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THE IMPACTS OF WIND FARMS ON CUMULUS DEVELOPMENT IN THE CENTRAL GREAT PLAINS

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A THESIS

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ABSTRACT

Cumulus clouds have a net cooling effect on the surface radiative balance by reflecting more downwelling solar radiation than absorbing upwelling terrestrial radiation. As boundary layer cumuli form from buoyant, moist plumes ascending from the surface, their growth may be hindered by the turbulent deformation of the plume by wind farms. A natural laboratory to study the impact of wind farms on cumulus formation is Iowa and Nebraska as these two states vary vastly in their wind power offerings. This study uses Geostationary Operational Environmental Satellite (GOES) visible satellite imagery from the summers of 2009 to 2013 to investigate cumulus development upstream and downstream of wind farms in Iowa and Nebraska with the intent to show the impacts of wind farms on fair weather cumulus development at various stages of cloud development. Analysis of the mean cloudy state both upstream and downstream of wind turbines shows that a statistically significant change in the amount of cloudiness is not present.
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1. Introduction

The Earth’s radiative budget is significantly influenced by clouds. As fair weather cumulus (FWC) clouds comprise a fractional cloud cover of 10 to 30 percent (Weilicki and Welch 1986), they have an important impact on this budget, especially in the boundary layer (e.g. Ramanathan et al. 1989, Albrecht 1981, Stull 1985). FWC are net coolers of the surface due to greater reflection of incoming shortwave radiation than absorption of longwave radiation (Berg et al. 2011). It is known that cumulus clouds range in size from a few meters up to several kilometers, though they have an average length of ~ 1 km, as stated by Chandra et al. (2013) and Rodts et al. (2003). Observations of FWC using aircraft photos (e.g. Plank 1969, Hozumi et al. 1982) show FWC clouds range in size from 30 m to 10 km, with modal diameters of approximately 1-2 km. As FWC form due to buoyant, moist ascending plumes from surface fluxes (e.g. Brown et al. 2002, Lemone and Pennell 1976, Betts and Viterbo 2005), their growth may be impacted by the turbulent deformation of the plume by wind farms. As these plumes rise, they transport sensible heat away from the surface, as well as generate and transport kinetic energy, but that kinetic energy can be removed from the boundary layer as it gets converted by turbines into mechanical and electrical power. During this process, these turbines may be destroying the plumes through forced entrainment. Dry environmental air that comes into contact with the cumulus through the entrainment process causes the cumulus to reduce its liquid water content and buoyancy, and increase its decay rate. As a result, dissolves into the environment (de Rooy et al. 2013).
Wind power in the United States continues to grow. The U.S. currently produces more wind energy than any other nation in the world, with more than 167 billion kWh produced in 2013 (American Wind Energy Association 2014a). The country’s cumulative installed wind energy capacity has increased by more than 22-fold since 2000 (U.S. Department of Energy 2012). Despite modest wind power growth since the expiration of tax credits in 2012 that subsidized wind power installation, by the end of 2014 the United States possessed a total of 65 gigawatts (GW) of wind power—enough energy to power more than 18 million homes (American Wind Energy Association 2015a). The U.S. currently receives 4.1 percent of its total power from wind overall, with Plains states such as Iowa and South Dakota receiving more than 25 percent of their power from wind (American Wind Energy Association 2015b).

