisture and event-
 137 scale runoff ratio. Therefore, considering the basin drainage areas of our study,
 138 we use a three-day period following a triggering threshold rainfall for definition
 139 of rainfall-runoff event. A schematic of the event definition for this method is
 140 shown in Fig. 2.

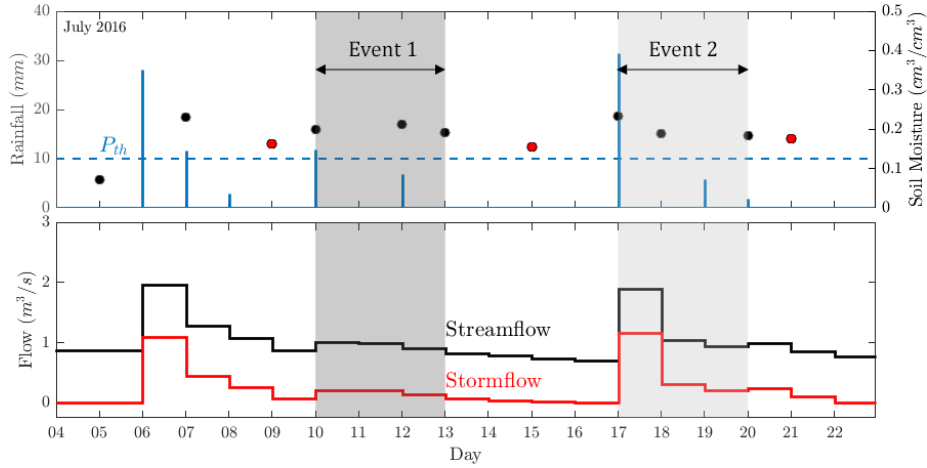


Figure 2: Schematic of rainfall-runoff event (highlighted gray) definition after Crow et al. (2017) and pre-storm soil moisture (red circles). Top panel: Basin-averaged rainfall depth (blue bars) and daily average soil moisture (black circles); Bottom panel: streamflow (black line) and stormflow (red line).

141 2.3.3. Method 2 – Stormflow based ($M2$)

142 We use stormflow time series for identifying the beginning and end times-
 143 tamps of the rainfall-runoff events by finding local minima of the daily mean
 144 stormflow calculated by Eq. (2). We calculate event-scale runoff ratio by ac-
 145 cumulating the streamflow/stormflow over the duration of an event. We use
 146 both ascending and descending SMAP orbits' soil moisture estimations. For

consistency with M1, the antecedent soil moisture of an event is defined as the minimum basin-averaged soil moisture of two days prior to initiation of the event. A schematic for the definition of rainfall-runoff event using stormflow is shown in Fig. 3.

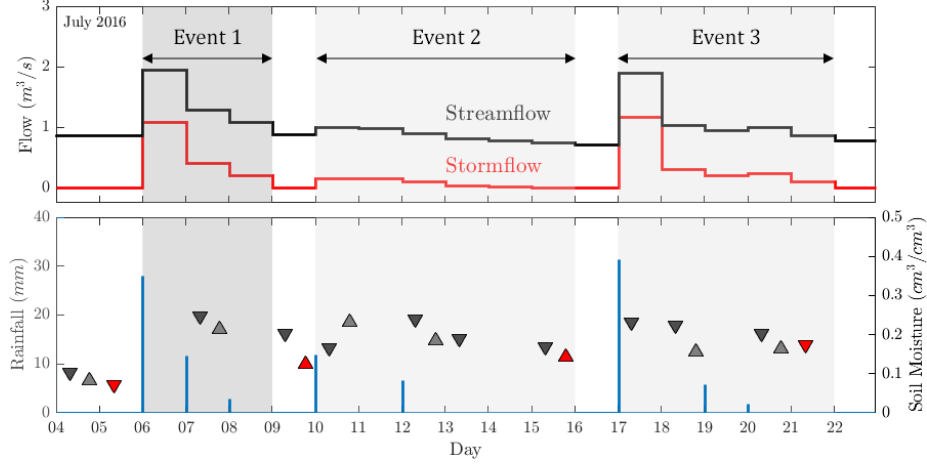


Figure 3: Rainfall-runoff event definition by using local minima of the stormflow time series. Top panel: Daily streamflow (black line) and stormflow (red line); Bottom panel: Rainfall (blue bars), ascending (upward triangles) and descending (downward triangles) orbit’s SMAP soil moisture, antecedent soil moisture of events (red triangles).

2.3.4. Method 3 – Event definition based on Model Routed Rainfall (M3)

We used the HLM (Hillslope Link Model) implemented at the Iowa Flood Center (e.g. Krajewski et al. (2017); Quintero et al. (2016)), with the assumption of impervious surface (i.e. a constant runoff ratio of 100%). The main motivation for using a model for translating rainfall into streamflow is to identify the minimum travel time of the event rainfall, including the effect of rainfall variability in space and time during a rainfall-runoff event.

