AIR POLLUTION-ECOSYSTEM FEEDBACKS: OBSERVATIONAL CONSTRAINTS ON OZONE-FOREST INTERACTIONS FROM AN UNMANNED AERIAL VEHICLE

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Abstract

Tropospheric ozone (O\textsubscript{3}) is an air pollutant and key atmospheric oxidant. Global chemical transport models suggest 15–30% of tropospheric O\textsubscript{3} is lost by deposition to the Earth’s surface annually. We require knowledge of O\textsubscript{3} losses to predict O\textsubscript{3} variability in the troposphere; however, there are few direct measurements of the atmosphere-surface loss rate, known as the deposition velocity. Here, we describe a method for observationally-deriving the O\textsubscript{3} deposition velocity using a flux-gradient approach combined with a light-weight low-power measurement payload onboard an unmanned aerial vehicle (UAV). Using indoor and outdoor test flight data, we demonstrate that combined uncertainties in O\textsubscript{3} concentration and horizontal wind measurements are small enough to derive O\textsubscript{3} deposition velocities on the order of those observed over a variety of vegetated landscapes. Here, we present UAV payload design, the derivation for deposition velocity, and preliminary flight data.

Introduction

Tropospheric ozone (O\textsubscript{3}) is a pollutant that is harmful to humans (Cohen et al., 2017; Jerrett et al., 2009) and plants (e.g., Ashmore, 2005; Reich, 1987). O\textsubscript{3} plant damage has been observed in forests (Ainsworth et al., 2012; references therein) and linked to decreases in global crop production (Avnery et al., 2011a, 2011b; Wilkinson et al., 2011), with the severity of O\textsubscript{3} effects varying as a function of plant species and development stage (Bergman et al., 1995; Fuhrer et al., 2003; Prozherina et al., 2003). O\textsubscript{3} is a greenhouse gas that also affects climate indirectly (IPCC, 2013), altering ecosystem gross and net primary productivity (Fares et al., 2013; Paoletti and Grulke, 2010; Tai et al., 2014; Wittig et al., 2007, 2009) and contributing to the production of secondary organic aerosol (Jokinen et al., 2015; Liu et al., 2011).

Global chemical transport models suggest 15–30% of tropospheric O\textsubscript{3} is lost by deposition to the Earth’s surface annually (Wild, 2007; Young et al., 2013), with deposition to plant canopies via stomatal uptake being generally the dominant loss process over terrestrial ecosystems (30–90%) (e.g., Cieslik, 2004; Clifton et al., 2017; Fares et al., 2014; Fowler et al., 2001, 2009). The O\textsubscript{3} velocity of deposition (v\textsubscript{d}) is highly variable with vegetation, land cover type, and environmental conditions that influence the rate of stomatal conductance (g\textsubscript{s}). O\textsubscript{3} v\textsubscript{d} over vegetation typically ranges from 0 to 1 cm s\textsuperscript{-1}, with higher deposition velocities over forests and croplands and lower values over grasslands and tundra (Hardacre et al., 2015). O\textsubscript{3} v\textsubscript{d} is both over and under predicted by models by a factor of two, with measurement-model discrepancies varying with vegetation type (Clifton et al., 2017; Fowler et al., 2009; Hardacre et al., 2015; Val Martin et al., 2014). While knowledge of O\textsubscript{3} v\textsubscript{d} is important to the global O\textsubscript{3} budget, O\textsubscript{3} deposition rates are among the most uncertain and poorly constrained terms (Wild, 2007). Uncertainties are due in part to lack of O\textsubscript{3} v\textsubscript{d} observations over the range of vegetative canopy types, with many global ecosystems under or unsampled (Young et al., 2018).

O\textsubscript{3} v\textsubscript{d} over vegetative canopies can be empirically determined from measurements of
the O₃ flux ($F_{O₃}$) using the eddy-covariance technique (Eq. 1). Eddy-covariance is a micrometeorological method based on principles of mass and momentum conservation, in which $F_{O₃}$ is equivalent to the turbulence-driven O₃ vertical mass transport through a reference layer, and computed as the deviation from the mean covariance of measured O₃ concentrations and vertical winds ($w$) (e.g., Baldocchi et al., 1988; Foken, 2006; McMillen, 1988) (Eq. 2).

$$O₃ν_{vd} = −F_{O₃}/[O₃]$$  \hspace{1cm} (1)

$$F_{O₃} = \int_0^t w'[O₃]' dt = \frac{1}{n} \sum_{i=1}^{n} (w_i - \bar{w}) ([O₃]_i - [O₃]) = w'[O₃]'$$  \hspace{1cm} (2)

In practice, these observations are collected from atop stationary research towers, representing homogenous plant canopies, with fast (generally 10 s⁻¹) 3-dimensional anemometers and high-precision sub-second time response chemical analyzers to capture higher-frequency eddy flux contributions. As a result, infrastructure investments are typically required, which may be substantial for taller plant canopies and difficult to maintain in remote areas. Moreover, there are few off-the-shelf commercially-available O₃ instruments that meet the analytical requirements of eddy-covariance.

