Evaluating the impact of land surface properties on simulated dust emissions and air quality

Erica Burrows

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EVALUATING THE IMPACT OF LAND SURFACE PROPERTIES ON SIMULATED DUST EMISSIONS AND AIR QUALITY

by

ERICA BURROWS

A THESIS

Submitted in partial fulfillment of the requirements for the degree of Master of Science in Atmospheric Science in The Department of Atmospheric Science to The School of Graduate Studies of The University of Alabama in Huntsville

HUNTSVILLE, ALABAMA

2020
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Erica Burrows 04/13/2020
Erinica Burrows (date)
THESIS APPROVAL FORM

Submitted by Erica Burrows in partial fulfillment of the requirements for the degree of Master of Science in Atmospheric Science and accepted on behalf of the Faculty of the School of Graduate Studies by the thesis committee.

We, the undersigned members of the Graduate Faculty of The University of Alabama in Huntsville, certify that we have advised and/or supervised the candidate of the work described in this thesis. We further certify that we have reviewed the thesis manuscript and approve it in partial fulfillment of the requirements for the degree of Master of Science in Atmospheric Science in the Department of Atmospheric Science.

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ABSTRACT

School of Graduate Studies
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Degree Master of Science College/Dept. Science/Atmospheric Science
in Atmospheric Science

Name of Candidate Erica Burrows

Title Evaluating the Impact of Land Surface Properties on Simulated Dust Emissions and Air Quality

Strong winds and dry surface conditions result in frequent occurrence of dusty conditions in the Southwestern United States (SW US) causing degraded air quality and harmful health effects. The Weather Research and Forecasting with Chemistry (WRF-Chem) model is often used to forecast such events. Biases in specifications of soil moisture and vegetation cover in the land surface component for initialization of WRF-Chem can result in systematic errors in forecasts. This study examines how WRF-Chem dust forecasts for the SW US can be improved through better prescriptions of soil and vegetation for the following cases: 27 April 2014, 23 March 2017, and 17 April 2018. Simulations of these events using the Global Forecast System (GFS) were compared against a set of simulations that used NASA Land Information System (LIS) and NESDIS green vegetation fraction (GVF) products to specify soil moisture and vegetation. Intercomparison with observations show that specification of vegetation and soil moisture improved dust forecasts with the latter having a larger impact.
ACKNOWLEDGMENTS

This work would not be possible without the support of those both inside and outside the department. I would like to thank my advisor Dr. Aaron Naeger for his constructive feedback and constant guidance throughout this process. Additionally, I would like to thank my committee chair Dr. Udaysankar Nair for his quality feedback and being a valuable resource, and committee members – Dr. Arastoo Biazar for insightful comments regarding air quality and literature relating to this work, and Dr. John Mecikalski for helping me keep the big picture in mind. The NASA SPoRT team was essential for providing an open science community and motivating this work. I would specifically like to thank John Case, Dr. Christopher Schultz, Dr. Christopher Hain, Kevin McGrath, Dr. Emily Berndt, and Jayanthi Srikishen from NASA SPoRT for their assistance with this work, as well as my fellow Graduate Research Assistants during my two years with NASA SPoRT – Douglas Kahn and Sebastian Harkema. I would also like to thank Dr. Sen Chiao and Dr. Mohammad Al–Hamdan for the opportunity with CAARE, which is how I discovered my passion for atmospheric aerosols. Furthermore, this work would not have been possible without my friends Kristen Pozsonyi, Xochitl Orozco, and Elena Rubio for their constant listening ear, and my mother, Andrea Baker, for supporting my dreams and all the sacrifices she had to make to get me this far. I will forever be grateful.
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CHAPTER 1

INTRODUCTION

Dust storms are the third largest weather related fatalities in the Southwestern United States (SW US) - behind flooding and extreme heat - with over 150 killed and 1300 injured over the past 50 years (Lader et al. 2016). As shown in Figure 1.1, the highest fine dust concentrations for Contiguous United States (CONUS) occurs over the SW US during the spring, which is attributed to strong surface winds and drier surface soil moisture. Soil moisture has been shown to be anticorrelated with dust emissions (e.g. Kim and Choi 2015) as the tension between particles increases with increasing water content. Although vegetation increases surface roughness, in turn increasing turbulence, it has also been shown to negatively impact dust emissions (Xu et al. 2006) as it protects the underlying soil. With the considerable impacts surface conditions have on the dynamics of dust particles, it is imperative to have accurate green vegetation and soil moisture maps to better forecast dust emissions across this region.

Dust storms are known for causing significant economic loss due to deteriorating visibility and reduced traction on roadways from sedimentation resulting road closures, detouring traffic, delay in delivery of goods, and increased car accidents.
causing injuries and fatalities. A prime example of such an event is the dust storm initiated on 19 June 2017 near 2350 UTC when scattered thunderstorms propagated over the Arizona/New Mexico border over Interstate 10 (I-10). As shown in Figure 1.2, the dust storm was initiated by high wind speeds, exceeding 15 m s\(^{-1}\). By 20 June 2017 00:13 UTC, the dust crossed over I-10, resulting in a 25 car pileup with 6 deaths. I-10 was closed in that region and traffic was detoured around the incident, adding an additional hour to the drive. Dust particles can also significantly impact air quality conditions by increasing the concentration of particulate matter (PM) in the atmosphere. For this event alone, the PM10 concentrations exceeded 140 \(\mu g m^{-3}\) (Figure 1.3). Recent studies have linked increased rates of asthma, stroke, cognitive decline, and Valley fever with high levels of PM (Al-Hamdan et al. 2014; Hu 2009;
Figure 1.2: NEXRAD reflectivity (a,c) and velocity (b,d) for KEMX (Tucson, AZ) on 19 June 2017 23:49 UTC and 20 June 2017 00:13 UTC. The major highways are denoted by the orange lines and the black ring is the maximum range of the radar. Black boxes denote the location of the dust storm and black triangle is the location of the EPA AQS sites.

Crouse et al. 2012) as these particles are able to enter the blood stream once inhaled. From 1998 to 2011, the number of Valley fever incidents increased eight-fold (Center for Disease Control 2013) with half to two thirds of reports coming from Arizona (Sunenshine et al. 2007) as the fungus lives in the soil of the SW US. From 1998 to 2016, there were an average of 200 deaths each year in which Valley fever was listed as primary or contributing cause of death (USDHHS et al. 2018) with the most cases occurring in those over 65 years of age (Balter 2016). Due to the considerable impacts
these dust aerosols have on public health and economy, realistic simulations of dust emissions are critical for forecasting air quality conditions over the region.

