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Key Points:

- Locally elevated water vapor levels are observed during an extreme heat event occurring in the Midwestern U.S.
- This anomaly is primarily caused by crop transpiration that we constrained using MODIS water vapor observations through an inversion
- Excess moisture aggravates the heat index (3.3 °C) not only through enhancing humidity but also by inducing positive radiative forcing

Supporting Information:

- Supporting Information S1

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Quantifying the Impact of Excess Moisture From Transpiration From Crops on an Extreme Heat Wave Event in the Midwestern U.S.: A Top-Down Constraint From Moderate Resolution Imaging Spectroradiometer Water Vapor Retrieval

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Abstract The primary focus of this study is to understand the contribution from excess moisture from crop transpiration to the severity of a heat wave episode that hit the Midwestern U.S. from 16 to 20 July 2011. To elucidate this, we first provide an optimal estimate of the transpiration water vapor flux using satellite total column water vapor retrievals whose accuracy and precision are characterized using independent observations. The posterior transpiration flux is estimated using a local ensemble transform Kalman filter that employs a mesoscale weather model as the forward model. The new estimation suggests that the prior values of transpiration flux from crops are biased high by 15%. We further use the constrained flux to examine the sensitivity of meteorology to the contributions from crops. Over the agricultural areas during daytime, elevated moisture (up to 40%) from crops not only increases humidity (thus the heat index) but also provides a positive radiative forcing by increasing downward longwave radiation ($13 \pm 4 \text{ W m}^{-2}$) that results in even higher surface air temperature ($+0.4 \text{ °C}$). Consequently, we find that the elevated moisture generally provides positive feedback to aggravate the heat wave, with daytime enhancements of heat index by as large as $3.3 \pm 0.8 \text{ °C}$. Due to a strong diurnal cycle in the transpiration, the feedback tends to be stronger in the afternoon (up to 5 °C) and weaker at night. Results offer a potential basis for designing mitigation strategies for the effect of transpiration from agriculture in the future, in addition to improving the estimation of canopy transpiration.

1. Introduction

Exposure to heat waves is one of the primary reasons for weather-related casualties in the Midwestern U.S. (Wang et al., 2018). Anthropogenic activities may contribute to the severity of such events. While a regional oscillation in climate over a course of year can result from major climatic drivers such as the El Niño-Southern Oscillation (ENSO), not all ENSO events are found to be conducive to an extreme event (Hunt, 2007). Similarly, the response of heat waves to anthropogenic forcing can manifest itself in non-stationary extremes that can hardly be disentangled from natural variabilities. As such, the sensitivity of heat waves to anthropogenic forcing is mostly relevant in a stochastic framework (Stott et al., 2004). On the other hand, the impact of human-induced land use/land cover changes on climate can be sufficiently large to represent an identifiable signal above the noise of natural variability. The deterministic quantification of these human-induced signals on weather and climate becomes feasible to be able to minimize their negative impacts. Some examples of these signals include wetlands (Marshall et al., 2003; Steyaert & Knox, 2008), rapid urbanization (Jacobson et al., 2015; Zhang et al., 2018), irrigation (Puma & Cook, 2010), and deforestation (Dickinson & Kennedy, 1992; Gullison et al., 2007), all of which can directly affect surface properties in a relatively short time span.

What makes the Midwest interesting to study is that the area is heavily agricultural, potentially providing a source of moisture and latent heat through irrigation and canopy transpiration (Wei et al., 2017). Fundamentally, irrigation cools down the surface temperature due to evaporative cooling (Cook et al., 2015). This source of water vapor can be sufficiently high such that irrigation in one place can

result in rainfall in other places downwind (de Vrese et al., 2016). However, moisture emitted from crops via transpiration induced by an atmospherically stagnant condition can pile up and exacerbate human-perceived heat by increasing humidity (heat index). This phenomenon, known as “corn sweat” (due to the dominant corn fields in the area), has implications for both the severity of heat waves and a better understanding of hydrological processes. Therefore, this study aims at quantifying the contributions of excess moisture from canopy transpiration to a heat wave episode that took place in the Midwestern U.S.

Canopy transpiration is a multifaceted quantity, controlled by a combination of soil properties, atmospheric environment, and physiological responses of vegetation to that environment. A study by Wei et al. (2017) found a solid relationship between leaf area index, vegetation class, and transpiration over the globe by combining measurements from various sources. They found that transpiration accounts for $57.2 \pm 6.8\%$ of the global budget of evapotranspiration. The transfer of water vapor from the plant stomata to the air outside is mainly dictated by canopy resistance. Various configurations for how weather and hydrological models treat canopy resistance exist (Zhang et al., 2016). The Noah Land Surface Model (LSM; Chen & Dudhia, 2001; Ek et al., 2003) is a widely used surface parameterization in weather models that formulates canopy transpiration based on a canopy resistance scheme adopted from Jacquemin and Noilhan (1990) and Noilhan and Planton (1989). In general, the resistance is dependent on solar radiation, air temperature, soil moisture, and vapor pressure deficit. The canopy resistance formulation in this model introduces some structural uncertainties exacerbated by feedback uncertainties resulting from the moisture flux parameters used in the resistance calculation (e.g., Xu et al., 2017).

