Online supplementary materials for

**Persistent Impact of Spring Floods on Crop Loss in U.S. Midwest**

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1. Probabilistic Flood Mapping

Given the log-transformed backscattering intensity ($\sigma^0$) of a pixel, the conditional probability of a pixel being flooded, $p(F|\sigma^0)$, is estimated as follows (Giustarini et al. 2016):

$$ p(F|\sigma^0) = \frac{p(\sigma^0|F)p(F)}{p(\sigma^0)} \quad (1) $$

$$ p(\sigma^0) = p(\sigma^0|F)p(F) + p(\sigma^0|F)\bar{p}(F) \quad (2) $$

where $p(\sigma^0|F)$ is the probability distribution of backscatter value $\sigma^0$ of water pixels ($F$) and $p(\sigma^0|F)$ is the probability distribution of backscatter value $\sigma^0$ of non-water pixels ($\bar{F}$). Also, $p(\sigma^0)$ is the marginal probability of recording a given backscatter value $\sigma^0$ for any pixel. The terms $p(F)$ and $p(F)$ are the prior probabilities of a pixel being flooded and non-flooded, respectively. The priors are chosen as $p(F) = p(\bar{F}) = 0.5$, which assigns an equal chance of a pixel being flooded or non-flooded (Westerhoff et al. 2013). Earlier studies indicate that flooding posterior probability density function is not significantly affected by priors' choice (Giustarini et al. 2016). To approximate $p(\sigma^0|F)$ and $p(\sigma^0|F)$ we chose a subset of SAR image that mostly includes flooded or non-flooded pixels and plot backscatter value histograms, which mimic a Gaussian distribution (Figure S2). Next we fit a normal distribution to the backscatter values, which results in an analytical expression of the $p(\sigma^0|F)$ and $p(\sigma^0|F)$.

2. Normalized Difference Vegetation Index

Normalized Difference Vegetation Index (NDVI) is defined as:

$$ NDVI = \frac{(NIR - Red)}{(NIR + Red)} \quad (3) $$

where $NIR$ and $Red$ are the reflectances in the near-infrared and red ranges of the electromagnetic spectrum. $NDVI$ ranges between -1 and +1: more positive values are associated with areas of dense vegetation, whereas negative values typically characterize snow and clouds. MODIS NDVI is computed using Equation 3 with the NIR1 (band 2, band center 858 nm) and Red (band 1, band center 648 nm) bands (Didan et al. 2015).

3. Stream Change-point Detection

Assuming that $K-1$ abrupt changes have occurred in the time series $Y_i, i = 1, 2, ..., n$ at unknown instants $t_j^*, 1 \leq j \leq K - 1$, the problem of change-point detection can be defined as estimating the vector of configurations (i.e. the normalized change points) $\tau^* = (\tau_1^*, ..., \tau_{K-1}^*)$. 


where \( \tau_j^* = t_j^*/n \), and the vector of statistical parameters for all the "intrachange" segments \( \theta^* = (\theta_1^*, ..., \theta_K^*) \). Denoting the space of parameters by \( \Theta_K = \{ \theta = (\theta_1, ..., \theta_K) \} \) and the space of configurations as \( T_K = \{ \tau = (\tau_0, \tau_1, ..., \tau_K), \tau_0 = 0, \tau_K = 1 \} \), the unknowns \( (\tau^*, \theta^*) \) can be estimated by minimizing the function (Lavielle 1999):

\[
J_n(\tau, \theta) = \sum_{k=1}^{K} W_n(Y_k, \theta_k)
\]

where \( W_n(Y_k, \theta_k) \) is the contrast function estimated over segment \( \kappa \) of the time series for a given configuration \( \tau \), denoted by \( Y_k \).