This study utilized the Weather Research and Forecasting with Chemistry (WRF-Chem) model with the NASA Land Information System (LIS) and NESDIS Green Vegetation Fraction (GVF) product along with satellite and ground-based observations to quantitatively understand the impact of land cover characteristics on dust emissions over the SW US. Previous WRF-Chem modeling studies have successfully captured the spatial extent of dust plumes, however the simulation of the aerosol optical depth (AOD) was generally overestimated (Bran et al. 2018). Other studies have shown that when utilizing the Global Forecast System (GFS) soil moisture fields, there is an overall moist bias as the Noah Land Surface Model (LSM), utilized within GFS, incorporates a climatologically averaged soil moisture field. By initializing the soil moisture conditions with a more realistic dataset, such as those from the NASA LIS product, it is expected that the dust emissions forecasted over the SW US will better compare to observations. The NASA LIS product is developed from data as-
simulation of precipitation and soil moisture retrievals from satellites. By updating the GVF field with a near real-time product, such as that from NESDIS, the model configuration is expected to better represent surface roughness and near surface wind speed, and therefore AOD. The Noah LSM, incorporated in GFS, utilizes a monthly climatological average for GVF, which can negatively impact dust emission forecasts.
CHAPTER 2

BACKGROUND AND LITERATURE REVIEW

This chapter provides a brief review of air quality impacts on dust and the role of vegetation and soil moisture on simulating dust emissions.

2.1 Air Quality Impacts

Wind erosion in arid and semi-arid regions is the primary source of dust emissions (e.g. Tegen and Fung 1995; Prospero 1999; Nordstrom and Hotta 2004). Once lofted, dust aerosols can influence the visibility and air quality conditions, along with radiation budget and chemical reactions in the atmosphere, which can lead to broad impacts across the Earth. In the Northern Hemisphere, the largest dust sources are from the Middle East and North Africa region (Prospero et al. 2002; Washington et al. 2003) accounting for more than half of globally emitted dust (Goudie and Middleton 2001). Although emissions in the US (20-50 g m$^{-2}$ yr$^{-1}$) are less significant compared to Africa (100-1000 g m$^{-2}$ yr$^{-1}$) (Chin et al. 2007; Goudie and Middleton 2001; Ozer 2001), the inhalation of these particles has proven to be an important health issue (e.g. Osornio et al. 1991; Alfaro et al. 1997).
For the SW US, approximately 50% of total PM2.5 (PM with a diameter less
than 2.5 µm) and 70% of PM10 (PM with a diameter from 2.5 to 10 µm) during
the spring months is attributed to dust (Hand et al. 2017). From 1995 to 2014,
Hand et al. (2006) found a 5% increase in spring time PM concentrations, primarily
in March. For every 10 µg m\(^{-3}\) increase in PM2.5 there is a 6% increased risk of
cardiopulmonary mortality (Pope et al. 2002). Trace elements (arsenic, nickel, etc.)
and biological compounds (bacteria, fungi, viruses) found among dust particles can
also lead to dermatological disorders, silicosis (desert lung syndrome), coccidiomycosis
(Valley Fever), among others (e.g. Goudie 2014). A multi-year study by Grineski
et al. (2011), focused in El Paso, TX, found a 1.11 times higher likelihood of asthma
admissions during dust days, with children being the most sensitive age group. Yang
et al. (2005) and Kang et al. (2013) found an increase in stroke hospitalizations
associated with dust days. In the SW US, Valley Fever incidents have risen eightfold
from 1998 to 2011 (Center for Disease Control 2013) with over half coming from
Arizona (Sunenshine et al. 2007). This increase may be attributed to increased soil
disturbance (Wilken et al. 2015) required to accommodate the rising population in
the SW US (U.S. Census Bureau 2011).

2.2 Land Surface Impacts on Dust Emissions

Tegen and Fung (1995) found that between 30% and 50% of the total atmo-
spheric dust loading originated from disturbed soil regions. Disturbed soils are a
result of deforestation, overgrazing, and agricultural activities required to sustain so-
ciety (Middleton 1992; World Resource Institute 1992). The Dust Bowl of the 1930s
is a well-known example for how agriculture and drought can lead to severe dust storms. Schubert et al. (2004) found that the Dust Bowl coincided with cool sea surface temperatures in the eastern tropical Pacific, also known as a La Nina. During a La Nina, the east to west flow is intensified, resulting in a high pressure system to form in the eastern Pacific. A typical La Nina produces dry conditions in the SW US which can decrease evapotranspiration, increase surface temperatures, and therefore prolong drought conditions (Namias 1991; Lyon and Dole 1995). Conditions such as these result in the southern Great Plains, Colorado Plateau, and the North American Deserts being major hotspots for dust emissions in the SW US (Tanaka and Chiba 2006; Reynolds et al. 2007; Rivera et al. 2010; Carmona et al. 2015; Prospero et al. 2002).

One method of characterizing land surface changes related to drought or disturbed soils is through analyzing the Normalized Difference Vegetation Index (NDVI), which uses spectral differences in satellite reflectance to calculate the greenness of vegetation. NDVI is calculated by:

\[
NDVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red}}
\]  

(2.1)

where $\rho_{NIR}$ and $\rho_{red}$ correspond to the near infrared and visible red channels. Kim et al. (2017) found that the NDVI is anti-correlated with dust emissions ($R = -0.65$) as vegetation protects the underlying soil and increases the surface roughness (Cowie et al. 2013; Pierre et al. 2012). Larger values of surface roughness means a higher wind speed threshold (i.e., minimum wind speed required or lofting aerosols).
is required for dust emissions. A range of wind speed thresholds (4 – 16 m s\(^{-1}\); Kurosaki and Mikami 2007) exist due to different vegetation types in the dust hot spot areas. Another common wind speed measurement is the threshold shear velocity, which is defined as the point when the wind shear velocity exceeds the erodibility of the surface, thus defining when emissions begin to occur. Li et al. (2018) defined the threshold shear velocity as anything between 0.17 and 0.78 m s\(^{-1}\), which is strongly dependent on soil moisture.

Under moist conditions, cohesive and adhesive forces between soil particles increases (Chepil 1945; Nickling 1978; Nickling and Ecclestone 1981), resulting in a larger threshold shear velocities for dust emissions. Many efforts have been made to quantify dust emissions for moistened sand (e.g. Ravi and D’Odorico 2005; Gillette et al. 1982). For example, Ishizuka et al. (2005) performed a field study measuring saltation and soil moisture in the Taklimakan Desert and found that under wet conditions, the threshold wind speed is 1.27 times (2 m s\(^{-1}\)) larger than that of dry conditions, which are consistent with the theoretical findings of Fecan et al. (1999). Another study by Kim and Choi (2015) utilized satellite observations to link mechanisms for dust events to soil moisture on a global scale. Using 11 years of data, Kim and Choi (2015) were able to develop a relationship between soil moisture, wind, and AOD, based on their findings that AOD values exceeding 1 only occurred under strong winds (> 6.5 m s\(^{-1}\)) for moist soil conditions.