One of the driving factors for the proliferation of wind power in the United States is the ability to generate electricity with substantially less carbon dioxide emissions than fossil fuel-powered electrical plants. In effect, wind power reduces surface radiative forcing by preventing the emission of greenhouse gases. However, wind power also contributes to turbulent deformation of the planetary boundary layer (PBL). Large wind farms increase the effective surface roughness experienced by the PBL, (e.g. Frandsen 1992, Calaf & Meneveau, 2010) such that the effective wind velocity at turbine-hub height decreases compared to a PBL without wind farms. Based on modeling, Fitch et al. (2012) suggests that wind farms may enhance turbulent kinetic energy in the flow at hub-height for up to 10 km downstream of the wind farm edge, and that wind speed profiles and other changes in properties within the PBL may extend more than 60 km down-
stream. The PBL is characterized by mechanical (wind shear) and thermal (buoyancy) turbulence processes, which are controlled by interactions with the surface and by entrainment with the atmosphere above (Fisch et al. 2004). Introduction of wind farms into the PBL enhances entrainment downstream of the farms in the turbulent wake and possible erosion of the forming cloud. It is important to identify the impact of wind turbines on FWC development to determine the true net radiative impact of this form of alternative energy, especially as wind power continues to grow in the United States.

A handful of studies have been completed regarding how wind farms impact weather processes. Wang and Prinn (2010) modeled the large-scale effects of wind farms on local meteorology and determined that using wind energy to meet 10 percent of global energy demand in 2100 could cause temperatures to rise by 1° C in the vicinity of the wind farms. Furthermore, they found smaller increases outside of wind farms and a perturbation to the general circulation pattern. A separate modeled analysis by the same group (Wang and Prinn 2011) indicates a drop in temperature by 1° C for wind turbines installed off shore due to enhanced latent heat flux from the sea surface to the lower atmosphere from an increase in turbulent mixing by wind farms, which was not offset by the concurrent reduction of mean wind kinetic energy. In contrast, Keith et al. (2004) modeled the large-scale effects of wind power and found that wind farms have a negligible effect on global-mean surface temperature, and would deliver global benefits by reducing emissions of CO₂ and air pollutants. Barrie and Kirk-Davidoff (2010) modeled a continent-scale wind farm and found that North American wind farms can potentially alter the storm development over the North Atlantic. Instead of modeling, Baidya &
Traiteur (2010) used field observations to show that wind farms modified near-surface air temperatures within and downwind of the farm. The sign of the temperature change depended on the stratification of the low-level air, with a stable stratification leading to a warming and an unstable stratification leading to a cooling. Using MODIS satellite observations, Zhou et al. (2012) found a significant warming trend over wind farms relative to nearby non-wind-farm regions.

The present study looks at how wind farms affect boundary layer-based weather phenomena by introducing a satellite-based analysis of the impacts of wind turbines on FWC development. Five years of GOES 1 km visible imagery are used to objectively identify FWC and investigate their development upstream and downstream of wind farms in Iowa and Nebraska in order to show the impacts of wind farms on the development of these at various stages of their life cycle.
2. Methodology

A number of steps were taken to organize the satellite and observation data into a format that was suitable for computational and visual analysis. After a domain was selected, the satellite data had to be processed and a cloud detection algorithm was created. Local wind speed and direction was used to calculate the average FWC cloudiness of pixels upstream and downstream of the wind farms. These pixels were analyzed to determine if there is a statistically significant increase or decrease in FWC.

2.1. Domain: Iowa and Nebraska

Despite Iowa and Nebraska’s similar synoptic forcing and prime location for wind resources, these two states vary vastly in their wind power offerings due to regulatory issues. In 1983, Iowa became the first state to guarantee a market for wind by passing the Renewable Electricity Portfolio Standard, which required the state’s investor-owned utility companies to purchase electricity from renewable energy resources. As a result of this law, Iowa currently generates 27 percent (5.1 GW) of its electricity from wind power and is ranked 3rd in the nation for installed wind capacity (American Wind Energy Association 2014b) despite the state being ranked 7th best wind resource in the nation (National Renewable Energies Laboratory 2011). In contrast, Nebraska is the only state in the nation to operate with 100 percent public power, in which utilities are government-owned, not investor-owned. Prior to 2007, only public power agencies could build wind power in the state of Nebraska, but few did so in order to comply with their legal mandate.
to provide electricity as inexpensively as possible. After changes in the legal structure, Nebraska has slowly increased its wind power offerings, but the overall amount is much reduced when compared to Iowa: despite being ranked 3rd in the nation for wind power potential, Nebraska only ranks 18th in amount of wind power produced. This region comprises an ideal natural laboratory to investigate the impact of wind turbines on small convective clouds. The prolific deployment of wind power in western Iowa provides ample data to determine what, if any, small-scale impact on FWC is caused by wind turbines, while intercomparisons between western Iowa and eastern Nebraska permit investigation of the large-scale effects.