In HLM, each basin is decomposed of hillslopes and links (i.e. river segment) whereas the median area of hillslopes is 0.3 km^2 . The change of channel flux at a given link could be calculated by solving two coupled nonlinear ordinary differential equations given as

$$\frac{dq}{dt} = \frac{q^{\lambda_1}}{\tau} [-q + q_{pc} \cdot A_h + q_{in}(t)] \quad (4)$$

$$\frac{ds_p}{dt} = p(t) \cdot RC - q_{pc} \quad (5)$$

163 where q (m^3/s) is the channel discharge at a given link in the basin's river
 164 network, $q_{in}(t)$ is the discharge entering the channel from the parent link(s)
 165 (upstream channel), A_h (m^2) is the area of the hillslope, λ_1 is the exponent
 166 of channel discharge and q_{pc} (m/s) is the flux from ponded surface storage to
 167 channel which is defined as

$$q_{pc} = \frac{v_h \cdot L}{A_h} s_p \quad (6)$$

168 where v_h (m/s) is overland flow velocity, L (m) is channel length. In Eq. (4),
 169 τ is the residence time of flow in a given link formulated as

$$\frac{1}{\tau} = \frac{v_r}{L(1 - \lambda_1)} \left(\frac{A_{up}}{A_r} \right)^{\lambda_2} \quad (7)$$

170 A_{up} is the upstream drainage area of the link, v_r is the channel reference velocity
 171 and λ_2 is the exponent of channel's upstream contributing area.

172 A schematic of the event definition using routed rainfall is shown in Fig. 4
 173 where events are highlighted as gray.

174 We solve in Eq. (4) and Eq. (5), implemented in HLM model to identify
 175 the rainfall-runoff events. As shown in Fig. 4, first, we find the local minimums
 176 of the routed rainfall time series. Then, we truncate the identified time to
 177 the beginning of the day (00:00 UTC-6) to be consistent with the daily scale
 178 streamflow data. Thereafter, we calculate the runoff ratio for the corresponding
 179 rainfall-runoff event. Finally, we select the minimum basin-averaged SMAP soil
 180 moisture of the two-day period prior to initiation of the rainfall-runoff event.
 181 Red triangles, in top panel of Fig. 4, are the soil moisture values considered
 182 as the antecedent soil moisture of the following rainfall-runoff event. Similar
 183 to Fig. 3, upward and downward triangles represent the basin-averaged SMAP
 184 satellite soil moisture.

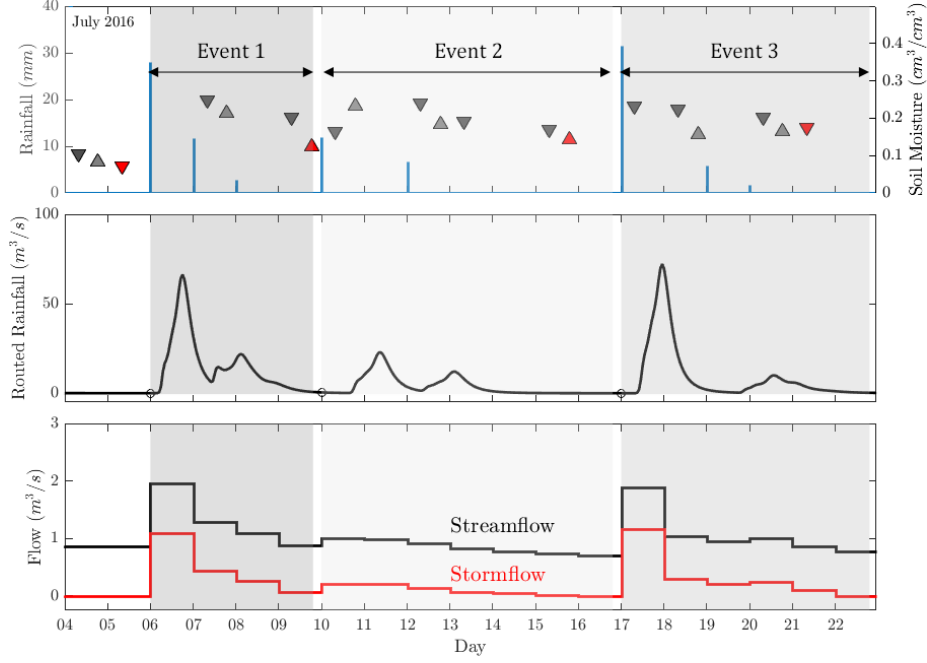


Figure 4: Event definition by using routed rainfall at the outlet of the basin. Top panel: Rainfall (blue bars), ascending (upward triangles) and descending (downward triangles) orbit’s SMAP soil moisture, antecedent soil moisture of events (red triangles); Middle panel: Routed rainfall (black line), Local minima of the routed rainfall timeseries; Bottom panel: Daily streamflow (black line) and stormflow (red line).

2.4. Correlation analysis

For the three event definitions, we investigate the relationship between event-scale runoff ratios with antecedent soil moisture, rainfall and soil moisture deficit-normalized rainfall. Deficit-normalized rainfall is the ratio of event-scale rainfall to available space in soil prior to initiation of the event and it is defined as

$$P_{def} = \frac{\sum P}{D_s(\phi - SM_i)} \quad (8)$$

where $\sum P$ (mm) is the event accumulated rainfall depth calculated by dividing the total rainfall volume for a given basin by its drainage area, ϕ (cm^3/cm^3) is soil porosity and SM_i (cm^3/cm^3) is antecedent basin-averaged soil moisture of the event and D_s (mm) is normalization length assumed as a constant depth of 50 (mm).