Numerous modeling studies have utilized the theoretical findings of soil moisture, wind speed, and vegetation dependencies for dust emissions. The WRF-Chem model has been shown to successfully capture the spatial extent of dust plumes, but
generally overestimates simulated dust emissions resulting in significant errors in the AOD (Bran et al. 2018; Ghotbi et al. 2016; Chen et al. 2014). Bran et al. (2018) simulated a dust storm event over the Arabian Sea and found only a $R = 0.55$ and 0.32 (51% and 57% error) when comparing the simulated AOD to satellite retrievals. Although this study attributed errors to aerosol properties such as refractive indices, characteristics of the dust source region may have been misrepresented due to the use of a multi-year average LSM. Fang et al. (2018) incorporated a near real time (NRT) GVF within the NASA Unified Weather Research and Forecasting (NUWRF) model and found a mean absolute difference of 0.126 between the NRT and climatological average of Noah LSM, with a difference of 0.2 for the Midwest, which is 20% lower than the original Noah LSM. Similar experiments were conducted by Miller et al. (2006) and Yin et al. (2016) where initializing the Noah LSM with a NRT GVF improved soil moisture simulations by 19% and soil temperature by 9%. Massey et al. (2016) found an overall 0.127 and 0.079 m$^3$ m$^{-3}$ difference for 5- and 25-cm soil moisture when comparing GFS soil moisture (which utilizes Noah LSM) to field observations. Increases in soil moisture have been shown to decrease 2-m temperatures during the day due to reduced thermal conductivity and evapotranspiration. A decrease of 0.12 m$^3$ m$^{-3}$ was shown to increase the surface temperature by as much as 5.4 °C (Massey et al. 2016) as soil moisture affects the surface sensible and latent heat fluxes. Latent and sensible heat fluxes also impact atmospheric stability and near-surface winds (e.g. Banta and Gannon 1995; Huang et al. 1996; Sun and Bosilovich 1996), making an accurate representation of soil moisture imperative for dust emission forecasts.
CHAPTER 3

METHODOLOGY

This chapter provides a review of the various datasets and methodologies that were used to study the land surface impacts on dust emissions.

3.1 Case Selection

To identify case studies over the SW US, the NASA Earth Observing System Data and Information System (EOSDIS) Worldview application was utilized to ensure that adequate satellite data would be available for validation. The Visible Infrared Imager Radiometer Suite (VIIRS) and Moderate Resolution Imaging Spectroradiometer (MODIS) true color imagery were used to identify dust plumes as they appear as brown clouds in true color red-green-blue (RGB). Once a plume was identified, the merged Dark Target/Deep Blue MODIS AOD product was then overlaid to ensure the dust plume had an AOD value exceeding a threshold of 0.5 to ensure it was a high aerosol loading event. Using this criteria, of the six cases identified only three were used (as shown in Table 3.1) as the unused cases were short lived and small-scale dust storms with insufficient validation data available.
Table 3.1: List of dust events with date of occurrence and geographic locations that were incorporated in this study.

<table>
<thead>
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<th>Case Study Date</th>
<th>Case Type</th>
<th>Case Number</th>
<th>Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>27 April 2014</td>
<td>Case Study</td>
<td>1</td>
<td>Southeastern Colorado, Southwestern Kansas, Western Oklahoma, Northwestern Texas</td>
</tr>
<tr>
<td>23 March 2017</td>
<td>Case Study</td>
<td>2</td>
<td>Southern New Mexico, Western Texas, North Central Mexico</td>
</tr>
<tr>
<td>17 April 2018</td>
<td>Golden Case</td>
<td>3</td>
<td>South Central, Southeastern Colorado</td>
</tr>
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3.2 Model Configuration

Each case was simulated using the WRF-Chem (version 3.9.1.1) model with a double-nested grid configuration consisting of an outer and inner domain at 15 km and 3 km grid spacing, respectively (Figure 3.1), with 51 vertical levels extending to 100 hPa. Table 3.2 provides the inner domain configuration for each case. Four day simulations with a 12 hour spin were used to capture the source and transport processes for each dust event. For the initial and lateral boundary conditions, the 0.5° GFS reanalysis was utilized. The Lin microphysics scheme (Lin et al. 1983) was used for predicting cloud and precipitation processes at cloud-resolving scales, while the Grell convective scheme (Grell and Devenyi 2002) parameterized deep convection at sub-grid scales. The Rapid Radiative Transfer Model (RRTMG; Mlawer et al. 1997) was used to represent the longwave and shortwave radiative transfer. The NOAH LSM (Chen and Dudhia 2001) and Monin-Obukhov (Janjic) surface layer scheme (Janjic 1996) were utilized to parameterize surface energy budget and surface
Figure 3.1: Nested grid configuration utilized in this study for case 3 where the outer box represents domain 1 and the white box represents the white box.

Table 3.2: Domain configuration for each case.

<table>
<thead>
<tr>
<th>Case Study Date</th>
<th># X Grid Cells</th>
<th># Y Grid Cells</th>
<th>Central Point</th>
</tr>
</thead>
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<tr>
<td>27 April 2014</td>
<td>541</td>
<td>701</td>
<td>36.85°N 97.697°W</td>
</tr>
<tr>
<td>23 March 2017</td>
<td>701</td>
<td>561</td>
<td>35.605°N 108.896°W</td>
</tr>
<tr>
<td>17 April 2018</td>
<td>606</td>
<td>501</td>
<td>38.094°N 106.585°W</td>
</tr>
</tbody>
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layer turbulence. The Noah LSM simulates many surface properties including soil moisture, soil temperature, skin temperature, and energy and water fluxes. The soil model is divided into four layers to mitigate truncation errors: 0.0–0.1, 0.1–0.4,
Figure 3.2: A schematic of the NOAH LSM. The red boxes denote the fields relevant to soil moisture and vegetation. Reproduced from Chen and Dudhia (2001).