2.2. Data

This study uses GOES 1 km visible imagery to identify summertime FWC from 2009 to 2013. Infrared imagery was not used as GOES 4 km resolution is not good for this application. Data for this range were chosen as wind power reached maturity in Iowa by that time with most of the large-scale wind farms in that state installed prior to 2009. In order to discern the average FWC presence over the domain, a cumulus detection algorithm using the visible satellite imagery had to be developed. The initial step was to calibrate and calculate reflectances from raw GOES satellite files using the Center for Satellite Application & Research Post-Launch Operational Calibration (Office of Satellite & Product Operations 2014). Clouds were identified from the calibrated data using a reflectance threshold. The resulting binary image was analyzed for connected components. Clouds that consisted of three or more connected pixels, representing clouds with
an ad hoc spatial extent of at least 3 km², were assumed to be too large to be FWC and were discarded. The remaining pixels were classified as FWC. Of note is that small-sized cumuli tend to be the most numerous, but cloud cover is not always dominated by the smallest clouds (e.g. Rodts et al. 2003, Benner and Curry 1998; Zhao and Di Girolamo 2007, Wood & Field 2011). Figure 2.1 shows a subset of the calibrated reflectance view over the domain, as well as the output of the cumulus detection algorithm.

Daily images from June through August of 2009 to 2013 were aggregated and the frequency of FWC was calculated for each of six times, representing various stages of development: 1715, 1815, 1915, 2015, 2115 and 2215 UTC. Equal subsets over Iowa and Nebraska were created from these times and were statistically analyzed using
difference of means t test at an 80 percent confidence interval to determine if a domain-averaged statistically significant increase or decrease in cloudiness was present. Sample image subsets at 1715 UTC is shown in Figure 2.2 (a) over Nebraska & (b) over Iowa.

No statistically significant difference between the turbine-dense and turbine-sparse regions of the Iowa and Nebraska domain resulted from the test. Therefore, if wind turbines do have an impact on cumulus cloud development, this impact cannot be observed on the regional scale.

The lack of a discernible signal on the regional scale, however, does not preclude the possibility that clouds are being affected on the scale of individual wind farms. An
investigation of the local cumulus frequency upstream and downstream of the wind turbines was undertaken. The FWC detection algorithm was used to analyze each of the satellite views that comprise the dataset used in the study; it was found that cumuli occurred within the domain on 116 separate days. For each wind farm, the wind direction at the time of analysis was obtained from the closest Automated Surface Observing System (ASOS) or Automated Weather Observing System (AWOS) station. Wind speed was thresholded with a cut-in speed of 3 m s\(^{-1}\) and a cut-out speed of 25 m s\(^{-1}\), which is consistent with Christiansen & Hasager (2005). Wind turbines start operating at a threshold called a cut-in wind speed, and depending on manufacturer, this ranges from \(~3-5\) m s\(^{-1}\). Wind turbines shut down at a cut-out speed of \(~25\) m s\(^{-1}\) for safety reasons. A swath of pixels representing 10 km upstream of the wind farm, the farm itself, and 10 km downstream of the farm was collected and subsets were analyzed for cloudiness. Finally, various combinations of pixels upstream and downstream of the wind farms were statistically analyzed using difference of means t test at an 80 percent confidence interval to determine if a statistically significant increase or decrease in cloudiness was present.
3. Results

The following pixels were evaluated: 2 km (2 pixels) upstream of each wind farm, 1 km (1 pixel) upstream of each wind farm, 2 km (2 pixels) downstream of each wind farm, 1 km (1 pixel) downstream of each wind farm, 1 km (1 pixel) upstream of each wind farm to 1 km (1 pixel) downstream, and 2 km (2 pixels) upstream of each wind farm to 2 km (2 pixels) downstream from all wind farms on the identified cumulus days. Results are listed as follows:

• 2 km upstream from wind farms, there is a statistically significant increase in cloudiness at 1715 & decrease at 2215.

