Seasonality in aerodynamic resistance across a range of North American ecosystems

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ABSTRACT

Surface roughness – a key control on land-atmosphere exchanges of heat and momentum – differs between dormant and growing seasons. However, how surface roughness shifts seasonally at fine time scales (e.g., days) in response to changing canopy conditions is not well understood. This study: (1) explores how aerodynamic resistance changes seasonally; (2) investigates what drives these seasonal shifts, including the role of vegetation phenology; and (3) quantifies the importance of including seasonal changes of aerodynamic resistance in “big leaf” models of sensible heat flux (H). We evaluated aerodynamic resistance and surface roughness lengths for momentum ($z_{0m}$) and heat ($z_{0b}$) using the $k^2 - 1$ parameter ($\ln(z_{0m}/z_{0b})$). We used AmeriFlux data to obtain surface-roughness estimates, and PhenoCam greenness data for phenology. This analysis included 23 sites and ~190 site years from deciduous broadleaf, evergreen needleleaf, woody savanna, cropland, grassland, and shrubland plant-functional types (PFTs). Results indicated clear seasonal patterns in aerodynamic resistance across most sites. Decreases in $z_{0b}$ across most sites. Decreases in $k^2 - 1$ during green-up are likely caused by increasing $z_{0b}$ in response to higher leaf area index. Accounting for seasonal variation in $k^2 - 1$ is key for predicting $H$ as well; assuming $k^2 - 1$ to be constant resulted in significant biases that also exhibited strong seasonal patterns. Overall, we found that aerodynamic resistance can be sensitive to phenology in ecosystems having
1. Introduction

The horizontal and vertical structure of vegetation creates an aerodynamically rough surface, generating mechanical turbulence that exerts significant control over aerodynamic resistance to heat transfer from the surface to the atmosphere (Brutsaert, 1982; Garratt and Hicks, 1973; Pitman, 2003; Verma, 1989). Surface roughness varies with land cover type (Lee et al., 2011), leaf area (Dolman, 1986; Raupach, 1994; Shaw and Pereira, 1982), and canopy height (Chu et al., 2018; Sonnentag et al., 2011), such that changes in vegetation structure lead to significant changes in aerodynamic resistance. Vegetation phenology triggers significant and rapid changes in the structure of the canopy (Richardson et al., 2013), altering surface roughness during green-up and senescence. Such phenology-driven impacts can influence the land-surface energy balance by changing aerodynamic resistance and hence sensible heat flux (H), in addition to other key biophysical processes such as evapotranspiration (Fitzjarrald et al., 2001; Moon et al., 2020; Schwartz, 1992). Capturing dynamics between phenology and aerodynamic resistance is therefore critical for accurately parameterizing the role of phenology in land-surface models (e.g., Richardson et al., 2012). More broadly, phenology driven changes in aerodynamic resistance can affect the atmospheric boundary-layer, including temperature profile development, boundary-layer height and cloud formation, and near-surface micro-climate (Baldocchi and Ma, 2013; Betts, 2004; Novick and Katul, 2020).

The magnitude of H is controlled by the difference between surface and air temperatures and the aerodynamic resistance to sensible heat transfer. Modeling and predicting aerodynamic resistance requires information on two key surface-roughness parameters: roughness lengths for momentum and heat (Verhoef et al., 1997). The roughness length for momentum (z_{0m}) defines the height above the surface that wind speed extrapolates to zero, and the roughness length for heat (z_{0h}) is the effective source height in the vertical temperature profile for sensible heat. In ecosystems with taller roughness obstacles (e.g., forests), an additional parameter is commonly needed: the zero-plane displacement height (d). Under such conditions, wind speed extrapolates to zero at height d + z_{0m}. Differences between z_{0m} and z_{0h} result in an “excess resistance” to heat transfer relative to momentum transfer. Specifically, heat transfer from z_{0h} → z_{0m}, is dominated by molecular diffusion, while heat transfer above z_{0m} is controlled by more efficient processes associated with eddy diffusion (Bonan, 2016; Thom, 1972). In land-surface modeling, the parameter kB^{-1} (ln(z_{0m}/z_{0h})) is used to quantify this excess resistance between z_{0m} and z_{0h} (Brutsaert, 1982; Owen and Thomson, 1963; Thom, 1972). Further details on the derivation of excess resistance and kB^{-1} are found in Section 2.1.