We explore the relationship between runoff ratio and antecedent soil moisture, rainfall and deficit-normalized rainfall by using Spearman correlation co-

efficient that is an indicator of the monotonicity of the nonlinear relationship between two variables. Spearman correlation coefficient (ρ_s) is defined as

$$\rho_s = \frac{cov(r_{gX}, r_{gY})}{\sigma_{r_{gX}} \sigma_{r_{gY}}} \quad (9)$$

where r_{gX} and r_{gY} are ranks of the two variables, $cov(r_{gX}, r_{gY})$ is the covariance and $\sigma_{r_{gX}}$ and $\sigma_{r_{gY}}$ are standard deviations of the ranks.

Due to short time period of SMAP mission, we combine the data for all of the basins that are used in this study. We test the significance of the nonlinear relationship of runoff ratio before and after baseflow separation for the three variables and for each method. We compare the correlations between our proposed event definitions (M2 and M3) with the event definition method M1 adopted from Crow et al. (2017) by event-scale basin-averaged rainfall depth.

2.5. Annual cycles of runoff ratio, rainfall and vegetation

We investigate temporal variability of runoff ratio for 17 years (2002-2018) by using event definition Method 2 (M2). We calculate event-scale runoff ratio using stormflow (baseflow separated flow) and event-scale rainfall for each event. Furthermore, we extract basin-averaged MODIS (MODerate resolution Imaging Spectroradiometer) Enhanced Vegetation Index (EVI) to investigate the impact of vegetation on temporal variability of runoff ratio. EVI is defined as

$$EVI = G \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + C_1 \cdot \rho_{red} - C_2 \cdot \rho_{blue} + L} \quad (10)$$

In Eq. (10), ρ_{NIR} , ρ_{red} and ρ_{blue} are atmospherically adjusted surface reflectance values corresponding to Near-Infrared (NIR), red, and blue bands respectively, L is the canopy background adjustment that accounts for nonlinear differential NIR and red radiant transfer through canopy, C_1 and C_2 are aerosol resistance coefficients that use blue band to correct reflectance for aerosol influences in red band and G is gain factor (Huete et al., 2002). Following Huete et al. (1994, 1997), the coefficients used in EVI algorithm are

$$L = 1, C_1 = 6, C_2 = 7.5, G = 2.5$$

We use Wilcoxon rank sum test for comparing medians of event-scale rainfall and runoff ratio distributions for each month. Wilcoxon test is a nonparametric test that examines if samples from two distributions have equal medians versus

alternative hypothesis that the medians of two distributions are not equal. For statistical tests, we set a 5% significance level.

3. Results

We divide our results section in three parts, first we present results on the variations of runoff ratio with antecedent soil moisture, rainfall and deficit-normalized rainfall for 4 years (2015-2018), respectively. Thereafter, we investigate the impact of event-scale rainfall, event-definition methodology and baseflow separation on the prominence of these relationships using Spearman correlation. Finally, we explore event-scale rainfall, and basin-averaged MODIS EVI to describe temporal variability of runoff ratio for 17 years (2002-2018).

3.1. Antecedent soil moisture and event-scale runoff ratio

Variation of runoff ratio with respect to the antecedent SMAP L3 soil moisture for rainfall-runoff events are shown in Fig. 5 as violinplots (Hintze and Nelson, 1998). In this figure, the shape of the violinplot represents estimated kernel density of the data points. The inner boxplot shows median (white circles), interquartile range from 25 percentile (q_1) to 75 percentile (q_3) and high and low whiskers that are calculated as $q_3 + 1.5(q_3 - q_1)$ and $q_1 - 1.5(q_3 - q_1)$, respectively. Each row, in this figure, corresponds to event definition method (denoted as M1, M2 and M3). The numbers shown at the top of each subplot, from top to bottom, refer to the number of rainfall-runoff events with runoff ratio values greater than 1 and less than 1, for a given antecedent SMAP soil moisture range, respectively.