In the context of discharge measured by the stream gage stations, both the mean and variance of time series can simultaneously vary as a result of rapid changes. Therefore, the statistical parameters for each segment, \( Y_k \) of length \( n_k \) are \( \theta_k = (\mu_k, \sigma_k^2) \), where \( \mu_k \) and \( \sigma_k^2 \) are the mean and variance, respectively, and the contrast function can be defined as (Lavielle 1999):

\[
W_n(Y_k, \theta_k) = \frac{\|Y_k - \mu_k\|^2}{n \sigma_k^2} + \frac{n_k}{n} \log \sigma_k^2
\]

The unknown parameters \( (\tau^*, \theta^*) \) can then be estimated by minimizing the function (Lavielle 1999):

\[
J_n(\tau, \theta) = \frac{1}{n} \sum_{k=1}^{K} \left( \frac{\|Y_k - \mu_k\|^2}{\sigma_k^2} + n_k \log \sigma_k^2 \right)
\]

Instead of searching for change-points in the discharge time series in the time domain, here we implemented the minimization on the wavelet coefficients, obtained from Maximal Overlap Discrete Wavelet Transform (MODWT) (Percival and Mofjeld 1997). Since the mean of the wavelet coefficient does not change in time, working with these coefficients reduces the optimization parameters in equation (6) to the variance of each segment (\( \sigma_k^2 \)), by setting \( \mu_k = \bar{\mu} \). Moreover, the benefits of using MODWT over regular Discrete Wavelet Transform (DWT) are: 1) in contrast to the DWT, which is restricted to samples sizes of integer multiples of \( 2^n \), MODWT is well-defined for any sample size, 2) MODWT is a zero-phase filter, enabling us to line up the wavelet coefficients with the original time series in a multiresolution analysis, and 3) due to the absence of down-sampling in multiresolution analysis through MODWT, the variance estimator of the wavelet coefficients is statistically more efficient (Percival and Mofjeld 1997).

Here we use the order two Daubechies wavelet, "db2", to estimate the wavelet coefficients of the discharge time series of each station, up to level 6, \( W_l, l = 1, ..., 6 \). Next, we apply the minimization procedure, explained above, on the obtained coefficients of each level separately to estimate the change-points \( t_i^* = (t_1^*, ..., t_6^*) \), assuming \( K = 1 \) (i.e., a single change-point). Only the
time series with $t_i^* \neq 0$ and $\max(t_i^*) - \min(t_i^*) < 365$ are flagged as ones with at least one change-point. Of 476 stations with more than 50 years of data entries and less than two consecutive years of data gaps, 16 were flagged as containing a change-point (Fig. S9). For these time series, removing the entries before the change-point (unless it occurs after 2015, in which case, the entries following change-point are removed), only the ones are kept that still satisfy the 50+ years length, leaving us with 471 stations for the following analyses.

4. Mann Kendall Trend Test

The Mann Kendall (M.K.) statistic for the sequence is estimated as:

$$S_t = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \text{sgn}(tD_j - tD_i)$$

(7)

where $tD_x$ is either the maximum discharge time series estimated using the moving-window maximum method, or the sequence of recurrence time estimated using the POT method. These values represent the magnitude and frequency of flooding events, respectively. Parameter $n$ is the length of the time series and $\text{sgn}$ is the signum function. The subscript $t$ denotes that the M.K. test is applied to the annual and each seasonal maximum discharge/recurrence time series, separately.

The variance of $S_t$ is estimated using:

$$\text{Var}(S_t) = \frac{1}{18} [m(m - 1)(2m + 5)]$$

(8)

Then $S_t$ and $\text{Var}(S_t)$ are used to estimate the test statistic $Z_t$ as follows:

$$Z_t = \begin{cases} 
(S_t - 1)/\text{Var}(S_t) & \text{if } S_t > 0 \\
0 & \text{if } S_t = 0 \\
(S_t + 1)/\text{Var}(S_t) & \text{if } S_t < 0 
\end{cases}$$

(9)

Next, we estimate the M.K. test $p$-value as:

$$p_t = 1 - N_{cdf}(|Z_t|)$$

(10)

where, $N_{cdf}$ is the Gaussian cumulative distribution function which operates on $|Z_t|$. We chose the sequences with $p$-values below 0.05, which is the chosen significance level for the M.K. test (95% confidence level). Lastly, the signed magnitude of the monotonic trend, $\beta$, is estimated as (Sen 1968):

$$\beta = \text{median} \left( \frac{tD_k - tD_l}{k-l} \right), \ \forall \ k > l$$

(11)

The results of this analysis are shown in Figures 4B and S6-S8.
5. Chi-Square test of independence