The kB^{-1} parameter varies significantly with land-cover type, leaf area, and other environmental variables (Brutsaert, 1982; Rigden et al., 2018). For example, a deciduous broadleaf forest acts as a permeable-rough surface, defined as having densely packed, porous elements and exhibiting relatively low kB^{-1} values (kB^{-1} generally ranges from 0–4). Conversely, in arid ecosystems, the canopy is characterized by uneven and sparse roughness elements (i.e., a bluff-rough surface), and kB^{-1} generally exhibits higher values (kB^{-1} ranges from 2–10) (Rigden et al., 2018). For bare soil, kB^{-1} has low values (ranging from 0–1), and negative kB^{-1} values have also been estimated (Yang et al., 2008). This variability in kB^{-1} among differing land cover implies differences in the physical arrangement and structure of surface-roughness elements strongly governs behavior of kB^{-1}. While this variability is well documented among varying land-cover, little work exists exploring seasonal changes in kB^{-1}, which may in part be driven by changes in canopy structure, including the amount and distribution of leaf area.

kB^{-1} displays strong temporal variability in response to multiple different environmental factors. At the diurnal scale for sparse canopies, solar radiation penetrates below the canopy, warming the soil, and causing z_{0h} to be effectively the height of the soil surface, thereby increasing kB^{-1}. Meanwhile, z_{0m} is constant at daily time scales (Brutsaert and Sugita, 1996; Kustas et al., 1988; Verhoef et al., 1997). At a seasonal time scale, some evidence suggests that changing leaf area over time causes a distinct negative relationship between leaf area index and kB^{-1} (Qualls and Brutsaert, 1996). These patterns can also be generalized for different time scales. Conceptually (Fig. 1), daily kB^{-1} peaks at midday as the diurnal cycle in solar radiation causes the magnitude of the temperature gradient at the top of the canopy to increase, ultimately altering z_{0h}. Similarly, the impact of vegetation green-up can also cause kB^{-1} to vary at seasonal time scales. For example, changes in z_{0h} may effectively track changes in z_{0m} leading to a constant kB^{-1} for the entire season. Conversely, z_{0m} may increase faster relative to z_{0m} leading to decreases in kB^{-1} during green-up transitions (Fig. 1).

Determining whether changes in z_{0m} or z_{0h} are the primary driver of seasonal variation in kB^{-1} is critical for identifying the biophysical drivers of aerodynamic resistance. A simple – and common – approach is to estimate z_{0m} based on mean canopy height (h_c) (e.g., z_{0m} = 0.1h_c; Bonan, 2016). d is similarly estimated as d = 0.7h_c. However, while this is a common method for estimating these roughness parameters, this approach has several important limitations. First, this approach cannot produce time series of changes in z_{0m} unless continuous measurements of h_c are recorded. Second, seasonal signals of estimated z_{0m} are complex and may not effectively track canopy height. For example, as the canopy fills in after leaf emergence, z_{0m} may display non-monotonic variation with leaf area, increasing in length before decreasing (Shaw and Pereira, 1982). Additionally, as leaf area increases, the coefficients mapping h_c to z_{0m} and d (e.g., z_{0m}/h_c = 0.1 and d/h_c = 0.7) are not constant and can decrease and increase, respectively (Sakai, 2000). Measurements of wind speed and turbulence from flux towers offer an alternative method for estimating z_{0m}. For example, if wind speed is available at multiple heights above the canopy, a vertical wind-speed profile can be used to estimate both d and z_{0m} (Monteith and Unsworth, 2008), and a similar approach may be used for z_{0h} using air temperature profiles. At towers where measurements are available at only one height, an effective or “aerodynamic” canopy height can be estimated using Monin–Obukhov similarity theory, and thereby allow for inference into changes in d and z_{0m} (Chu et al., 2018; Pennybacker and Baldocchi, 2016). However, this approach requires explicit canopy parameterization regarding d/h_c and z_{0m}/h_c. More details regarding Monin–Obukhov similarity theory and estimating z_{0m} and d can be found in sections 2.1 and 2.6.