Remote sensing is widely used for estimating regional and global evapotranspiration (Cleugh et al., 2007; Fisher et al., 2008; Guzinski & Nieto, 2019; Mu et al., 2011). Since this technology measures a wide range of atmospheric and terrestrial properties, various methods have been proposed for such application. They can be grouped into (i) an empirical way that bridges the measured values (e.g., using eddy covariance method) to satellite-derived vegetation properties; (ii) a more physical approach based on the Penman-Monteith equation with the knowledge of fraction of vegetation cover, weather information, and canopy/soil resistance; and (iii) algorithms using thermal bands, which establish a relationship between surface temperature and several vegetation indices (i.e., Ts-VI triangle method). A comprehensive review of these methods can be found elsewhere (Fisher et al., 2017; Zhang et al., 2016).

One way to improve our knowledge on transpiration is to use relevant observations to indirectly constrain moisture flux, that is, to infer how much moisture should have been released from canopy to match the relevant quantity (here atmospheric moisture) of the measured values. Such an estimation, known as “inverse modeling,” has been extensively used in optimizing various surface fluxes such as CO_2 (e.g., Liu, Bowman, et al., 2016), CH_4 (e.g., Jacob et al., 2016), and NO_x (e.g., Souri et al., 2016, 2018) but has received little attention in terms of transpiration.

Water vapor, a main product from canopy transpiration, has been continuously measured by visible (González Abad et al., 2019; Grossi et al., 2015; Wang et al., 2014, 2019), near infrared (NIR), infrared (IR), and microwave satellite instruments (King et al., 2003; Schröder et al., 2018). Unless the limitations of each satellite product are carefully characterized, each data set can be incorrectly incorporated into weather models, potentially forcing them to diverge. We use NIR observations that benefit from high signal to noise ratio and are available from currently high spatial resolution sensors such as the Moderate Resolution Imaging Spectroradiometer (MODIS). The main weakness of the NIR water vapor products lies in their lack of information over water (unless sun glint is present). Nonetheless, the usefulness of the data over land makes it suitable for our study. Owing to the fact that the MODIS NIR water vapor column product has potential biases (Li et al., 2003), characterization of its errors using GPS observations (Bevis et al., 1994) is crucial for an unbiased estimation of the canopy transpiration.

The purpose of this paper is twofold. We (i) provide a top-down constraint on canopy transpiration flux by incorporating MODIS water vapor products during an extreme heat wave in the Midwest, and (ii) after adjusting the transpiration flux, we assess the roles of the excess moisture from transpiration in the development of such an extreme event.

Figure 1. Simulation domain configuration. The GPS sites from SuomiNet are superimposed on d02.

associated with MODIS vary with time and space, we will determine the bias and covariances of the selected pixels using GPS observations.

2.2. GPS Water Vapor

We characterize the errors of the MODIS observations using GPS-derived water vapor product from SuomiNet network (Ware et al., 2000). We consider the GPS observations as the ground truth. The ray between a GPS satellite and a receiver is refracted while scanning the atmosphere as a result of both neutral and ionized parts of the atmosphere. Through an optimization procedure, the water vapor slant column is estimated and mapped into vertical column using a geometrical mapping function. Previous studies such as Li et al. (2003) and Ohtani and Naito (2000) found a strong agreement between GPS measurements and those from radiosondes and microwave radiometers with standard deviations of about 1–2 mm. The data have hourly resolution. The spatial distribution of the observations in our region of interest is shown in Figure 1.

2.3. Weather Research and Forecasting

We simulate a heat wave event using the Weather Research and Forecasting model (WRF) v3.9.1 (Skamarock et al., 2005) in a nested setup that encompasses a 36-km resolution outer domain and a 12-km resolution inner domain. The period of simulation is from 10 through 21 July 2011. The first week of simulation is used for spin-up in terms of meteorological variables such as winds, temperature, and atmospheric moisture. A number of studies suggested that a long spin-up is required for replicating soil moisture anomalies in land-atmosphere models (Lawston et al., 2015; Santanello et al., 2013). Consequently, we run the model from 1 January 2010 to 10 July 2011 (~18 months) to provide more realistic soil initial conditions at the beginning of our simulation. The parent domain has 120 west-east by 120 south-north grids, and 27 vertical sigma pressure levels covering the Gulf of Mexico, Mexico, and some portions of the United States and Canada. The nested domain focuses on the Midwest U.S. where the heat wave event happened. The nested domain will be the primary domain for the top-down canopy transpiration estimation as well as the sensitivity of heat wave to transpiration. The initial and lateral boundaries for the parent domain are provided by the National Centers for Environmental Prediction North American Regional Reanalysis (NARR) with 32 km and 3 hr spatial and temporal resolutions. To minimize the errors from the boundaries in the nested domain, we nudge the parent domain toward the reanalysis given that the reanalysis has been constrained by various observations (Mesinger et al., 2006). For the top-down estimation of canopy transpiration, we nudge the nested domain only with wind and temperature fields, as we do not want the external forces on moisture (from nudging) to undermine the effectiveness of our top-down estimation. The sea surface temperature and leaf area index are updated every 3 hr based on satellite measurements included in the