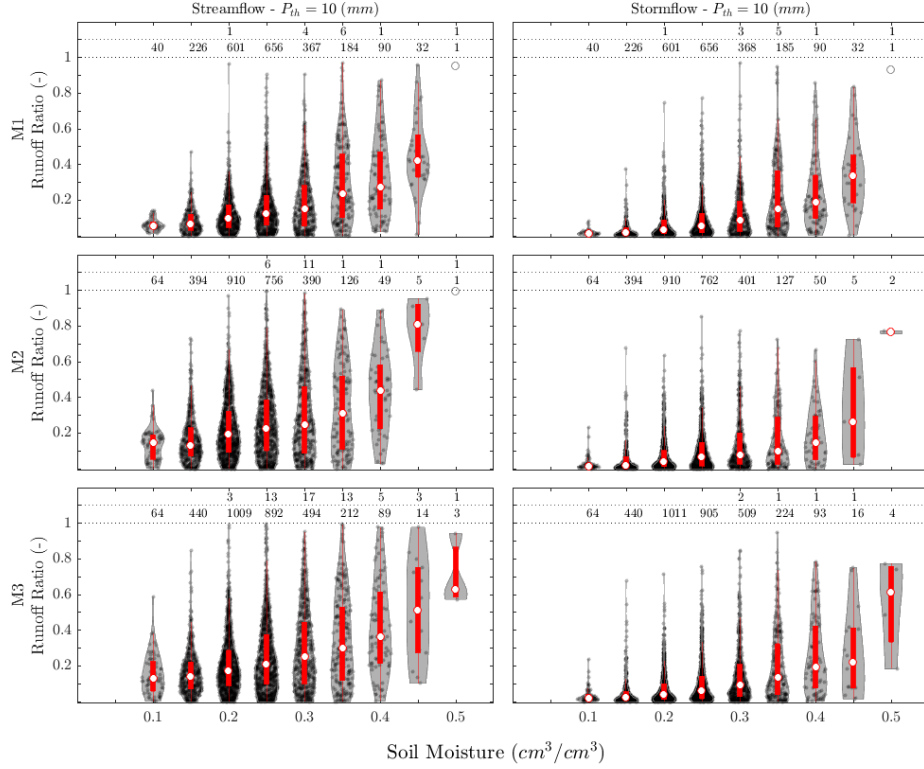


Figure 5: Violinplots of the event-scale runoff ratio (left column: streamflow, right column: stormflow) versus basin-averaged antecedent soil moisture from SMAP L3 for rainfall-runoff events with rainfall depth equal or greater than 10 (mm). The number of rainfall-runoff events with runoff ratio greater than 1 and less than 1 are annotated at the first row and second row at the top of each subplot for each corresponding antecedent soil moisture. Subplots in each row correspond to rainfall-runoff event definition (M1-M3).

240 The number of events detected by each method for event-rainfall depths
 241 larger than 10 (mm) are more than 2000, 2600 and 3200 by using methods
 242 M1 to M3, respectively. Runoff ratios and the number of events with runoff
 243 ratios greater than one decrease significantly by removing baseflow signal from
 244 streamflow (right column in Fig. 5).

245 Events with lower antecedent soil moisture tend to have lower runoff ra-
 246 tios while runoff ratio increases for higher antecedent soil moisture conditions
 247 whereas the range of variability for runoff ratio is higher compared to dry an-
 248 tecedent conditions.

249 As shown in Fig. 5, regardless of accounting for baseflow in runoff ratio
 250 calculation, median runoff ratio shows a positive trend with basin-averaged an-

251 tecedent SMAP soil moisture for all event definition methods. However, runoff
 252 ratios calculated by using stormflow show less variability and smaller interquar-
 253 tile range for lower antecedent soil moistures (i.e. dry conditions). On the other
 254 hand, runoff ratios calculated by stormflow only exhibit smaller values compared
 255 to using total streamflow.

256 3.2. Rainfall and event-scale runoff ratio

257 Fig. 6 illustrates the variations of runoff ratio with respect to event-scale
 258 rainfall. There is a positive trend between event rainfall and runoff ratio, and
 259 this trend is more pronounced in case of runoff ratios calculated using stormflow
 260 only. On the other hand, the probability of higher runoff ratios increases as the
 261 event scale rainfall increases.

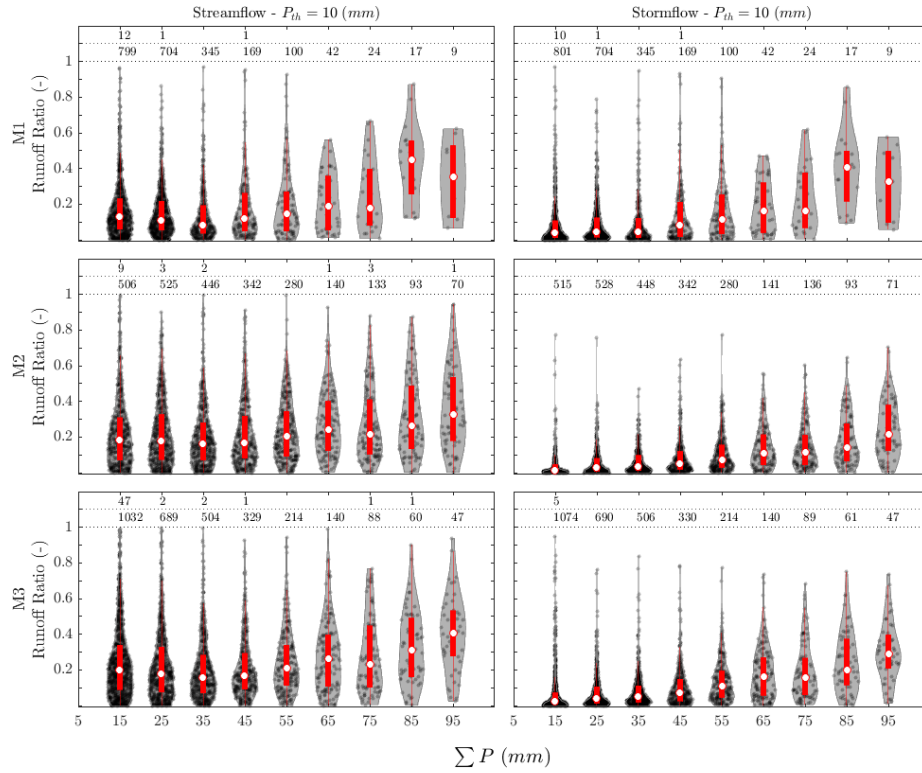


Figure 6: Violinplots of the event-scale runoff ratio (left column: streamflow, right column: stormflow) versus basin-averaged event scale rainfall for events with rainfall depth equal or greater than 10 (mm). The number of rainfall-runoff events with runoff ratio greater than 1 and less than 1 are annotated at the first row and second row at the top of each subplot.