The Chi-Square test of independence is a nonparametric approach to analyzes the association between frequencies or counts off two datasets, in which the observed frequency and expected frequency for particular outcomes are compared (Maxwell 1961). The null hypothesis states that the two parameters are independent. To perform the test, for each county, we consider two states of flooded and non-flooded and two states of delayed and early greenup (or zero and non-zero prevent plant acres). Thus the crosstabulation table includes the frequency of counties flooded/delayed greenup, flooded/early greenup, non-flooded/delayed greenup, and non-flooded/early greenup. The so-called degree of freedom is $df = (r - 1) \times (c - 1)$, where $r$ and $c$ are number of row a coulombs in crosstabulation table equal to 2 and 2 here and are the numbers of possible outcomes for flood status and greenup status. Given total number of counties ($n$), counties flooded/delayed greenup ($n_{11}$), flooded/early greenup ($n_{12}$), non-flooded/delayed greenup ($n_{21}$) and non-flooded/early greenup ($n_{22}$), the observed Chi-Squares statistic ($\chi^2$) is

$$
\chi^2 = \sum_{i=1}^{2} \sum_{j=1}^{2} \frac{(O_{ij} - E_{ij})^2}{E_{ij}}
$$

(12)

Where $O_{ij}$ is the observed frequency at the $i$th row and $j$th column of crosstabulation table and $E_{ij}$ is defined as

$$
E_{ij} = \frac{\sum_{i=1}^{2} n_{i} \times \sum_{j=1}^{2} n_{ij}}{n}
$$

(13)

To reject the null hypothesis, the observed Chi-squares statistic should be larger than its theoretical value.
Figure S1. Monthly precipitation data aggregated over the study area shown in Figure 1. Source: ECMWF-ERA5 provided through the Copernicus Climate Change Service.
Figure S2. Example of SAR image acquired on 2019/05/11, UTC001336 with a center coordinate of Lon: -96.9845° and Lat: 43.6207°. A. Log-transformed amplitude image. B. Probabilistic flood map, C. Flooded and Non-flooded pixel backscatter value distribution for the subset shown in panel A.
Figure S3. An example showing the index map 'flood-index-15' for images acquired on May 21 and May 31 (top-left) and a flood map 'flood-457' for date 2019/05/30 and UTC time 23:55:51 (top-right), whose center location is marked by number 257 in index map. The probability values close to 1 indicate flooding. To access all of the flood maps, see https://drive.google.com/drive/folders/1ox9Pqrdz0L7DjgsVWRed0rWVY5U22O5l?usp=sharing. Also, a Sentinel-2 optical image (bottom-right) shows the flood extent for May 31, 2019. Shown is a band combination of 11-8-3 illustrating water/flood as blue, cloud as white and everything else as green.
**Figure S4.** Distribution of the greenup Day of Year for years 2010 through 2019 obtained from an analysis of the NDVI time series.
**Figure S5.** A. Example of stream discharge time series associated with a station located in Iowa (Lat: 41.767°, Lon: -90.535°). Yellow color marks the discharge values associated with spring and red circles are annual spring discharge maximums. B. The histogram of the maximum spring discharge of all the discharge stations used in this study and the fitted Extreme Value Distribution (EVD) to this histogram (black line). Inset shows the cumulative EVD associated with the histogram.
Figure S6. Trends in the magnitude of flood events at the annual scale, estimated through Box Maximum method. Out of 200 stations with a trend (red and blue triangles) in the magnitude of flood events at 5% significance level, ~68% (137) and ~32% (63) show an increase and decrease in the magnitude of flood events, respectively.
Figure S7. Trends in the magnitude of flood events at the seasonal scale, estimated through Box Maximum method. During spring (A), 140 stations have trends with ~64% (89) and ~36% (51) showing increasing and decreasing trends, respectively. Corresponding estimates for summer (B) are 212, ~70% (148), and ~30% (64), for autumn (C) are 212, 81% (172) and 19% (40), and for winter (D) are 241, 89% (214) and 11% (27), respectively.
**Figure S8.** Trends in the frequency of flood events at the annual scale, estimated through Point over Threshold method. Out of 190 stations with a trend (red and blue triangles) in the frequency of flood events at 5% significance level, ~78% (149) and ~22% (41) show an increase and decrease in the frequency of flood events, respectively.
Figure S9. The discharge time series for 16 stations flagged as containing a single change-point. The original time series and the sub-segment used for the analysis of magnitude and frequency are shown with blue and black curves, respectively. The vertical red dashed line shows the timing that change-point has occurred. The number on each panel denotes the station I.D. number.
References