2. Measurements, Modeling, and Methods

2.1. MODIS NIR Water Vapor

The primary satellite observation used in this study for inverting the canopy transpiration is based on the MODIS NIR Precipitable Water Vapor (MOD05) product from both Terra (~10:30 LT) and Aqua (~13:30 LT) platforms (Kaufman & Gao, 1992). The retrieval mainly relies on the water vapor transmittance in NIR channels, which permits an estimation of the total number of water vapor molecules based on a line-by-line atmospheric transmittance calculation from the HITRAN2000 database. Since deriving water vapor transmittance from a single band requires precise knowledge of surface properties, the retrieval algorithm uses the ratios of water vapor absorption at wavelengths around $0.94 \mu\text{m}$ with other nonabsorbing water vapor NIR channels at 0.86 and $1.24 \mu\text{m}$. Using the ratio technique in the retrieval substantially removes the dependency on surface properties. The spatial resolution of the product is 5 km. We select only qualified pixels based on the retrieval quality and cloud mask (95% confidence in clear sky) flags. Previous validation of this product against GPS observations (Li et al., 2003), microwave radiometers (King et al., 2003), and AERONETs (Prasad & Singh, 2009) suggested a good correlation (~0.80–0.90) among the data sets. Because the errors

Table 1
Major Configuration of the WRF Setup

Domains	d01	d02
Horizontal resolution	36 km	12 km
Number of grid cells	120 × 120	196 × 181
Time step	120 s	40 s
Microphysics	WSM-6	WSM-6
PBL	YSU	YSU
Surface model	Noah LSM	Noah LSM
Cumulus subgrid parameterization	KF	KF
Short and longwave radiation	RRTMG	RRTMG

Note. WSM-6 = WRF Single-Moment 6-Class (Hong & Lim, 2006); YSU = Yonsei University (Hong, Noh, & Dudhia, 2006); KF = Kain-Fritsch (Kain, 2004); RRTMG = The Rapid Radiative Transfer Model for Global models.

reanalysis data. All domains are shown in Figure 1. The model configuration and parameterization are listed in Table 1.

2.4. Experiments

The influence of excess moisture from canopy transpiration on the heat wave is determined through an experiment consisting of two simulations; the first simulation includes the contributions of moisture and latent heat flux from all types of vegetation (CONTROL), while the second one removes those from croplands (NOCROP). In other words, we cease crops to transpire during the heat wave episode while keeping the surface energy constant to be able to isolate the impact of the excess moisture and the latent flux on the atmosphere. This alteration is only applied to the nested domain to have consistent boundary conditions. For these two sensitivities, we fully detach the nested domain from the grid nudging to rule out the external influences. To generate this experiment, we apply

a factor depending on the cropland fraction such that a fully cropland grid cell yields a zero value in canopy transpiration. The factor is applied outside of the Noah LSM module to isolate the impact of moisture and latent heat fluxes on the atmosphere only (i.e., to decouple their direct effect on the land model). Other characteristics of crops in the model including their surface friction, vegetation fraction, albedo, canopy temperature, and emissivity are kept unchanged in both experiments to have roughly consistent surface energy and water balance between two scenarios. A major assumption made in designing the NOCROP experiment is that the buried moisture content will neither escape to the atmosphere nor increase the top-layer soil moisture within a week.

2.5. Inverse Modeling

In this study, the procedure of the inversion follows a local ensemble transform Kalman filter (LETKF; Hunt, Kostelich, et al., 2007) which is a Monte Carlo approximation of the Bayesian formulation involving prior knowledge of an unknown ($\mathbf{x}$, surface transpiration moisture flux) and observed values ($\mathbf{y}$, column water vapor) that requires assumptions on the uncertainties associated with both quantities. Following common practice for Monte Carlo approximations, we randomly perturb the transpiration moisture flux based on a probability distribution $P(\mathbf{x})$ and conduct deterministic forward model estimations of total column water vapor using WRF, $P(\mathbf{y}|\mathbf{x})$, thereby allowing an estimate of the maximum likelihood of $P(\mathbf{x}|\mathbf{y})$.