Common approaches to parameterizing kB^{-1} in predictions of H include simple assumptions. One such assumption is z_{0m} = z_{0h} (i.e., kB^{-1} = 0) (Campbell and Norman, 1998). While assuming kB^{-1} = 0 simplifies calculations of H, it can cause significant bias (Yang et al., 2008), and is therefore not commonly used. Another approach is to assume kB^{-1} is a non-zero constant. For example, kB^{-1} ≈ 2 is a common assumption, and shows good performance during the growing season for agricultural and forested land-cover types (Garratt and Fransen, 1978; Zhao et al., 2016).

Despite extensive literature focused on kB^{-1}, few studies have explored how aerodynamic resistance changes seasonally, what drives these changes, and what the consequences are of such variation in aerodynamic resistance for predicting seasonal patterns in H (e.g., Moon et al., 2020; Sugita and Kubota, 1994). Furthermore, estimates of H from vegetated surfaces in land-surface models directly rely on model assumptions linking surface roughness to changes in leaf area and canopy height, further motivating the need for clearer understanding of how phenology may influence surface roughness (Lawrence et al., 2019;...
Zeng and Wang, 2007). Here, we address the following questions: (1) how does aerodynamic resistance change at seasonal time scales across a range of plant functional types and climate regimes, (2) what are the mechanisms that lead to changes in aerodynamic resistance, including the role of plant phenology, and (3) how does assuming $k^{B \text{-}1}$ to be constant influence estimates of $H$ at seasonal time scales? To address these questions, we analyzed data from 23 sites that are part of both the AmeriFlux and PhenoCam networks, covering deciduous broadleaf, evergreen needleleaf, cropland, grassland, woody savanna, and shrubland land-cover types, and spanning a broad climatological gradient across North America.

2. Materials and methods

2.1. Basic theory

Whole ecosystem $H$ is commonly modeled using a “big leaf” approach, which considers that ecosystems behave as a single layer, and therefore does not account for vertical differences from the soil through the canopy (Knauer et al., 2018; Raupach and Finnigan, 1988). Under this “big leaf” approach, $H$ is a function of the difference between the aerodynamic surface temperature ($T_{\text{surf}}$) and air temperature at tower height ($T_h$), as well as aerodynamic resistance to heat transfer ($R_{\text{ah}}$):

$$H = \frac{\rho c_p (T_{\text{surf}} - T_h)}{R_{\text{ah}}} \tag{1}$$

where $\rho$ is air density (kg m$^{-3}$) and $c_p$ is a constant for the specific heat of dry air (1004.834 J K$^{-1}$ kg$^{-1}$). The total aerodynamic resistance to heat transfer ($R_{\text{ah}}$; s m$^{-1}$) is the sum of the resistance to momentum transfer ($R_{\text{am}}$) and an excess resistance term ($R_{\text{eh}}$) representing differences between roughness lengths for momentum ($z_{0m}$) and heat ($z_{0h}$),

$$R_{\text{ah}} = R_{\text{am}} + R_{\text{eh}} \tag{2}$$

To calculate $R_{\text{ah}}$, $R_{\text{am}}$, and $R_{\text{eh}}$, we used the methods described by Verma (1989) and published in the ‘bigleaf’ R package (Knauer et al., 2018). Specifically, we estimated $R_{\text{am}}$ using the definition:

$$R_{\text{am}} = \frac{u^2}{u^*} \tag{3}$$

where $u$ and $u^*$ are tower-measured horizontal wind speed (m s$^{-1}$) and friction velocity (m s$^{-1}$), respectively. The excess resistance, $R_{\text{eh}}$, is defined as:

$$R_{\text{eh}} = \frac{1}{k u^*} \left[ \ln \left( \frac{z_{0h}}{z_{0m}} \right) - \psi_h + \psi_m \right] \tag{4}$$

Here, $k$ is the unitless von Kármán constant (0.41), and $\psi_m$ and $\psi_h$ are stability functions for momentum and heat exchange using formulations from Dyer (1970) and Businger et al. (1971). Following Rigden et al. (2018) and Verma (1989), we used the common, simplified definition of $R_{\text{eh}}$ ignoring stability effects over the short distance $z_{0m} \rightarrow z_{0h}$.