262 As shown in Fig. 6 the relationship between event runoff ratio and event

scale rainfall becomes clear by using stormflow. Furthermore, event definition method M1 shows a slight decrease in median runoff ratio for events with larger basin-averaged rainfall magnitudes. While the positive trend of median runoff ratio is more distinct and monotonic for event definition methods M2 and M3.

Given the differences in definitions of events, overall, all three event definition methods exhibit a positive association in median runoff ratios with respect to basin-averaged event scale rainfall. It should be noted that for smaller magnitudes of event-scale rainfall, runoff ratios calculated by M2 method exhibit least variability among other methods.

3.3. Soil moisture deficit-normalized rainfall and runoff ratio

Distributions of runoff ratio with deficit-normalized rainfall for events with event-scale rainfall equal or greater than 10 (mm) are shown in Fig. 7.

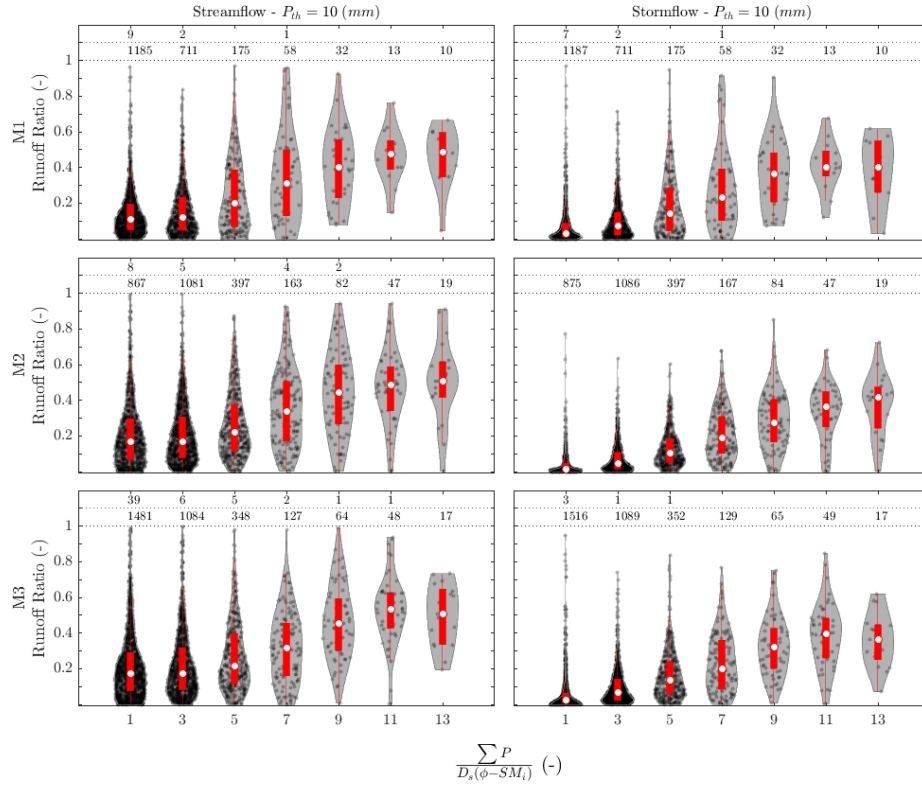


Figure 7: Violinplots of the event-scale runoff ratio (left column: streamflow, right column: stormflow) versus deficit-normalized rainfall for events with rainfall depth equal or greater than 10 (mm). The number of rainfall-runoff events with runoff ratio greater than 1 and less than 1 are annotated at the first row and second row at the top of each subplot.

275 The runoff ratio shows an asymptotic increase with an increasing deficit-
 276 normalized rainfall, whereas for large deficit-normalized rainfall, median runoff
 277 ratio tends to become a constant value. In contrast to runoff ratios calculated
 278 by streamflow (left column in Fig. 7), the interquartile range is smaller by using
 279 stormflow (right column in Fig. 7). The median of the runoff ratio distribution
 280 shift toward larger runoff ratios by approaching to larger deficit-normalized
 281 rainfall.

282 3.4. Summary of correlation and significance

283 A summary of Spearman correlation coefficients between event-scale runoff
 284 ratio with antecedent soil moisture, event-scale rainfall, and deficit-normalized
 285 rainfall calculated by using the three event definitions is shown in Fig. 8. Cor-
 286 relations correspond to events with event-scale basin-averaged rainfall ($\sum P$)
 287 greater or equal to values ranging from 5 to 30 (mm).