• 2 km downstream from wind farms, there is a statistically significant decrease in cloudiness at 1715.

• 1 km downstream from wind farms, there is a statistically significant decrease in cloudiness at 1715 and increase at 2215.

• 2 km upstream to 2 km downstream from wind farms, there is a statistically significant increase in cloudiness at 2015 & decrease at 2215.

• 1 km upstream to 1 km downstream from wind farms, there is a statistically significant increase in cloudiness at 2215.

Figure 3.1 shows the results for the six analyzed times. While some individual times and locations indicate a statistically significant difference, overall there is no coherent pattern to the increases and decreases either spatially or temporally. Without
consistent statistically significant increases or decreases, there is no clear signal to indicate that wind farms hinder or aid the development of cumulus clouds. To determine if impacts would only be felt from the very largest wind farms, a separate analysis that consisted of just farms with 100 or more wind turbines over the same temporal range was also conducted, resulting in 14 farms for analysis. Similar to the aggregate dataset, however, no statistically significant increases or decreases were found within the same time range discussed above, indicating that wind farm size does not have an impact on the signal.
Figure 3.1. (a) Average cloudiness 10 pixels upstream and downstream from all wind farms from June through August 2009 through 2013 in Iowa and Nebraska at 1715 UTC. Wind flow is to the right. The x axis is the pixel number, number 11 being where the wind farm is located (black dashed line). Pixels to the left of the wind farm are upstream and pixels to the right of the wind farm are downstream. The y axis is the average cloudiness from 0 to 1, zoomed in to see detail. (b) Same as (a) but for 1815.
Figure 3.1. (c) Same as (a) but for 1915. (d) Same as (a) but for 2015.
Figure 3.1. (e) Same as (a) but for 2115. (f) Same as (a) but for 2215.
4. Summary and conclusions

Due to the surface-based nature of FWC, the sensitivity of FWC to entrainment, and the presence of mechanically induced mixing in the boundary layer from wind turbines, it is reasonable to inquire what impact the presence of wind turbines has on the development of these clouds. This study attempts to answer this question through analysis of multiple years of GOES 1 km visible satellite to identify the relative frequency of the formation of FWC over a large-scale domain as well as upstream and downstream of individual wind farms in Iowa and Nebraska.

Using this method, no signal was found identifying that FWC development is hindered or aided by the presence of wind farms. This means that the beneficial impact of wind turbines on surface radiative forcing through the reduction of greenhouse gas emissions for electrical generation is not being offset by a reduction in planetary albedo through destruction of cooling clouds. However, this method naturally has some limitations, and a signal may still be present. A primary issue is the small size of boundary layer cumulus. The 1 km spatial resolution, while currently the best available from geostationary satellites over the continental United States, may still be too coarse to capture many FWC. A similar study conducted several years into the future, after the next generation of geostationary satellites has collected ample data, may provide new insights that the current one cannot. An additional issue is that wind farms were treated as a single point due to the limitations imposed by the wind farm location dataset.
However, wind farms often stretch over tens of square kilometers and can occupy several satellite pixels; the analysis technique employed here is unable to account for the spatial extent of these farms. Finally, he natural differences in soil moisture and/or land use differences could cause variability that inhibits the ability to recognize a signal that is present. It is recommended that future work use large eddy simulation or cloud resolving modeling to simulate the impacts of wind-turbine-based deformation on cumulus growth.
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