Fig. 1. Hypothesized behavior of $k^{B \text{-}1}$ at multiple time scales. The left column of panels displays idealized diurnal behavior for short-statured vegetation at DOY 180 and how solar radiation may cause shifts in $z_{0h}$ and $k^{B \text{-}1}$. Panels on the right-hand side depict behavior of $k^{B \text{-}1}$ at a seasonal time scale. At seasonal time scales, the behavior of $z_{0m}$ and $z_{0h}$ relative to each other will determine $k^{B \text{-}1}$. Two different potential behaviors are depicted above. The dashed curve ($z_{0h,1}$) represents a potential scenario where $z_{0h}$ proportionally tracks $z_{0m}$ resulting in a constant $k^{B \text{-}1}$ for the entire year. Alternatively, the dotted curve ($z_{0h,2}$) represents a scenario where $z_{0h}$ increases faster relative to $z_{0m}$ in response to green-up, resulting in a decrease in $k^{B \text{-}1}$. The faded green line represents canopy greenness while the vertical line indicates a theoretical green-up date. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
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Equation (5) can be used to estimate the roughness length ($z_{0h}$) of a surface, which is a measure of the roughness of the surface. The equation is:

$$ R_{gh} = \frac{2}{\ln \left( \frac{z_{0h}}{z_0} \right) } $$

We tested the impact of not including stability effects when estimating $R_{gh}$ using Eq. (5) and found that this only had minor impacts on our results (Fig. 5). The $kB^{-1}$ parameter characterizes differences between $z_{0h}$ and $z_0$, and is defined as:

$$ kB^{-1} = \ln \left( \frac{z_{0h}}{z_0} \right) $$

Substituting Eqs. (5) and (6) yields:

$$ R_{gh} = \frac{1}{ku} kB^{-1} $$

$kB^{-1}$ has been well studied across a broad range of ecosystems but cannot be measured directly. Multiple methods have been proposed to model and estimate $kB^{-1}$. These methods range from simple functions of $u_*$ or the roughness Reynolds number ($Re_*)$ (Brutsaert, 1982; Rigden et al., 2018; Thom, 1972; Verhoef et al., 1997), to more complex models that account for variation in the vertical and horizontal distribution of vegetation (Massman, 1999; Yang and Friedl, 2003). Here, our goal was to better understand the seasonality of $kB^{-1}$, and therefore we did not develop new prognostic models for $kB^{-1}$. Instead, we focused on estimating $kB^{-1}$ by optimizing the value that best predicted tower-measured $H$ at relatively fine time scales (i.e., 3-days). Further details can be found in Section 2.4.

2.2. Tower data

We used eddy covariance measurements from 23 AmeriFlux sites (Novick et al., 2018; https://ameriflux.lbl.gov/) that also had PhenoCams. These sites were selected because they spanned a broad gradient in climate and vegetation structure across North America, while also having a minimum of two years of overlap between AmeriFlux and PhenoCam data records. Mean annual temperatures ranged from 1.5 to 17.6 °C and mean annual precipitation ranged from 275 to 2452 mm. Growing season canopy heights ranged from 0.3 m in the US southwest to 60 m in the US northwest and leaf area index (LAI, m$^2$ m$^{-2}$) ranged from 0.3 to 8.7 (Table 1). While we required a two-year minimum overlap between AmeriFlux and PhenoCam, we used a longer time series of tower measurements based on data availability and continuity. For each site, we used measurements of precipitation, net radiation ($R_{n}$), $T_{a}$, $H$, and $u_*$. We used radiometric surface temperature ($T_{s}$) as a proxy for $T_{a}$ (Eq. (1)). $T_{a}$ was computed using separate measurements of upwelling ($R_{ud}$) and downwelling ($R_{ld}$) longwave radiation, which is given by:

$$ T_{a} = \sqrt{\frac{R_{ud} - (1 - \varepsilon)R_{ld}}{\varepsilon \sigma}} $$

Here, $\varepsilon$ is emissivity and $\sigma$ is the Stefan-Boltzmann constant ($5.67 \times 10^{-8}$ W m$^{-2}$ K$^{-4}$). Emissivity values for each vegetation type were obtained from Tao et al. (2013). Hour or half-hour tower data were filtered for mid-day only (10:00-14:00 local time) with $R_{n} > 50$ W m$^{-2}$, $H > 50$ W m$^{-2}$, and $u_* < 0.2$ m s$^{-1}$. Days with lower $R_{n}$ were excluded to remove measurements with proportionally higher uncertainty (i.e., $R_{n} < 50$ W m$^{-2}$) (Hollinger and Richardson, 2005). We included a filter for $H$ (i.e., $H < 50$ W m$^{-2}$) to remove anomalously high values of $kB^{-1}$ obtained through our optimization approach when $H$ is near zero. We excluded low $u_*$ values to remove observations having insufficient turbulence (Papale et al., 2006). Finally, we excluded days where any precipitation was recorded between 20:00 hr the previous day to 14:00 hr of the current day. All tower data were downloaded from the AmeriFlux server (https://ameriflux.lbl.gov), and dataset version numbers and download dates are provided in Table S1.

Table 1

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2.3. PhenoCam data

To capture vegetation phenology, we used the V2.0 PhenoCam public data release (Milliman et al., 2019; Seyednasrollah et al., 2019a; Seyednasrollah et al., 2019b). Here, we only provide a brief overview of PhenoCam data; a full description is presented in Richardson et al. (2018) and Seyednasrollah et al. (2019b). The PhenoCam network uses high-frequency imagery from digital cameras to track vegetation phenology. Following a standard protocol, cameras are mounted overlooking the vegetation of interest, and three-channel RGB images were recorded multiple times per day (typically every 30 min). For each site, a region-of-interest (ROI) in the image field-of-view is delineated to focus on the canopy. Using all pixels in this ROI, statistics summarizing RGB digital numbers (DN) are generated to quantify relative changes in canopy color over time. This canopy color information can be used to accurately identify phenological time series and transition dates (e.g., spring leaf emergence and fall senescence; Keenan et al., 2014). However, canopy color from PhenoCam does not explicitly measure the physical structure of the canopy (e.g., LAI or roughness). In our analysis, we used time series of the green-chromatic coordinate \( (G_{CC}) \) to measure canopy greenness and extract transition dates, \( G_{CC} = \frac{G_{DN}}{G_{DN} + R_{DN} + B_{DN}} \) (9).

Daily values of \( G_{CC} \) were calculated from all daytime images under a 1- or 3-day moving-window (Sonntag et al., 2012). The V2.0 data release provides four \( G_{CC} \) statistics for each moving window: mean, median, 75th percentile, and 90th percentile. In this analysis, we used the statistic that minimizes the root mean squared error (RMSE) between daily \( G_{CC} \) values and a locally weighted regression smoother (loess) at each site. The smoothing span for the loess curve was determined by minimizing a Bayesian Information Criterion (BIC) (Richardson et al., 2018), and the smoothed loess-derived values were further used to identify phenological transition dates. In our analysis, we used the 3-day moving window to visualize seasonal patterns in greenness and the 1-day product to estimate transition dates. This was necessary as transition dates could not be identified in some of the dryland sites using the 3-day product. For this study, we used the start-of-season green-up date (i.e., “green-up”) as our primary measure of spring phenology, as it characterizes the date of leaf emergence and acts as a clear separator between dormant and growing seasons. Specifically, this green-up date was equated to the day when 10% of the total seasonal amplitude in \( G_{CC} \) was reached. For evergreen needleleaf sites, changes in \( G_{CC} \) are caused by changes in foliage pigments on seasonal time scales, and are not related to changes in leaf area (Bowling et al., 2018; Seyednasrollah et al., 2021). The V2.0 release has been screened to remove low-quality imagery and image masks have been adjusted to account for camera field-of-view shifts. Only cameras set to fixed white balance were included, to remove negative impacts from auto-white balancing under default camera settings (Seyednasrollah et al., 2019b). Finally, we also conducted a brief supplementary comparison between \( G_{CC} \) time series and flux-tower derived estimates of broadband NDVI (e.g., Jenkins et al., 2007). We found strong similarities between these time series, indicating that PhenoCam \( G_{CC} \) can capture seasonal changes in vegetation that are also captured by radiometric measurements. Details on these comparisons are provided in Appendix S1 and Fig. S2. Additional metadata information for each PhenoCam site, as well as example imagery and maps of vegetation cover, can be found in Table S1 and Fig. S3.