The dust mission scheme selected for this study was Shao et al. (2011; hereafter S11), which is a simplified form of Shao (2004; hereafter S04). S04 is a size-resolved dust emission scheme that takes into account saltation bombardment (sand blasting) and aggregate disintegration (breakdown of particles by striking a surface; Chappell 1998). S11 utilized data from JADE (a field study in Australia) and found that wind speed had no impact on the dust particle size distribution, therefore eliminating the
aggregate disintegration effect and simplifying the emission of particle size $d_i$ to:

$$F(d_i) = c_y \eta_{m,i} (1 + \sigma_m) \frac{gQ}{\mu_*^2}$$

(3.1)

where $F(d_i)$ is the dust flux for a particle with a diameter of $i$, $Q$ is the saltation flux averaged over a range of particle sizes, $\mu_*$ is the threshold friction velocity, $c_y$ is the dust emission coefficient, $\eta_{m,i}$ is the amount of free dust, $\sigma_m$ is the bombardment efficiency, and $g$ is gravity. The simple Goddard Chemistry Aerosol Radiation and Transport (GOCART) model is used to represent aerosol processes for dust sizes ranging from 0.1 to 6 $\mu$m (Ginoux et al. 2001). Dust concentration within each bin from GOCART is used to calculate the AOD following the methodology of Chin et al. (2002):

$$\tau = \sum_{i=0}^{p_{top}} \tau(p)$$

(3.2)

where

$$\tau(p) = \sum_{i=1}^{5} 0.75 \times 10^{-6} Q_i M_i \rho \rho_i r_m(i) \Delta Z \times 10^3$$

(3.3)

where $Q$ is the extinction coefficient, $M$ is the dust loading, $\rho$ is the density of the atmosphere, $\rho_i$ is the dust density, $r_m$ is the model effective radius, $\delta Z$ is the change in geopotential height, and $i$ denotes each dust bin.

### 3.3 Control Simulations

Our Control (CTRL) simulation used the standard soil moisture and GVF fields, derived from the Noah LSM, within the GFS data. Large moist biases have been
noted over the SW US when using GFS to represent the soil moisture field (Massey et al. 2016) which can lead to unrealistically low dust emissions. Large vegetation differences between near real time (NRT) and the Noah LSM have been noted globally, as Noah LSM is a climatological average, which influences simulated surface roughness and energy balance (Yin et al. 2016). For CONUS, root mean square deviation (a measure of difference between a model and observations) between NRT and Noah LSM exceed 50% in winter/autumn and exceed 15% in the spring/summer with the largest differences in the vegetated regions (Yin et al. 2016).

3.4 Experimental Simulations

3.4.1 NASA LIS

For the experimental (EXP) simulations, the standard soil moisture field (GFS) is replaced with the NASA LIS product for initializing WRF-Chem. The NASA LIS product provides soil moisture conditions based on rain gauges, radar estimates, and/or satellite measurements, at a 3-km resolution (Case et al. 2011). For the desert regions of SW US where rain gauge data is sparse, improvements in the NASA LIS product result from the Integrated Multi-Satellite Retrievals for GPM (IMERG) and Soil Moisture Active Passive (SMAP) retrievals. The IMERG algorithm is able to estimate liquid and solid precipitation rates by incorporating microwave and microwave-calibrated infrared precipitation estimates onto a 0.1° grid at 30-min resolution (Huffman et al. 2017), while SMAP uses onboard radar and radiometer measurements to provide retrievals of volumetric water content in the top 5-cm of soil at a spatial reso-
olution down to 9-km (Entekhabi et al. 2013). For cases 2 and 3, NASA LIS and NASA LIS + SMAP runs (EXP1 and EXP2 respectively) were compared- however SMAP was not available for case 1 as it had not been launched yet. The GVF between the CTRL and NASA LIS runs do not differ as they both utilize the Noah LSM climatological average data, thus the GVF field was updated with NESDIS NRT GVF maps for EXP3.

3.4.2 NESDIS GVF

The GVF map utilized in this study is a daily product provided by NESDIS with a 4-km resolution derived from the Visible Infrared Imager Radiometer Suite (VIIRS) sensor onboard Suomi National Polar-orbiting Partnership (SNPP) satellite. Details on the NESDIS GVF product can be found in Jiang et al. (2017), a description is provided here. The NESDIS GVF product utilizes VIIRS surface reflectance from bands 0.490 ($\rho_{blue}$), 0.640 ($\rho_{red}$), and 0.865 µm ($\rho_{NIR}$) which are mapped to the GVF grid. The VIIRS surface reflectance maps are composited to a rolling weekly map where a view-angle soil adjusted vegetation index (VA–SAVI) is computed to select pixels close to nadir view unless the pixels are cloud contaminated:

$$VA - SAVI = (1 + L) \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} - \rho_{red} + L} - C \times VZ^2 \quad (3.4)$$

where $VZ$ is the view zenith angle, $C$ is a constant to minimize soil-brightness, $L$ is the canopy background adjustment factor (set to 0.05), and $\rho_{NIR}$ and $\rho_{red}$ correspond to surface reflectance for 0.865 and 0.640 nm. The VA–SAVI technique was used over
Figure 3.3: (a) NOAA/NESDIS VIIRS GVF and (b) difference between GFS and NESDIS VIIRS for case 1. In the GVF map (a), brown tones represent barren soil and blue/green are more dense vegetation. In the difference map (b), GFS having less vegetation is represented by the orange tones and green tones correspond to GFS having more dense vegetation.

The traditional maximum value composite (MVC) based on NDVI as NDVI favors observations in the forward scatter direction, causing shadows to form in the red and near-infrared channels. The maximum VA–SAVI is selected to represent the composition period. The enhanced vegetation index (EVI) is calculated from the VIIRS rolling weekly composites:

\[
EV I = 2.5 \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + 6\rho_{red} - 7.5\rho_{blue} + 1}
\] (3.5)

and smoothed over 15 weeks to reduce high frequency noise, and then used to calculate GVF aggregated at 4-km resolution:

\[
GV F = \frac{EV I - EV I_{min}}{EV I_{max} - EV I_{min}}
\] (3.6)

A sample of the NESDIS GVF map is provided in Figure 3.3, which shows that the GFS overestimates the amount of vegetation across CONUS by as much as 0.37.
3.5 Validation