O₃ νvd can also be measured using the flux-gradient method with light-weight, low-power, commercially-available equipment. Flux-gradient methods quantify $F_{O₃}$ as a function of the vertical atmospheric concentration and horizontal wind speed ($u$) gradients, and the Von Kármán constant ($k$), a measure of the turbulent fluid flow gradient at a boundary (Eq. 3 & 4) (Keenan et al., 2012).

The flux-gradient method has been implemented to determine O₃ νvd from multiple platforms, including tethered balloons (Broder et al., 1981), aircrafts using O₃ columns measured with LIDAR systems (Couach et al., 2003), as well as modeled (Kramm et al., 1995; Sitch et al., 2007), but is most commonly measured from stationary research towers or ship masts (Bocquet et al., 2011; Colbeck and Harrison, 1985; Droppo Jr, 1985; Duyzer et al., 1983; Duyzer and Westrate, 1995; Enders, 1992; Fontan et al., 1992; Galbally and Allison, 1972; Garland and Derwent, 1978; Hargreaves et al., 1992; Hole et al., 2004; Horvath et al., 1998; Kramm et al., 1991; Matsuda et al., 2005; Mikkelsen et al., 2000; Muller et al., 2009; Neirynek et al., 2012; Zapletal et al., 2011). Agreement between flux-gradient and eddy-covariance derived O₃ νvd and flux-gradient and modeled O₃ νvd have been reported (Bocquet et al., 2011; Droppo Jr, 1985; Duyzer and Westrate, 1995; Hole et al., 2004; Mikkelsen et al., 2000; Muller et al., 2009; Wohlfahrt et al., 2009).

Unmanned aerial vehicles (UAVs) have increasingly become a platform for atmospheric sampling, including the deployment of instrumentation to measure greenhouse gases (Berman et al., 2012; Brosy et al., 2017; Illingworth et al., 2014; Li et al., 2017; McGonigle et al., 2008; Rüdiger et al., 2018; Thomas et al., 2012; Watai et al., 2006), O₃ concentrations (Illingworth et al., 2014; Li et al., 2017), pollen (Crazzolara et al., 2018), and reactive organic gas collection for offline analysis (McKinney et al., 2018). The quick to deploy mobile sampling has proven advantageous for research over things such as volcanic plumes (Díaz et al., 2015; McGonigle et al., 2008; Mori et al., 2016; Rüdiger et al., 2018).

In this paper, we describe a novel application of the flux-gradient method to determine O₃ νvd from onboard an unmanned aerial vehicle (UAV). The UAV-based system can be easily deployed to ecosystems not readily sampled with eddy-covariance or tower-based flux-gradient approaches. First, we describe the flux-gradient method. Second, we describe the UAV system. Third, we describe UAV flight planning to derive vertical O₃ and $u$ gradients.
Finally, we describe the study site where future science flights will take place.

**Flux-gradient method**

An alternative method to observationally determining O\(_3\) \(v_d\), known as the flux-gradient method, using slower time response O\(_3\) instrumentation has found wide application. Here, \(F_{O3}\) can be inferred from the vertical concentration gradient scaled by the eddy diffusivity constant (\(K\)), where \(K\) accounts for the rate of vertical mixing (Businger et al., 1971; Dyer and Hicks, 1970; Webb, 1970) (Eq. 3). The flux-gradient method is based off of micrometeorological similarity theory, wherein turbulent eddies carry all atmospheric constituents equally (e.g., O\(_3\) and CO\(_2\)), such that \(K\) determined for one constituent represents all constituents (i.e. \(K_{O3} = K_{CO2}\)) (Oke, 1987). Eq. 3 is an analog of Fick’s Law of Diffusion, with vertical transport due to the random movement of air parcels by turbulent diffusion along the concentration gradient (Denmead, 2008; Denmead and Bradley, 1985). As a result, molecular movement of a given trace gas follows the direction of high to low concentration of that species.

\[
F_{O3} = -K \frac{\partial C_{O3}}{\partial z} \tag{3}
\]

Numerous equations have been developed to calculate \(K\) from measurements, such as momentum flux, sensible heat flux, friction velocity, and horizontal wind gradient (Denmead and Bradley, 1985; Droppo Jr, 1985; Goldstein et al., 1996; Meredith et al., 2014). In the latter case, \(K\) can be defined as a function of the horizontal wind speed \((u)\), von Kármán constant \((k)\), and measurement height \((z)\) (Eq. 4) (Oke, 1987).

\[
K = k^2 \left( \frac{z - z_1}{\ln \left( \frac{z_2}{z_1} \right)} \right)^2 \frac{\partial u}{\partial z} \tag{4}
\]

Flux-gradient theory is best applied to species that are unreactive on timescales of turbulent transport and only valid under neutral atmospheric stability conditions, when wind speeds and radiation fluxes are constant over the measurement period (Oke, 1987), and using measurements collected above the roughness sublayer (Raupach and Legg, 1984).