2.4. Estimating seasonal variation in aerodynamic resistance

We quantified \( R_{ab} \), as well as the underlying components \( R_{an}, R_{am}, \) and \( kB^{-1} \), at a 3-day timestep to effectively visualize and identify potential seasonal patterns in these aerodynamic resistance terms among different ecosystems. First, we calculated \( R_{an} \) at a half-hour timescale using Eq. (3). Second, we used Eqs. (1) and (2) and our predictions of \( R_{am} \) to estimate a single value of \( kB^{-1} \) that minimized prediction error of \( H \) across all half-hour values every three days. This value of \( kB^{-1} \) at a 3-day timestep allowed \( R_{ab} \) to be calculated using Eq. (7). Finally, we smoothed the time series for each variable using a loess curve. The span for the loess curve for each variable and site was optimized by minimizing the BIC, and this was the same method used for smoothing PhenoCam greenness data (see Section 2.3). By smoothing over a time series of non-overlapping 3-day estimates, our approach captures shifts occurring during phenological transitions, even under a short time duration. We chose a 3-day time scale for this averaging and subsequent smoothing because it was consistent with the time scale used with PhenoCam. We note that our method of estimating \( R_{ab} \) as a residual of \( R_{ab} \) and \( R_{am} \) will result in any errors in \( H \) being propagated into our estimates of \( R_{ab} \) and \( kB^{-1} \). Errors in \( H \) could be derived from multiple sources, but are not likely a major concern. For example, it is possible that lack of energy balance closure could influence our results, especially if there is strong seasonality in the amount of closure occurring in concert with seasonal changes in the Bowen ratio. However, at the handful of sites where we examined this in detail, we found no evidence of strong seasonality in mid-day energy balance closure, and no emerging patterns that would allow us to link poor energy balance closure to strong seasonal variation in \( R_{ab} \). Furthermore, while random or systematic measurement errors in \( H \) data could influence estimates of \( R_{ab} \), our filtering approach was designed to minimize the impact of systematic errors (see Section 2.2) and by averaging mid-day fluxes over three days, the magnitude of random errors is also greatly reduced (e.g., Hagen et al., 2006; Hollinger and Richardson, 2005).

Any variable exhibiting strong seasonal variability will inherently have cyclical peaks and valleys. Here, we identified the timing of peaks and valleys for both \( R_{ab} \) and \( kB^{-1} \) (hereafter referred to as periods characterized by either “maximum” or “minimum” values, respectively). These maximum and minimum periods were then related to green-up. To do this, we first computed the 25th or 75th percentiles of the whole time series for each variable at each site. We then identified the days-of-year where each variable occurred above or below these 75th and 25th percentiles, equating these days to the timing of seasonal maximum and minimum values, respectively. The start-, middle-, and end-point for each maximum and minimum time period was identified by the 10th, 50th, and 90th percentiles across these days-of-year values. To calculate these relative day-of-year statistics, we used directional statistics using the “Circular” package in R (Agostinelli and Lund, 2017). To visualize and compare the timing of seasonal transitions in \( R_{ab} \) and \( kB^{-1} \), we plotted the transition dates for each of these variables against each other, as well as green-up date. The transition dates for \( R_{ab} \) and \( kB^{-1} \) used for this visualization were the “end” points (i.e., 90th percentile) of the distribution for transition maximum \( R_{ab} \) and \( kB^{-1} \) values, indicative of when \( kB^{-1} \) begins to decrease (e.g., see Figs. 3 and 5). Seasonal signals in \( kB^{-1} \) were much noisier compared to canopy greenness from PhenoCam, making it harder to precisely identify transition dates. Thus, our method here is undoubtedly accompanied by comparably higher uncertainty, and therefore transition dates for \( R_{an} \) and \( kB^{-1} \) may not align with PhenoCam dates. Nevertheless, these values as transition dates are currently our best estimate of the timing of when \( R_{an} \) or \( kB^{-1} \) begins to decrease, and are still valuable for exploring linkages between phenology and changes in aerodynamic resistance.