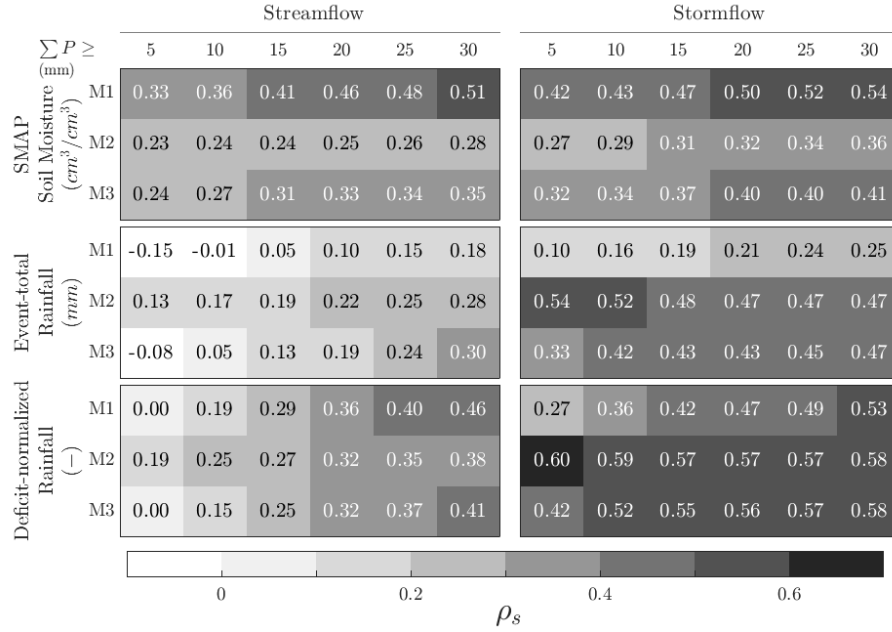


Figure 8: Spearman correlation coefficient for different methods and event-scale rainfall depths. Runoff ratio calculation methods are denoted in left hand side.

288 The correlation coefficient between antecedent soil moisture and runoff ratio
 289 increases as the event-scale rainfall depth increases. The highest Spearman cor-
 290 relations correspond to constant event duration method (M1). Right tail (pos-

itive correlation) Spearman correlation test with 95% confidence level suggests that correlations are statistically significant for both runoff ratio calculation methods (streamflow/stormflow).

The correlations for event-scale rainfall and runoff ratio calculated by streamflow indicate weak or no relationship. For this case, the statistical test was not able to reject the non-existence of significant positive association between these two variables. In contrast, the correlations between runoff ratio and event-scale rainfall are higher and statistically significant by using stormflow only for runoff ratio calculations especially for stormflow-based event definition (M2). This indicates that baseflow separation is a critical step in calculation of runoff ratio.

Deficit-normalized rainfall yields higher Spearman correlation coefficients compared to antecedent soil moisture and rainfall. Exclusion of events by larger rainfall thresholds in Fig. 8, increases the monotonicity of the relationship between deficit-normalized rainfall and runoff ratio for M1 and M3, while M2 shows less sensitivity to event-scale rainfall depth. With this respect, event definition M2 has the highest correlation coefficient whereas the interquartile ranges of runoff ratio are smaller than other two methods (see Fig. 7).

3.5. Annual cycles of runoff ratio, rainfall and vegetation

Fig. 9a and Fig. 9c show variation of event scale runoff ratio and event scale rainfall for each month and Fig. 9b shows basin-averaged MODIS EVI at the beginning of each rainfall-runoff event. The number of events at each month and events with runoff ratio greater than 1 are annotated at the top of this figure. Note that data shown in Fig. 9 correspond to more than 16000 rainfall-runoff events for the period of 17 years (2002-2018).