We simulate ensemble models ($\mathbf{x}^{b(i)} : i = 1, 2, \dots, k$) with 50 members ($k = 50$) by applying randomness to canopy transpiration flux in the Noah LSM module. One can calculate the mean and covariance of the a priori of flux by:

$$\bar{\mathbf{x}}^b = \frac{1}{k} \sum_{i=1}^k \mathbf{x}^{b(i)}, \quad (1)$$

$$\begin{aligned} P^b &= \frac{1}{k-1} \sum_{i=1}^k \left(\mathbf{x}^{b(i)} - \bar{\mathbf{x}}^b \right) \left(\mathbf{x}^{b(i)} - \bar{\mathbf{x}}^b \right)^T \\ &= \frac{1}{k-1} \mathbf{X}^b \cdot \mathbf{X}^{bT}, \text{ where } \mathbf{X}^{bT} \text{ is the vector of } \mathbf{x}^{b(i)} - \bar{\mathbf{x}}^b \text{ (i.e., perturbations)}. \end{aligned} \quad (2)$$

P^b has at most $(k-1)$ rank ($= \text{rank of } \mathbf{X}^b$), which makes it noninvertible for minimizing the cost function that has been commonly targeted in Kalman filter (e.g., Souri et al., 2018). In order to address this, Hunt, Kostelich, et al. (2007) defined an intermediate variable ($\mathbf{w}$) that acts as a Gaussian filter with mean $\mathbf{0}$ and covariance of $(k-1)^{-1} \mathbf{I}$, such that $\mathbf{x} = \bar{\mathbf{x}}^b + \mathbf{X}^b \mathbf{w}$. Consequently, one can update the a priori by minimizing the following quadratic cost function:

$$J(\mathbf{w}) = (k-1) \mathbf{w}^T \mathbf{w} + [\mathbf{y}^o - H(\bar{\mathbf{x}}^b + \mathbf{X}^b \mathbf{w})]^T (\mathbf{R}^{-1} E) [\mathbf{y}^o - H(\bar{\mathbf{x}}^b + \mathbf{X}^b \mathbf{w})], \quad (3)$$

where H is the Jacobian matrix for projecting the state vectors onto the observational space, $\mathbf{y}^o$ is the observations (water vapor columns), $\mathbf{R}$ is the covariance matrix of the observations, and E is the spatial localization computed from the physical distance of observations from the model grid (discussed later). $\mathbf{R}$ is

quantified by comparing MODIS with GPS observations. Under the assumption that the relationship between both observations and unknowns are linear, we can approximate:

$$H(\bar{\mathbf{x}}^b + \mathbf{X}^b \mathbf{w}) = \bar{\mathbf{y}}^b + \mathbf{Y}^b \mathbf{w}, \quad (4)$$

where $\bar{\mathbf{y}}^b$ denotes the mean of simulated water vapor columns from all the members and $\mathbf{Y}^b$ represents the deviation of each member from that mean. Then, the solution for the cost function is given by:

$$\tilde{\mathbf{w}}^a = \tilde{\mathbf{P}}^a (\mathbf{Y}^b)^T (\mathbf{R}^{-1} \mathbf{E}) (\mathbf{y}^o - \bar{\mathbf{y}}^b), \quad (5)$$

$$\tilde{\mathbf{P}}^a = \left[(k-1) \mathbf{I} + (\mathbf{Y}^b)^T (\mathbf{R}^{-1} \mathbf{E}) \mathbf{Y}^b \right]^{-1}, \quad (6)$$

and the a posteriori mean and covariance are estimated according to the following formula:

$$\mathbf{x}^a = \bar{\mathbf{x}}^b + \mathbf{X}^b \tilde{\mathbf{w}}^a, \quad (7)$$

$$\mathbf{P}^a = \mathbf{X}^b \tilde{\mathbf{P}}^a (\mathbf{X}^b)^T. \quad (8)$$

Since the target of our study is the moisture flux from canopy transpiration, we focus on only perturbing the canopy transpiration flux to generate the ensemble simulations. We specifically apply the randomness just right after the canopy transpiration is initially calculated in Noah LSM module (*module_sf_noahlsf.F*) to be able to account for its physical impacts on other land/atmosphere processes. The randomness coefficients applied to each member is drawn from a lognormal distribution with a mean of 1 and a variance equal to our initial assumption on the flux uncertainty which is set to 50%. The coefficients are kept constant temporally and spatially in order to generate a reasonable spread in the ensemble by minimizing the canceling effect (Dai et al., 2019).

The LETKF technique requires both localization in time and space (Dai et al., 2019; Hunt, Kostelich, et al., 2007; Liu, Bowman, et al., 2016; Liu, Chen, et al., 2016), which means that the posteriori is independently estimated in each model grid cell at a given time within a defined radius. We determine the spatial localization (E) using the normalized cumulative semiovariogram of observations (Şen, 1997), which strongly fit ($R^2 = 0.97$) the Cressman formula: $E = \frac{(D^2 - d^2)}{(D^2 + d^2)}$. This function weighs the observations based on their Euclidian distance d to the model grids; D is the influence radius of the observations that is set to 0.25° based on trial and error. With regards to temporal localization, due to the presence of several gaps resulting from cloudiness and other retrieval errors, we average the MODIS observations for the entire 5-day period so that TERRA constrains the morning (06:00–11:59 LST), while the AQUA constrains the afternoon (12:00–18:00 LST).