A thorough validation of CTRL and EXP experiments was conducted using high-quality aerosol retrievals from the ground-based AERONET across the SW US, specifically for the AOD and size distribution. AERONET is a global ground-based aerosol monitoring network consisting of a Sun-sky scanning radiometers with a 1.2° viewing angle and provides aerosol property retrievals from UV to near-IR wavelengths (Holben et al. 1998). The WRF-Chem model simulates size distribution for the concentration of dust aerosols in five bins, which was compared to the AERONET V3 level 2 volume size distribution measurements. The volume size distribution is developed from sky radiances and the inversion algorithm from Dubovik et al. (2000). AERONET V3 has an AOD bias of +0.02 and a 1σ uncertainty of 0.02 (Giles et al. 2019). As described in Giles et al. (2019), the spectral AOD is calculated from a cloud-free sample as follows:

\[
\tau(\lambda)_{\text{aerosol}} = \tau(\lambda)_{\text{Total}} - \tau(\lambda)_{\text{Rayleigh}} - \tau(\lambda)_{H_2O} - \tau(\lambda)_{O_3} - \tau(\lambda)_{NO_2} - \tau(\lambda)_{CO_2} - \tau(\lambda)_{CH_4}
\]

(3.7)

where the ozone optical depth (\(\tau(\lambda)_{O_3}\)) is calculated from the absorption coefficient of ozone, the optical air mass, and the climatological ozone concentration from the Total Ozone Mapping Spectrometer (TOMS). Similarly, the nitrogen dioxide optical depth (\(\tau(\lambda)_{NO_2}\)) is calculated using the absorption coefficient and the climatological concentration from the Ozone Monitoring Instrument (OMI). The carbon dioxide and methane optical depths (\(\tau(\lambda)_{CO_2}\) and \(\tau(\lambda)_{CH_4}\) respectively) use station-elevation
formulas and absorption constraints from the high-resolution transmission molecular absorption database (HITRAN). The water vapor optical depth ($\tau(\lambda)_{H_2O}$) is a linear equation dependent on perceptible water and filter-dependent coefficients. Lastly, the Rayleigh optical depth ($\tau(\lambda)_{Rayleigh}$) is a pressure corrected calculation based on the optical air mass, the assumptions defined in Holben et al. (1998), and the equation found in Bodhaine et al. (1999).

The comparison between simulated PM (2.5 and 10) concentrations and observed PM concentrations from the United States Environmental Protection Agency (EPA) Air Quality System (AQS) and the Interagency Monitoring of Protected Visual Environments (IMPROVE) networks allowed for a quantitative error analysis of the forecasts to determine whether the EXP runs improve the air quality forecast. EPA AQS has over 1000 sites over CONUS, of which 43 were included in this study. The EPA AQS network reports mean hourly concentrations of particulates (PM10 and PM2.5), criteria gases (ozone, sulfur dioxide, carbon monoxide, and nitrogen dioxide), toxics (HAPs and VOCs), precursors (NONOxNOy), and lead. The IMPROVE network consists of 158 sites across the CONUS, 34 of which were available for this study, and report aerosol and visibility conditions every 3 days (Prenni 2019). Figure 3.4 provides a map with the distribution of both AERONET, EPA AQS, and IMPROVE sites for the SW US domain. PM (2.5 and 10) concentrations were analyzed as these particle concentrations increase with increased dust emissions and are known to be correlated with numerous public health concerns such as Valley Fever.

This work also used a suite of NASA satellites to validate the WRF-Chem simulations. The AOD simulations were compared with multiple instruments/satellites...
Figure 3.4: AERONET (red diamond), EPA AQS (blue plus), and IMPROVE (green circle) station locations within the SW US domain.

including: the Aqua/Terra MODIS, Terra Multi-angle Imaging SpectroRadiometer (MISR), and Geostationary Operational Environmental Satellite (GOES). Details on MODIS, MISR, and GOES can be found at Sayer et al. (2014); Diner et al. (2002); Fuell et al. (2016) respectively, but a brief description of each is provided here.

The MODIS instrument is a multispectral radiometer with 36 bands aboard both Aqua and Terra that passes the United States around 10:30 AM (Aqua) and 1:30 PM (Terra) local time. Two retrieval algorithms have been developed for this instrument: Dark Target and Deep Blue. The Deep Blue algorithm was designed to improve measurements over bright, highly reflective surfaces while Dark Target
is designed for dark or vegetated surfaces (Misra et al. 2015; Hsu et al. 2013; Sayer et al. 2014). The collection 6.1 merged Dark Target-Deep Blue AOD product with a 10-km resolution was utilized for this study, specifically the 550 nm wavelength, and was upscaled to match the inner 3-km domain for a quantitative comparison. MISR provides measurements at four spectral bands (446.4, 557.5, 671.7, and 866.4 nm) for nine different angles: 0.0° (nadir), 26.1°, 45.6°, 60.0°, and 70.5° (both forwards and backwards of nadir). The MISR 555 nm AOD level 2 product with a 4.4-km resolution was utilized and resampled to match the inner domain resolution for a quantitative analysis.

For the first case, the GOES-13 Aerosol/Smoke Product (GASP) product was used, which provides AOD retrievals every 15 minutes at a 5-km resolution. GASP is only available for the first case, thus the GOES-16 Dust RGB was utilized for a qualitative analysis on the spatial distribution of the dust plumes. The Dust RGB product is produced by a false color combination by utilizing the difference between 12.3 and 10.3 µm channels for red, difference between 11.2 and 8.4 µm channels for green, and 10.3 µm channel for blue (a sample is shown in Figure 3.5). The RGB product does have some limitations including: 1) high clouds obscuring the dust plumes beneath them, 2) dust layer thickness cannot be determined, and 3) low clouds can appear to be dust layers when over the ocean. Furthermore, the National Weather Service Next Generation Weather Radar (NEXRAD) reflectivity and correlation coefficient data were utilized to compare the spatial distribution at the surface to the dust plumes identified in the GOES dust RGB imagery. This data is available with a 5-minute frequency and has been used in previous studies.
to identify location, area, and motion of dust storms (e.g. Raman et al. 2014). The correlation coefficient represents the correlation between the backscattered horizontal and vertical polarized signals to determine the shape of the particles (Ryzhkov 2001). Reflectivity was also utilized in the study to identify outflow boundaries (i.e., weak radar signatures with a bow shape), as these can be precursors for dust storms.

To verify our meteorological conditions (specifically the 10-m wind speed, 2-m temperature, and 2-m dew point) 319 stations from the Automated Surface Observing Systems (ASOS) Network were incorporated. Although ASOS units report data as frequently as 1-min when weather conditions change rapidly, the hourly data for 10-m
wind speed, 2-m temperature, and 2-m dew point data were utilized to match the resolution of our WRF simulations. The precipitation observations were not included in the validation efforts as it was not the main focus of this study.