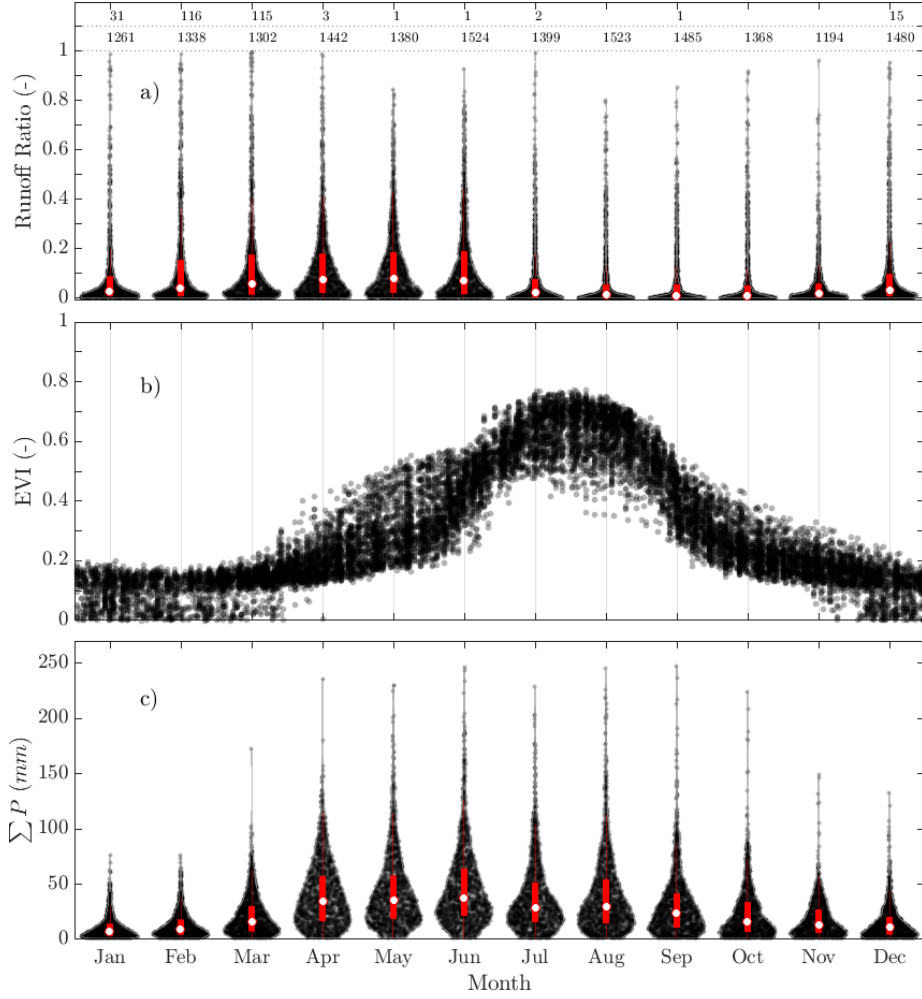


Figure 9: Temporal variation of (a) runoff ratio, (b) MODIS basin-averaged Enhanced Vegetation Index ($EVI < 0$ not shown) and (c) event-scale rainfall over 17 years (2002-2018). The number of rainfall-runoff events with runoff ratio greater than 1 and less than 1 are annotated at the first row and second row at the top.

315 There is a positive trend in median runoff ratio from January to May while
 316 median and interquartile range of runoff ratios decrease significantly from June
 317 to September (Fig. 9a) whereas in August and September the median runoff
 318 ratio is lower compared to May and June.

319 Basin-averaged EVI calculated from MODIS satellite data for each rainfall-
 320 runoff event during 2002-2018 (Fig. 9b) suggests that, for majority of the basins,
 321 peak EVI occurs in a period starting from mid-July to mid-August. Higher
 322 variability of EVI during some time periods (e.g. April-June) is due to year to

year change and variability of EVI from one basin to another.

As shown in Fig. 9c, there is seasonality in event-scale rainfall whereas lowest and highest median event-scale rainfall depths correspond to January and June, respectively.

Using 95 % confidence level, two-tailed Wilcoxon statistical test was not able to reject the null hypothesis of equal medians for event-scale rainfall distribution in August and April. However, the test result on distributions of runoff ratio suggested that there is statistically significant decrease in median value of the runoff ratio in August compared to April.

4. Discussion

Our analysis of the relation between runoff coefficients and antecedent soil moisture conditions using Enhanced SMAP L3 soil moisture data (Fig. 5) show agreement with findings from Crow et al. (2017).

It is important to account for SMAP soil moisture uncertainty in interpretation of our results for relationship between antecedent soil moisture and event-scale runoff ratio (Fig. 5). SMAP satellite soil moisture has an average unbiased root mean square error (ubRMSE) in a range from 0.04-0.055 (m^3/m^3) (Chan et al., 2018; Colliander et al., 2018; Zhang et al., 2019) which is close to SMAP mission's ubRMSE requirement. While SMAP soil moisture has shown a better performance compared to other satellite soil moisture products (Stillman and Zeng, 2018), however, it is also found that SMOS and SMAP soil moisture dry-downs are more rapid than in-situ observations following rainfall events (Rondinelli et al., 2015; Shellito et al., 2016).

In contrast to results from Crow et al. (2017), the relationship between event-scale rainfall and runoff ratio (right column in Fig. 6) is more distinct after baseflow separation. Moreover, results from methods M3 and M2 have higher correlations than M1 for event-scale rainfall and runoff ratio (Fig. 8). Consecutive rainfall storms, which increases cumulative rainfall, during a rainfall-runoff event eventually increase the soil moisture that consequently lead to a potentially higher runoff ratio. Previous studies used antecedent precipitation index (API) as a proxy to soil moisture conditions (e.g. Brocca et al. (2008); Crow

et al. (2005); Fedora and Beschta (1989)) for estimation of antecedent conditions.

Deficit-normalized rainfall, introduced as a combination of event total rainfall with antecedent soil moisture of the event, decreased the interquartile range of probable runoff ratios compared to rainfall or antecedent soil moisture relationships with runoff ratio (Fig. 7). To be consistent with SMAP satellite soil moisture sensing depth, we used a constant depth of $D_s = 50$ (mm) for normalization of rainfall by soil moisture deficit. Previous studies have found that representative sensing depth of L-band microwave emission depends on the soil moisture and temperature profiles Escorihuela et al. (2010); O'Neill (1982). Also, Akbar et al. (2018) have estimated the hydrologic storage length scales for Contiguous United States (CONUS) by minimizing the difference between reconstructed time series of soil moisture from rainfall observations and Enhanced SMAP L3 soil moistures. Their estimation of hydrologic depth for Iowa, suggests values in ranges of 30 to 210 (mm).

Iowa is in a heavily agricultural region, where more than 75 percent of its area is cultivated cropland (Homer et al., 2007) and it is planted mainly by corn and soybean, respectively. Previous results from field experiments by Frasson and Krajewski (2011), conducted during full development of maize plant (July 21 to August 26), have shown that maize canopy modifies the rainfall intensity and decreases accumulated rainfall depth underneath the maize plant. Indeed, our results for annual cycle of runoff ratio (Fig. 9a) confirms that median runoff ratio is significantly lower after full development of vegetation. During this time period, median runoff ratio decreases significantly favoring lower runoff ratios. On the other hand, event-scale runoff ratio (Fig. 9a) from October to December indicate an increasing trend which corresponds to time period after active harvesting season for corn in Iowa, between October 5th to November 9th (U.S. Department of Agriculture, 2010).