3. Results and Discussion

3.1. Characterization of a Heat Wave in the Midwest and Uncertainties Associated With Observations

We begin by detecting a heat wave episode over the corn belt area shown a red box in Figure 2 in the Midwest. According to Figure 2, this area encompasses ~52% of croplands category (Figure S1 in the supporting information). The fraction of irrigated cropland areas seems insignificant compared to nonirrigated ones. There is no universal definition of heat wave as the perception of it is subjective to location. Here, we follow Robinson (2001) who used both the daily maximum and minimum heat index (HT) to identify a heat wave if the threshold values for $HT_{\max} = 40.6^\circ\text{C}$ and $HT_{\min} = 26.7^\circ\text{C}$ are met in two consecutive days. Following this definition, we detect only one episode over the area from 2005 to 2018 using the NARR reanalysis data, which occurred from 16 to 20 July 2011. This particular year witnessed several climate extreme events in the United States including a severe drought in Texas, tornado outbreak in the southern states, and the aforementioned heat wave (Luo & Zhang, 2012; Peterson et al., 2012). Figure 3 shows the anomaly at 500 mb geopotential height (left panel) and that of air temperature at 2 m (right panel) based on the subtraction of their daily averaged values during the episode from the climatology (1981–2011). It is evident that the Midwest

Figure 2. The 24-class category U.S. Geological Survey (USGU) land-use classification map. The box A subsets a heavily agricultural area known as “corn belt.”

experienced a high pressure system associated with persistent high temperature that reached 6°C above the norm. The daily HT_{max} during the episode is $44.7 \pm 0.9^{\circ}\text{C}$ over the corn belt area.

Figure 4 shows the MODIS/Aqua Integrater Water Vapor (IWV) July climatology derived with observations extending from 2000 till 2018 (panel a), the MODIS/Aqua IWV observations averaged for the 5-day heat wave period overplotted with corresponding GPS observations (panel b), and the difference between the climatology and the 5-day observations (panel c). We observe a pronounced water vapor signal over the corn-belt during the heat wave. The IWV anomaly for those days reaches values as high as 40 mm. A sensitivity experiment using WRF with and without canopy transpiration gives little indication that water vapor input from the Gulf of Mexico is a major contributor to this signal (Figure S2). Instead, canopy transpiration is dominant in the densely agricultural area. To quantify the sources of moisture, we examine daytime moisture fluxes from wet canopy interception, direct soil evaporation, and canopy transpiration in the WRF Noah model during the episode (Figure 5). Over the domain, the magnitude of moisture fluxes from wet canopy interception ($0.38 \pm 0.56 \text{ mm day}^{-1}$) and direct soil evaporation ($0.46 \pm 0.34 \text{ mm day}^{-1}$) are much smaller than that from canopy transpiration ($4.00 \pm 1.9 \text{ mm day}^{-1}$). The ratio of canopy transpiration to the total evapotranspiration over the box A is $89 \pm 16\%$. This is higher than that reported by Wei et al. (2017). A comprehensive review of in situ measurements of crop-specific evapotranspiration partitioning suggested that the ratio for row crops such as cotton and corn are within the range of 70–80% (Kool et al., 2014). To our knowledge, there is no direct validation of models’ evapotranspiration partitioning for crops during a heat

Figure 3. The anomalies of daily 500 mb geopotential height (left) and the air temperature at 2 m (right) for the corn sweat episode (16–20 July 2011) based on the NARR data.

Figure 4. Contour maps of (a) MODIS climatology of integrated water vapor (IWV) in July (2000–2018) using the MODIS on Aqua spacecraft (~13:30 LST), (b) MODIS IWV during the heat wave episode (16–20 July 2011) contrasted with GPS observations (circles), and (c) their differences.

wave to gather information on how differently both stomatal physiology and the partitioning work under heat stress.

In assessing potential biases in the MODIS product, we compare GPS IWV observations with those from the MODIS sensors onboard the TERRA and AQUA satellites. Both observations are coregistered in time (<10 min) and space (<10 km) and are selected if they fall into WRF's nested domain. Figure 6 depicts the scatter plot of the comparison. Generally, a good correlation ($r = 0.81$) exists between the datasets. The results indicate that MODIS IWV is biased high with a scale factor of 1.1 and an offset of 2.3 mm ($R^2 = 0.66$). The result is in agreement with previous studies, which compared MODIS data with those from GPS and AERONET (Li et al., 2003; Prasad & Singh, 2009; Chang et al., 2019). To remove the biases associated with the MODIS product, we correct all MODIS observations using the fitted scale factor and offset. Furthermore, the covariance matrix of the observations used in the inversion is set to 17%, based on the ratio of the root mean square error (RMSE) from the comparison to the averaged values of MODIS. It is worth mentioning that there is no noticeable difference between the performance of MODIS AQUA and TERRA (Figures S3 and S4).