3.5.1 Validation Statistics

Within this study, a vast amount of statistics that are commonly found throughout the literature were incorporated to quantify the validation efforts. The coefficient of determination ($R^2$) measures how close the data are fitted to a 1:1 regression line (i.e. how the data are correlated) but it cannot determine a bias, which is why the mean bias error (ME) was incorporated. ME is calculated as:

$$ME = \frac{1}{N} \sum_{i=1}^{N} \frac{F_i - O_i}{O_i}$$

where $N$ denotes the number of pixels, $F$ is the simulated value, and $O$ is the observed value. To determine the magnitude of the errors in the simulations, the mean absolute error (MAE) and root mean square error (RMSE) were calculated as:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (F_i - O_i)^2} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (F_i - F)(O_i - O)}$$

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |F_i - O_i|$$

Both RMSE and MAE range from 0 to $\infty$ however RMSE, unlike MAE, gives a greater weight to large errors and is therefore more useful when large errors are undesirable.
CHAPTER 4

RESULTS

4.1 WRF Intercomparison

All the cases selected for this case study were initiated by strong winds associated with the passage of a cold front. For case 1, it was difficult to identify the exact dust source region due to cloud cover (Figure 4.1a). Through analyzing the WRF dust aerosol fields, the source region can be estimated as the northern New Mexico and Southern Colorado region (Figure 4.1b). Although the simulation has a secondary dust plume to the south, this plume is not shown in the satellite imagery and the AOD at a nearby AERONET site is less than 0.15, thus it is assumed to be an error in the WRF configuration. This secondary plume originates over Baja California and has continuous emissions throughout the simulation (including our 12 hour spin up). Although the dust plume originating over the Texas panhandle was short lived, the dust was transported across Oklahoma before dissipating (Figure 4.2b), an estimated distance of nearly 500 km. For case 2, the MODIS Aqua RGB imagery shows a clear dust plume over El Paso, TX and appears to remain over that region with minimal transport. Lastly, case 3 has a dust plume originating in South Central Colorado and is transported to the Southeast corner of Oklahoma, an approximate distance of 1050
Figure 4.1: The (a) MODIS Aqua RGB and (b) WRF AOD for forecast hour 31 for case 1.

In all three cases, the wind speed near the source regions exceeded 30 knots with visibilities dropping as low as 2 miles (e.g. Figure 4.3).

When comparing the CTRL to EXP1, there is an overall moist bias in the CTRL run for all cases (as shown in Figure 4.4). The largest moist biases appear in cases 1 and 3 with values exceeding 0.2 m$^3$m$^{-3}$, and an average bias of 0.18 m$^3$m$^{-3}$. When comparing LIS and LIS with SMAP (EXP1 and EXP2) there were minimal differences, less than a 0.04 m$^3$m$^{-3}$ within the source regions. The purple artifacts shown in Figure 4.5 are present in other studies (e.g. Kumar et al. 2008) and are a result of smoothing performed within LIS. Since none of the artifacts from smoothing are found within the dust source regions, the differences in simulated AOD between EXP1 and EXP2 were negligible.
Lastly, the GVF difference between EXP3 and the other simulations (i.e., CTRL, EXP1, and EXP2) for the dust source region in each case varies. Since the GVF field for CTRL, EXP1, and EXP2 were identical, as they were initialized with the GFS data, Figure 4.6 represents the GVF difference between EXP3 and the other simulations. Case 3 was shown to have the largest vegetation bias in the dust source region (Figure 4.6c) with one source region exceeding a bias of 0.2 and the second having an average bias of –0.125. Case 1 and case 2 had a dense vegetation bias for all simulations with an average of 0.125 and 0.08 in the dust source regions, Figure 4.6a and Figure 4.6b respectively.

As aforementioned, one of the goals of this study was to determine the surface properties with the largest impacts on dust simulations along with characterizing the

Figure 4.2: The (a) MODIS Aqua RGB and (b) WRF AOD for forecast hour 45 for case 1.
Figure 4.3: ASOS conditions during pre, active, and post periods of the dust event for case 3. The time period of the dust event is shaded in yellow. The colored lines are individual ASOS stations near the source region and the black line is the 30 minute average of all stations.
Figure 4.4: Soil moisture difference for (a) case 1, (b), case 2, and (c) case 3 between CTRL and EXP1 for forecast hour 00. The red boxes denote the approximated dust source regions.

Figure 4.5: Soil moisture difference for (a) case 2 and (b) case 3 between EXP1 and EXP2 for forecast hour 00. Case 1 was excluded from this analysis as SMAP was not available yet. The red boxes were incorporated to emphasize the dust source regions.
Figure 4.6: GVF difference for (a) case 1, (b), case 2, and (c) case 3 between CTRL and EXP3 for forecast hour 00. The red boxes denote the approximated dust source regions.

Figure 4.7 provides the AOD differences for forecast hour 30 for each case with the first column corresponding to each CTRL, the second column is EXP1, and the third column is EXP3. The rows are corresponding to case number with the top being case 1 and end being case 3. For each case, the CTRL simulated lower AOD compared to the EXP runs. On average, EXP1 resulted in larger AOD values for the dust plume of interest with an increase of 0.15 when compared to that of the CTRL, with case 3 exceeding 0.2. As shown in Figure 4.8, although the wind speed differences are minimal between CTRL and EXP1 (an average of 2 m s$^{-1}$ larger in CTRL), the AOD is higher in EXP1, which is related to the fact that the threshold wind speed is higher under moist conditions than dry (e.g. Ishizuka et al. 2005). Increased vegetation increases the surface roughness and in turn turbulence, therefore decreasing the surface wind speed. With a larger GVF in EXP1, the wind speed is expected to be lower than
Figure 4.7: Comparing the simulated AOD for all cases with CTRL on the left, EXP1 in the middle, and EXP3 on the right. Forecast hours are 38 for case 1 (top row), 48 for case 2 (second row), and 46 for case 3 (bottom row). The plumes of interest are highlighted with the red boxes/ellipses.
Figure 4.8: Sample comparison of the wind speed (top row), AOD (bottom row), and associated differences (third column) for case 3 for CTRL (first column) and EXP1 (second column).

that of EXP3. When comparing EXP1 to EXP3 (Figure 4.9), the surface wind speed in EXP3 is overall lower near the dust source regions than that of EXP1 resulting in lower AOD values. The differences in AOD are only slightly lower (less than 0.1), meaning the soil moisture field has a larger impact on the aerosol loading than that of the vegetation field.
4.2 Validation

4.2.1 ASOS

319 ASOS stations were utilized in this study to validate the overall meteorological conditions. The validation effort included the RMSE, $R^2$, and bias error (e.g. Table 4.1 and 4.2) as values for hits, misses, and false hits and misses were unable to be determined for 2-m temperature, 10-m wind speed, and 2-m dewpoint. When compared with the observed 10-m wind speed, EXP1 had an overall 5% improvement in wind speed. The differences between EXP3 and CTRL runs varied per case with case 3 decreasing the bias error by 12% and case 2 increasing the bias error by 0.5%.