Under neutral conditions, buoyancy effects have little impact on measured concentration and wind gradients (Oke, 1987). Atmospheric stability can be determined using the Richardson number (\(Ri\)), which is a function of \(u, z, \) potential temperature \((\theta)\), and acceleration due to gravity \((g)\) (Bocquet et al., 2011; Kaimal and Finnigan, 1994) (Eq. 5). When \(Ri = 0 \pm 0.01\), conditions are neutral; when conditions are near-unstable \((-0.1 < Ri < -0.01)\) or near-stable \((0.01 < Ri < 0.1)\), an empirical correction using the value of \(Ri\) is applied to Eq. 3 (Bocquet et al., 2011; Oke, 1987).

\[
Ri = \frac{g}{\theta} \left( \frac{\Delta \bar{u}}{\Delta \bar{z}} \right) = \left( \frac{\Delta \bar{u}}{\Delta \bar{z}} \right)^2 \tag{5}
\]

Because near the canopy surface, turbulence is influenced by the roughness of the canopy top, creating wake turbulence and altering the vertical concentration and wind gradients of the atmosphere (Baldocchi et al., 1988; Neirynck et al., 2012; Oke, 1987), measurements should be collected above the so-called roughness sublayer. The roughness sublayer is approximately \(h + 1.5L_c\), where \(h\) is the canopy height and \(L_c\) is the width of an average tree crown (Baldocchi et al., 1988; Raupach et al., 1980). Above the roughness sublayer, vertical flux divergence or convergence is less than 10 percent of the flux, making it an approximately constant flux layer (Oke, 1987).

We combine O\(_3\) concentration and horizontal wind speed data to derive \(F_{O3}\) using the flux-gradient method (e.g., Bocquet et al., 2011).

**UAV System**

A hex-rotor UAV (DJI M600 Pro) has been modified to support a 6 kg, 300 W payload measuring O\(_3\) concentration (205 O\(_3\) analyzer, 2B Technologies); and horizontal wind speeds
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**Study Site**

Test flights were conducted at the UVA JPJ Basketball Arena and the Milton Field Airport, near Charlottesville, Va. Subsequent science flights will take place at the Virginia Forest Laboratory (VFL). The VFL is located in the forested Piedmont region of Virginia at the eastern base of the Blue Ridge Mountains ((37.92°N, 78.27°W). The canopy is 24 meters tall, comprised of mixed deciduous trees with patches of conifer, representative of second-growth forests throughout the region.

**Test Flights**

First, to characterize rotor interference on the anemometer data, test flights were completed indoors at the UVA JPJ Basketball Arena, a near-windless environment, and no difference was found in the anemometer measurements with the rotors on and with the rotors off, indicating that the rotors of the UAV do not interfere with the wind speed measurements (Fig. 2).

Combined uncertainties in O₃ concentration and horizontal wind velocities are small enough to sample O₃ deposition velocities of 0.02 cm s⁻¹ at 10 second averaging times at S/N = 3. This detection limit is low enough to capture previously observed variability over a variety of vegetated landscapes of 0.1–0.5 cm s⁻¹ in months when photosynthetic activity is high (Hardacre et al., 2015). The UAV is flown in a three-phase square wave (Fig. 3). Sampling occurs ahead of UAV movement to minimize disruption of vertical atmospheric structuring. The UAV is flown above the roughness sublayer in the constant flux layer.

The instrumentation on the UAV is able to capture the vertical variability in the O₃ mixing ratio and the wind speed (Fig. 4 & 5).

**Future Work**

Spring–summertime observations will be made from above the forest at the VFL. We will compare the UAV-based O₃ \( \nu_d \) to O₃ \( \nu_d \) derived using eddy-covariance O₃ flux measured at the VFL research tower with in the UAV footprint. We will qualify and

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(DS-2 Sonic Anemometer, Decagon Devices) (Fig. 1). The O₃ analyzer is mounted underneath the UAV body. The anemometer is mounted atop a 0.5 m pole affixed to the UAV body. Additionally, the UAV contains a flight computer and batteries for the instrumentation and computer, both mounted to the body of the UAV.
quantify uncertainties associated with the UAV-based $O_3 v_d$ measurements.

**Summary**

This work describes a novel methodology for observationally-deriving the $O_3$ deposition velocity. Using a flux-gradient approach combined with a light-weight low-power measurement payload, $O_3$ and horizontal wind speed can be measured onboard an unmanned aerial vehicle (UAV) at multiple altitudes. The test flight data demonstrates that the rotors do not interfere with the wind speed measurements and that combined uncertainties in $O_3$ concentration and horizontal wind measurements are small enough to derive $O_3 v_d$ on the order of previously modeled and observed values.

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**References**