3.2. Estimation of Canopy Transpiration Moisture Flux

Our aim is to constrain the canopy transpiration flux during the heat wave event. To this end, we make use of MODIS NIR water vapor products from both TERRA and AQUA platforms to minimize the cost function (equation 3), which mathematically leads to an optimal estimation of the flux. To gather a general view of the discrepancies in IWV between the WRF model and MODIS observations, we plot a contour map of the simulated IWV (left panel), the corrected MODIS observations (middle panel), and the ratio of two (right panel) in Figure 7. The model tends to overestimate IWV in the high and low latitudes while underestimate it on the west side of the corn belt. This tendency applies to both the morning and afternoon times. The disagreement between the simulated water vapor variability and the satellite observations may be attributed to a number of factors, including (i) inability of the model to capture the low-level wind pattern, (ii)

Figure 5. Contour maps of daytime moisture fluxes from canopy wet interception (left), direct evaporation from soil (middle), and canopy transpiration (right) during the heat wave episode (16–20 July 2011) modeled by the WRF model.

Figure 6. Point-to-point comparison of GPS and MODIS IWV during the heat wave episode in the WRF nested domain. Corr: correlation coefficient, IOA: index of agreement, MB: mean bias (GPS minus MODIS), MAB: mean absolute bias, RMSE: root mean square error.

uncertainties associated with external sources of moisture (especially from the Gulf of Mexico), and (iii) errors in the canopy transpiration flux. As mentioned earlier, we attempt to minimize the first two influences by grid nudging using the NARR reanalysis. To assure that the model is fairly skillful at reproducing the low-level wind pattern, we compare u and v wind components from more than 1983 surface meteorological stations to those from the model (Figure S5). The average wind speed over the entire domain is found to be 2.43 m/s and 2.41 m/s for the model and the measurements, respectively, and the RMSE between two data sets is 1.24 m/s. The general clockwise motion of the high pressure system is properly captured by the model. Similarly, the assimilation of several polar-orbiting microwave sensors in NARR and the solid parameterization of evaporation from open waters in combination with observation-based sea surface temperature in our model setup should be able to minimize the second source of error. Thus, under the assumptions that the model has high skill dealing with wind speed and evaporation from open water and that the uncertainty of IWV mainly comes from canopy transpiration flux (within 50% error range), we use MODIS IWV observations to constrain the transpiration flux in the LETKF framework.

Figure 8 depicts the a priori moisture flux from canopy transpiration (left panel), the a posteriori estimation (middle), and their relative difference (right). We observe that the relative difference is highly correlated with the ratio of MODIS to WRF IWV, suggesting that the inversion attempts to reduce the difference between them. Reductions in the flux are seen in both the high and low latitudes. The uncertainty estimation calculated from equation 8 is found to be 30–50% over the cropland areas. We do not observe a noticeable difference between the a priori and the a posteriori over the hotspot of transpiration ($>5 \text{ mm day}^{-1}$). This is consistent with the fact that the difference between the model and the satellite observations is relatively small over the hotspot area (Figure 2). Enhancement in the canopy transpiration is seen over the west areas of the croplands. Overall, the inversion reduces the canopy transpiration flux by 15% (from 4.00 to 3.39 mm day^{-1}) in the whole nested domain. The overestimation of the canopy transpiration by the model is problematic. It can propagate in subsequent sensitivity experiments, inducing a bias in the amplitude of impact of the excess moisture from canopy

Figure 7. Comparison between the simulated IWV and the satellites observations. The first column shows the WRF IWV at the time of the satellite observation, the second column demonstrates the MODIS observations corrected using GPS observations, and the third column shows the ratio of the satellite to the model.

Figure 8. Contour maps of daytime moisture fluxes from the a priori knowledge estimated from WRF (left), the top-down estimation using MODIS observations (middle), and their relative differences (right) during the heat wave episode (16–20 July 2011).

transpiration on the heat wave. Therefore, we mitigate such an overestimation by scaling the model-calculated transpiration flux using the ratio of the a posteriori to the a priori (i.e., the constrained model).

3.3. Impact of Excess Moisture from Crop Transpiration on the Severity of the Heat Wave

Figure 9 shows the daytime surface water vapor mixing ratios (Q_v) at 2 m for CONTROL (left panel), NOCROP (middle), and their relative difference with respect to values in the CONTROL experiment (right) during the episode. The left and middle panels on Figure 9 also include in situ water vapor measurements from integrated surface database (ISD) meteorological stations (circles). The difference between the two simulations is more pronounced in the agricultural areas (box A in Figure 2). Leaving the crop transpiration out of the model results in a significant reduction (up to 40%) of surface humidity. The noticeable difference between the surface measurements and NOCROP simulation suggests a major role of transpiration in shaping the extremely humid conditions during the heat wave (middle panel in Figure 4).