Figure 4.9: Sample comparison of the wind speed (top row), AOD (bottom row), and associated differences (third column) for case 3 for EXP1 (first column) and EXP3 (second column).
<table>
<thead>
<tr>
<th>Measurement</th>
<th>Bias Error</th>
<th>$R^2$</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>CTRL</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AERONET</td>
<td>-0.224</td>
<td>0.230</td>
<td>0.226</td>
</tr>
<tr>
<td>ASOS (Dewp)</td>
<td>3.258</td>
<td>0.362</td>
<td>6.778</td>
</tr>
<tr>
<td>ASOS (Temp)</td>
<td>4.988</td>
<td>0.421</td>
<td>7.937</td>
</tr>
<tr>
<td>ASOS (Wind Speed)</td>
<td>-1.197</td>
<td>0.098</td>
<td>7.040</td>
</tr>
<tr>
<td>MISR</td>
<td>-0.246</td>
<td>0.043</td>
<td>0.272</td>
</tr>
<tr>
<td>MODIS</td>
<td>-0.346</td>
<td>0.123</td>
<td>0.361</td>
</tr>
<tr>
<td><strong>EXP1</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AERONET</td>
<td>-0.223</td>
<td>0.278</td>
<td>0.225</td>
</tr>
<tr>
<td>ASOS (Dewp)</td>
<td>1.632</td>
<td>0.487</td>
<td>8.069</td>
</tr>
<tr>
<td>ASOS (Temp)</td>
<td>5.949</td>
<td>0.545</td>
<td>9.122</td>
</tr>
<tr>
<td>ASOS (Wind Speed)</td>
<td>-2.545</td>
<td>0.100</td>
<td>6.967</td>
</tr>
<tr>
<td>MISR</td>
<td>-0.241</td>
<td>0.042</td>
<td>0.260</td>
</tr>
<tr>
<td>MODIS</td>
<td>-0.328</td>
<td>0.122</td>
<td>0.365</td>
</tr>
<tr>
<td><strong>EXP3</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AERONET</td>
<td>-0.224</td>
<td>0.278</td>
<td>0.226</td>
</tr>
<tr>
<td>ASOS (Dewp)</td>
<td>1.275</td>
<td>0.485</td>
<td>8.309</td>
</tr>
<tr>
<td>ASOS (Temp)</td>
<td>6.108</td>
<td>0.544</td>
<td>9.118</td>
</tr>
<tr>
<td>ASOS (Wind Speed)</td>
<td>-2.540</td>
<td>0.101</td>
<td>6.904</td>
</tr>
<tr>
<td>MISR</td>
<td>-0.239</td>
<td>0.053</td>
<td>0.258</td>
</tr>
<tr>
<td>MODIS</td>
<td>-0.663</td>
<td>0.046</td>
<td>0.367</td>
</tr>
</tbody>
</table>

The RMSE worsened by less than 1% for all experimental runs making it statistically insignificant. For 2-m temperature, EXP1 improved the bias error by 26% whereas EXP3 improved the bias error by an additional 7%. As mentioned in Chapter 2, vegetation plays a large role in the surface energy balance through evapotranspiration and the latent and sensible heat fluxes. With the large dense vegetation bias present in the CTRL, it is expected to have large differences in the latent and sensible heat fluxes when compared with EXP3, and in turn large differences in the 2-m temperature.
Table 4.2: Average percent difference for all the cases where validation data was available. Bold numbers represent where the EXP run outperformed the CTRL. AERONET validation was only available for case 2 and case 3.

<table>
<thead>
<tr>
<th>Measurement</th>
<th>EXP1</th>
<th>EXP3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bias Error</td>
<td>R²</td>
</tr>
<tr>
<td>AERONET</td>
<td>0.56%</td>
<td>9.17%</td>
</tr>
<tr>
<td>ASOS (Dewp)</td>
<td>52.52%</td>
<td>4.53%</td>
</tr>
<tr>
<td>ASOS (Temp)</td>
<td>25.91%</td>
<td>2.28%</td>
</tr>
<tr>
<td>ASOS (Wind Speed)</td>
<td>5.10%</td>
<td>0.33%</td>
</tr>
<tr>
<td>MISR</td>
<td>2.73%</td>
<td>11.95%</td>
</tr>
<tr>
<td>MODIS</td>
<td>1.72%</td>
<td>6.07%</td>
</tr>
</tbody>
</table>

4.2.2 AOD

There were minimal high-quality AOD retrievals available for validation due to cloud cover during the dust cases. Of the cloud-free data that was available, the statistical analysis was further restrained to the dust source region and nearby transport pathway. To limit uncertainties in the simulated meteorological fields, the validation was also confined to the 48–h period after initial dust emission. As a result, case 3 had the most validation data available. As our cases are in close proximity to cloud cover, it makes validation near the dust source and transport thereafter difficult. When restraining our statistical validation, there were still larger errors when compared to observations (Table 4.1 and Table 4.2). On average, the bias error was -0.239 for MISR and -0.663 for MODIS. Large biases may be due to the configuration of our model as well as the AOD satellite retrievals are not solely dust retrievals. The satellite validation was constrained to a subdomain to contain the dust source region as well as restraining the validation to 48 hours of initiation to try to mitigate this issue, however the majority of the data was missing due to cloud cover.
cover. AERONET stations were then utilized to further validate the simulated AOD, however previous studies have found the MISR algorithm to have significant errors when compared to AERONET (e.g. Kahn et al. 2005). As shown in Figure 4.10, MISR had an AOD of 0.25 whereas the simulations do not exceed 0.11. The associated AERONET site (denoted by the black star) only had 0.09 at 1800 UTC, a bias of 0.16. When comparing the simulated AOD to the White Sands AERONET site there was a bias of only 0.02. Overall, the simulated AOD resulted in an average bias of -0.224 for AERONET although this bias improved within EXP1 and EXP3 (Table 4.1). With the significant discrepancies for AOD observations between datasets and large data gaps in cloud contaminated pixels, the GOES dust RGBs were incorporated in order to validate dust transport and spatial extent.