According to our results shown in Fig. 9c June was identified as the peak frequency for distribution of annual maximum daily rainfall for Iowa. We further found that median event scale rainfall values are equal for April and August. Thus, based on previous literature and our data analysis on long-term temporal variation of runoff ratio and MODIS EVI, the statistically significant decrease in

387 median runoff ratio, from April to August, can be attributed to fully developed
388 vegetation in August compared to lower vegetation cover or bare ground in
389 April. Similar reduction in runoff ratio is expected in similar regions such as
390 Midwest United States where corn and soybean are dominant. We highlight
391 that other than soil moisture, vegetation can significantly decrease the runoff
392 production.

393 First limitation of our study is the coarse spatial resolution of radar rainfall
394 (≈ 4 km) and SMAP satellite-based soil moisture (≈ 9 km). Also, we have used
395 aggregated quantities (e.g. spatial average) for simplification of our analysis
396 while each quantity has spatial variability and associated inherent errors in space
397 and time. We have used three different methods to define a rainfall-runoff event
398 based on daily streamflow observations. There are differences in approximations
399 of runoff ratio by each rainfall-runoff event definition. Therefore each method
400 could introduce errors to estimated runoff ratio. We note that associating a
401 portion of streamflow at a given time to a specific rainfall event is challenging.
402 We have used an empirical method for baseflow separation which may introduce
403 errors in calculation of runoff ratios. Therefore, an accurate baseflow separation,
404 event definition, and runoff ratio estimation demands more field observations
405 such as application of isotopes.

406 5. Conclusions

407 In this study, we investigated the role of antecedent SMAP satellite soil
408 moisture, rainfall, and soil moisture deficit-normalized rainfall on runoff ratio.
409 We used 4 years (2015-2018) of soil moisture, rainfall and streamflow data for
410 38 basins with areas ranging from 80 to 1000 km^2 in Iowa, USA. We examined
411 the dependence of these relationships on the methodology, such as impact of
412 event-scale rainfall depth, baseflow separation and rainfall-runoff event defini-
413 tion in the calculation of runoff ratio. We applied three different methods for
414 event definition such as the one proposed by Crow et al. (2017). We summarized
415 our results for the relationship of soil moisture, rainfall and deficit-normalized
416 rainfall with event-scale runoff ratio using Spearman correlation coefficient. We
417 further explored temporal variability of runoff ratio based on 17 years of data
418 and tried to explain its physical controls by MODIS EVI and event-scale rain-

419 fall. Considering all above-mentioned points, the following conclusions could be
420 drawn:

- 421 • The positive trend of runoff ratio (with and without baseflow separation)
422 with respect to antecedent soil moisture implies that SMAP satellite soil
423 moisture, without data assimilation, is by itself skillful for estimation of
424 event-scale runoff ratio. Therefore, our study shows that the relationship
425 shown by Crow et al. (2017) exists in Iowa, which more than 75% of it is
426 covered by cropland (corn and soybean).
- 427 • Although baseflow separation decreases the runoff ratio estimates, we have
428 found that the significance of the relationship between antecedent soil
429 moisture and runoff ratio is independent of the methodology.
- 430 • In contrast to results by Crow et al. (2017), event-scale rainfall has a
431 significant relationship with runoff ratio and it is revealed after removing
432 the baseflow signal from streamflow hydrograph.
- 433 • We showed that deficit-normalized rainfall has more predictive power for
434 estimation of basin-scale event runoff ratios compared using SMAP an-
435 tecedent soil moisture and event-scale rainfall individually.
- 436 • Long-term analysis of enhanced vegetation index (EVI) indicated that
437 vegetation peak occurs in a time period from mid-July to mid-August
438 which correspond to time period of full development of crops, after which
439 runoff ratio decreases significantly.
- 440 • In addition to antecedent soil moisture and event-scale rainfall, vegeta-
441 tion also plays a significant role in determination of runoff ratio in an
442 agricultural region.

443 We have demonstrated a potential application of remote sensing data for un-
444 derstanding the rainfall-runoff partitioning and main physical controls on runoff
445 ratio in basin scale. We used MODIS satellite data along with L-band radio-
446 metric SMAP satellite soil moisture, and S-band radar rainfall that complement
447 the essential information for understanding hydrologic processes. An analysis
448 of runoff production and its controls with a similar spatial coverage and time
449 period as used in this study could be challenging without remote sensing data.

Our findings are useful for regions that have similar climate and cropland conditions. Such similarities are found in regions within Upper Mississippi and Ohio River basins (Schilling et al., 2015).

For practical flood forecasting purposes, we introduced deficit-normalized rainfall, as a dimensionless index, that could be used for assessment of the severity of forecast rainfall with respect to available space in top soil and estimation of runoff. In this case, daily total rainfall forecast and antecedent soil moisture could be used for estimating runoff production and local flash flood warnings.

Our approach could be used for evaluating the degree of coupling between antecedent soil moisture, rainfall and impact of vegetation on runoff ratio in hydrologic models, similar to study done by Crow et al. (2018), in agricultural regions.

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