The difference between the two simulations (i.e., CONTROL–NOCROP) for six meteorological variables including the 2 m water vapor mixing ratio (Q_v), surface pressure, planetary boundary layer (PBL) height, downward longwave radiation (DLR) at the surface, surface air temperature, and cloud fraction is shown in Figure 10. The black dots represent statistically significant differences based on a normal distribution at the 95% confidence level if $|\mu/\sigma| > 1.96$, where μ and σ are the mean and standard deviation of the normalized differences, respectively. Since the inclusion of canopy transpiration changes both the mass of water vapor (crucial for radiation and cloud microphysics) and latent heat, we observe variability in both the sign and amplitude of the response. As a response to the higher water vapor content in the CONTROL simulation, we would expect a higher likelihood of cloudiness. The cloud fraction difference indicates a substantial enhancement in cloud formation on the right side of the high pressure system. The enhanced cloudiness results in colder daytime surface temperature in the same locations, apparent in a sharp reduction in downward shortwave radiation at the surface ($41 \pm 18 \text{ W m}^{-2}$; Figure S6). The increase in the surface air

Figure 9. Contour maps of daytime surface water vapor mixing ratios (Q_v) at 2 m from the WRF model with cropland moisture flux (left), without cropland moisture flux (middle), and their relative differences with respect to values in the CONTROL experiment (right) during the heat wave episode (16–20 July 2011). We also include in situ water vapor measurements from integrated surface database (ISD) meteorological stations (circles).

Figure 10. Differences between CONTROL and NOCROP simulations for six major meteorological variables. The dots denote the statistically significant difference based on 95% confidence interval for a normal distribution.

temperature over the major cropland area ($+0.4$ K) due to canopy transpiration is not explainable by the change in cloudiness. It is a common perception that water vapor molecules are responsible for increased IR radiation to the lower-level atmosphere which leads to surface warming (Santer et al., 2007; Willett et al., 2007). It is because of this reason that we observe enhanced DLR over the croplands (13 ± 4 W m $^{-2}$). Subsequently, the enhanced DLR increases surface air temperature. Therefore, the excess moisture from transpiration can not only makes the atmospheric water vapor content larger but also provides a radiative forcing that amplifies the heating and evaporation rate. We observe that the response of PBL heights to canopy transpiration correlates ($r = 0.70$) with surface air temperature. The general reduction in surface pressure over the croplands (0.9 ± 0.4 hPa) is caused by a combination of colder temperature and drier air in NOCROP than in CONTROL.

We further calculate the heat index for both simulations using the Robinson (2001) formula. Figure 11 demonstrates the heat indices for CONTROL (left), NOCROP (middle), and their difference (right). By virtue of the enhanced humidity and air temperature over the surface due to the excess moisture from transpiration, the heat wave is exacerbated. The mean daytime heat index increases over the croplands (box A in Figure 2) by 3.3 ± 0.8 °C. The hotspot of the heat enhancement coincides with the maximum moisture

Figure 11. Contour maps of heat indices calculated using the Robinson (2001) formula for CONTROL (left), NOCROP (middle) WRF simulations, and their difference (right). Note that crop transpiration exacerbated the severity of the heat index.

Table 2
The Parameters Used in the SAVAS and GRASS Scenarios

Type of land cover	Vegetation fraction (%)	Number of roots	Minimum stomatal resistance (s/m)	Radiation stress constant	Vapor pressure deficit constant	Leaf area index
Savanna	50	3	70	65	54.33	3.7
Grassland	80	3	40	100	36.35	2.9
Crop	80	3	40	100	36.25	5.7

content in Figure 9, supporting the conclusion that the enhanced heat index is mostly due to increased moisture rather than temperature.

The above experiments are intended to theoretically quantify the impact of the excess moisture from canopy transpiration from crops on the severity of the heat wave. One may argue that such an experiment may not entirely reflect the real world because a natural vegetation cover can potentially replace croplands due to both existence of fertile soil and suitable climate in the Midwest. Accordingly, we conduct two additional experiments to identify to which extent natural vegetation can influence the atmospheric moisture. A precise prediction of the distribution of natural plants taking the place of the cropland area is beyond the scope of this study. We simply choose Savannas (SAVAS) and Grasslands (GRASS) defined in the modified MODIS Noah classification as a surrogate for the natural vegetation. These experiments are designed to only study the impact of the canopy transpiration on the amount of atmospheric moisture; therefore, we only changed the canopy resistance and the vegetation fraction parameters in the model at those grid cells where cropland is present. The relevant parameters are listed in Table 2. Figure 12 depicts the four experiments in terms of Q_v at 2 m. Due to a lower LAI and a larger canopy resistance for Savanna, we observe a decrease in Q_v for SAVAS suggesting that the crop transpiration is larger. The difference between CONTROL and GRASS

Figure 12. Contour maps of daytime surface water vapor mixing ratios (Q_v) at 2 m from the WRF model with cropland moisture flux (CONTROL), without cropland moisture flux (NOCROP), with Savanna as a replacement for cropland (SAVA), and with grassland as a replacement for cropland (GRASS), during the heat wave episode (16–20 July 2011).

Figure 13. Time series of several meteorological variables during the heat wave event (16 to 20 July 2011) averaged over box B in Figure 10. The green and red lines represent CONTROL and NOCROP simulations, respectively.

suggests that grassland on average contributes 10% less than crop to the moisture through only transpiration. A more detailed land-atmosphere analysis should be performed in the future to fully elucidate the impact of a possible land use/land cover change on the regional climate and heat waves.