Unfortunately, GOES Dust RGBs were only available for case 3. These RGBs were used to validate if WRF–Chem is able to accurately simulate the dust plume and transport. A statistical analysis is not able to be performed on the GOES data as the RGBs are not a quantitative dataset. As shown in Figure 4.11, the simulations are able to capture the overall dust plume signature. The darker plume located over Nebraska cannot be validated due to cloud cover. The dust RGBs were further compared with NEXRAD reflectivity, R², and differential reflectivity. From the radar signatures shown in Figure 4.12, we are able to say with certainty that the dust RGBs are a good representation of the dust plume signatures. The dust plumes have relatively low reflectivity values than that of precipitation (does not exceed 15 dBZ) so the reflectivity images were skewed to accentuate the dust plumes. For KDDC, the R² had an average value of 0.8 and an average differential reflectivity of -2 dBZ for case
Figure 4.10: AOD values for (a) MISR, (b) CTRL, (c) EXP1, ad (d) EXP3 for case 3 with the dust source outline by the black box. The black star corresponds to the location of the White Sands AERONET site.
Figure 4.11: GOES Dust RGB (c) for case 3 associated with forecast hour 44 for (a) CTRL and (b) EXP1.
Figure 4.12: Comparing (d) GOES Dust RGB with (a) reflectivity, (b) $R^2$, and (c) differential reflectivity data from the KDDC NEXRAD station, outlined by the white box in the RGB.
3, however without the reflectivity images it would be difficult to identify the dust plumes since the surrounding noise has similar signatures.

4.2.3 Air Quality

The air quality validation was compared on a site by site basis where PM2.5 was more readily available than that of PM10. The observed PM concentrations near the dust source compare well to our simulations as shown in Figure 4.13 and Figure 4.14. Since the AOD differences were minimal between EXP1 and EXP3, the PM concentrations are similar as shown in Figure 4.13. The further the dust is transported, the larger the errors in PM concentrations however this is to be expected as EPA AQS systems measure all particulates. Since it is not possible to exclude all particulates except dust from the PM observations, the overall signatures of the individual time series were compared to determine the accuracy of the simulations. Figure 4.13, for example, illustrates how WRF-Chem is able to spatial represent air quality during the dust event as well as transported dust impacts. Minimal errors were seen near dust source regions with minimal error during the dust event (e.g. the yellow box in Figure 4.13).
Figure 4.13: PM2.5 time series for case 3 with the main dust plume period outlined enclosed with the yellow rectangle and an initial plume outline with the red rectangle. The red line is the observed PM2.5 whereas the solid blue line is the calculated CTRL and the dashed lines are associated with (a) EXP1 and (b) EXP3.
Figure 4.14: The spatial comparison of PM10 for early in the dust event (top row) and transport (bottom row) for case 3. The green ellipses highlight EPA AQS stations in agreement with our simulation and the black ellipses highlight stations that observed larger values than the simulations.
CHAPTER 5

CONCLUSIONS

5.1 Summary

In this study, the WRF-Chem model was used to simulate dust emissions and transport for three cases in the SW US: 27 April 2014, 23 March 2017, and 17 April 2018. The NASA EOSDIS Worldview web mapping application was used to determine that sufficient satellite data was available for validating the dust simulations. GFS 0.5° reanalysis data was utilized for the initial and lateral boundary conditions, including monthly climatological values for soil moisture and vegetation data from the Noah LSM. The main objectives of this study were: determine if WRF-Chem is able to accurately simulate dust emissions and transport processes, update the soil moisture field using NASA LIS to enhance dust simulations within the model framework, update GVF field by incorporating NESDIS GVF data to further enhance dust emissions and air quality forecasts and determine which field had the largest impact on the simulations.
5.2 Conclusions

5.2.1 Identifying WRF-Chem Simulation Accuracy

This study utilized WRF-Chem with the S11 and GOCART simple emissions to simulate dust emissions for three cases in the SW US. The third case (17 April 2018) was identified as the golden case as it had the most validation data available. When compared with the observations from ground-based networks (AERONET, EPA AQS, and IMPROVE) and satellite (MODIS, MISR, and GOES), it was determined that although the CTRL run generally underestimated dust emissions, and therefore unrealistically improved air quality, the configuration was able to capture the dust source and duration of the dust storm.

5.2.2 Incorporating NASA LIS in Dust Forecasts

When compared with the CTRL, the NASA LIS EXP runs had overall higher AOD values as the CTRL runs had a moist bias of 0.18 m$^3$ m$^{-3}$ within the dust source regions, whereas other regions exceeded 0.25 m$^3$ m$^{-3}$. Case 2 and case 3 had NASA LIS with SMAP available, however differences between the two runs were minimal within the dust source regions, less than 0.04 m$^3$ m$^{-3}$, as the regions were relatively dry leading up to the dust events. When compared with MISR(MODIS), EXP1 decreased the standard error, bias error, and RMSE by 27%(7%), 3%(2%), and 2%(1%). The larger simulated AODs resulted in larger PM25 and PM10 concentrations, thus reducing air quality across the region. The simulations were able to capture the
spatial distribution of PM25 and PM10, however PM10 concentrations were severely underestimated within in the simulations with EXP1 reducing this error.

5.2.3 Vegetation Impacts on Dust Forecasts

Lastly, the GVF field was updated with the NESDIS GVF product. The CTRL runs were found to have more dense vegetation than that of EXP3 by an average of 0.1 in the dust source regions whereas others exceeded 0.2. In comparison with EXP1 and EXP2, the AODs were lower by 0.1 but still exceeded those of the CTRL run. As a result, EXP3 was found the be a better representation of regional air quality than that of the CTRL with a decreased bias error, $R^2$, and RMSE for MISR(MODIS) by 3%(0.3%), 5%(2%), and 24%(-1%). When compared with EXP1, the differences in bias error for MODIS, MISR, and AERONET were statistically insignificant (less than 1%), thus confirming the hypothesis that soil moisture field has a larger impact on the simulations than GVF.

5.3 Future Directions

The methodology from this study can be further applied to other regions including East Asia, the Middle East, and North Africa as these regions are known to significantly impact the global dust concentration and cross continental air quality. African dust has been found to impact air quality in Europe, the Middle East, South America, and the eastern US. North Africa and the Middle East account for over half the global annual dust concentration (Goudie and Middleton 2001). East Asian dust can reach the free troposphere, and be transported as far as the western US. With the
significant impacts these regions have on global dust emissions, it is imperative to be able to forecast these dust events with accuracy. Future dust case studies over these regions can incorporate the EXP methodologies here to enhance the dust emission forecasts. The validation effort for the dust RGB’s can also be expanded to determine a relationship between AOD and the dust RGB pixel value. This would allow for both a qualitative and quantitative validation on a 5-min resolution for the SW US.
REFERENCES


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