Much of the above analysis is based on the averaged daytime values; however, there is still potential for diurnal variability to be important. Therefore, we plot a set of time series for several meteorological variables over box B (in Figure 11) in which major changes occur due to transpiration (Figure 13). We observe that surface Q_v from CONTROL simulation is persistently higher than that of NOCROP. But the difference is smaller at nighttime when transpiration ceases because of plant stomata closure. The reduction in surface pressure happens gradually over the time period as the dominant controlling factor here is the large scale synoptic condition. We observe that the PBL heights increase mostly during the day, and the enhanced DLR is nonnegligible during the night. Due to small differences in moisture between the simulations at night and reduced sensitivity of heat index to humidity at lower air temperatures, we do not see a significant deviation between the simulations with respect to heat index during the nighttime. Finally, the model suggests that the excess moisture from crops is responsible for augmenting the values of heat index by as much as 5 °C at the peak of daily temperatures that predominantly happened in the afternoon.

4. Summary

We constrained the transpiration flux from croplands using the characterized MODIS NIR water vapor product in an effort to assess the impact of crops on a heat wave event in the Midwest U.S. from 16 to 20 July 2011. During the heat wave, MODIS revealed a substantial deviation of IWV up to 40 mm from the climatology (2000–2018), which was not related to advected moisture from outside of the domain. We observed that MODIS NIR IWV observations are generally correlated with GPS observations ($r = 0.81$), but MODIS IWV tended to be higher (16%). Hence, we corrected the bias associated with MODIS observations and estimated their random errors to provide a constraint on canopy transpiration using an LETKF method with 50 ensemble members. A comparison of IWV values simulated by the WRF model and observed by MODIS indicated that the model overestimated canopy transpiration flux. The results from the top-down estimation showed

that the a posteriori of canopy transpiration flux (4.00 mm day^{-1}) was 15% lower than the a priori (3.39 mm day^{-1}). Furthermore, our estimation yielded a lower uncertainty (30–50%) on the magnitude of the transpiration flux compared to our initial assumption (50%). We mitigate this bias of the canopy transpiration by applying the ratio of the posteriori to the a priori for the subsequent sensitivity experiments (i.e., the constrained model).

An important goal of this study was to explore the influence of excess moisture from canopy transpiration on atmospheric variables during the heat wave. Therefore, we designed an experiment consisting of two simulations; the first simulation considered the constrained moisture and latent heat fluxes from croplands (CONTROL); the second simulation excluded these fluxes (NOCROP). These two experiments were decoupled from the land surface processes to (i) provide a consistent surface energy and water balance and (ii) to isolate the impact of excess moisture and latent heat flux from croplands on the weather. Hence, we assumed that the lack of canopy transpiration in the NOCROP experiment would not cause the buried moisture content to evaporate into the atmosphere or to enhance soil moisture over the course of a week. The lack of moisture contribution from crops in the NOCROP run result in a large reduction in daytime water vapor mixing ratio ($\sim$ up to 40%), which led to a significant discrepancy with the surface meteorological observations. This provided evidence that moisture flux from crops was the primary reason for shaping the extremely humid conditions during the heat wave episode. In response to this source of moisture through crop transpiration, we observed more cloudiness on the eastern side of the heat wave, resulting in lower surface air temperature (and heat index). Over the majority of the agricultural area that was dominated by an anticyclone, the elevated moisture increased DLR by $13 \pm 4 \text{ W m}^{-2}$ that led to a surface warming of $0.4 \text{ }^{\circ}\text{C}$. Increases in the surface air temperature and humidity went hand-in-hand and increased daytime heat index by as large as $3.3 \pm 0.8 \text{ }^{\circ}\text{C}$ over the cropland area. Due to a strong diurnal cycle in transpiration, the feedback was found to be the strongest in the afternoon (up to $5 \text{ }^{\circ}\text{C}$) and weaker at night. Furthermore, we designed two additional experiments by substituting the canopy resistance and vegetation fraction over croplands with those values from savannas (SAVAS) and grasslands (GRASS) to be able to identify to which extent the natural vegetation can contribute to the atmospheric moisture. Both scenarios yielded to a drier atmosphere compared to cropland.

Many studies have investigated the impact of different parameterization, initialization, and inputs used for LSMs on regional atmospheric conditions (e.g., Avissar & Pielke, 1991; Case et al., 2008; Chen & Zhang, 2009; Chen et al., 2010; Jin et al., 2010; Niu et al., 2011; Ozdogan et al., 2010; Xu et al., 2017; Zeng et al., 2016; Zhu et al., 2017), but to our knowledge, this is a first study that specifically quantified and constrained the effect of excess moisture from crop transpiration on a heat wave event in the Midwest U.S. Our analyses highlight the interaction between excess moisture from cropland and atmospheric conditions. However, we are aware of the limitation of our study, which is not accounting for possible changes in soil thermodynamics, plant structure, soil moisture, and emissivity under the NOCROP experiment, which requires a follow-up long-term study to elucidate to what extent those parameters can balance out the deficit in transpiration.

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