\( kB^{-1} \) is also frequently modeled as a response to the Reynolds roughness number \( (Re_{R}) \) (Rijgden et al., 2018), where \( Re_{R} \) is defined as:

\[
Re_{R} = \frac{U_{*} H}{v}
\]

Here, \( v \) is the kinematic viscosity (Massman, 1999). Thus, we plotted \( kB^{-1} \) against \( Re_{R} \) for each season (dormant and growing) to visualize and compare our results more easily to past studies. For this simple visualization, we identified the growing season as those dates between the 50% green-up threshold and 50% green-down threshold (Richardson et al., 2018). The dormant season was identified as the period prior to
green-up.

2.5. Attribution analysis

We can attribute variability in $R_{ah}$ to either $R_{am}$ or $R_{ah}$, (i.e., $R_{ah} = R_{am} + R_{ah}$ Eq. (2), and understanding which of these factors has a stronger correspondence would provide key information to infer the primary drivers of $R_{ah}$. To conduct an attribution analysis, we used statistical properties defining the variance of the sum of two random variables (Rice, 2007),

$$Var(X + Y) = Var(X) + Var(Y) + 2Cov(X, Y)$$

(11)

Here, $Var$ and $Cov$ are the variance and covariance functions, respectively. We used Eq. (11) in combination with the relationship in Eq. (2) to attribute the relative contribution of total variance of $R_{ah}$ or the covarying relationship between $R_{am}$ and $R_{ah}$.

$$Var(R_{ah}) = Var(R_{am} + R_{ah})$$

$$Var(R_{ah}) = Var(R_{am}) + Var(R_{ah}) + 2Cov(R_{am}, R_{ah})$$

(12)

Calculations assumed N-1 degrees of freedom, with N being the number of independent 3-day periods. This analysis was done separately for each site using the unsmoothed time series.

2.6. Quantifying seasonal changes in surface roughness parameters

Seasonal shifts in $k_B^{-1}$ must be in response to either $z_{0m}$ or $z_{0h}$. To help diagnose whether changes in $k_B^{-1}$ are associated with changes in $z_{0m}$ or $z_{0h}$, we first quantified $z_{0m}$ by estimating aerodynamic canopy height ($h_c$) at a 3-day timestep. We then use these patterns of $z_{0m}$ in conjunction with $k_B^{-1}$ to infer how $z_{0h}$ changes, ultimately allowing for inference into the drivers of $k_B^{-1}$. For example, if $k_B^{-1}$ decreases while $z_{0m}$ increases, we may infer those changes in $z_{0h}$ are likely having a stronger influence on $k_B^{-1}$, as increases in $z_{0hm}$ by itself should lead to increases in $k_B^{-1}$ (e.g., Fig. 1). $z_{0hm}$ is most commonly prescribed as simple functions of mean canopy height ($h_c$) (e.g., $z_{0hm} = 0.1h_c$), with measured canopy heights reported by site PIs. However, $z_{0hm}$ has been shown to vary significantly with leaf area (Yang and Friedl, 2003), indicating physical $h_c$ measurements may be limited at capturing seasonal changes in $z_{0hm}$. Aerodynamic canopy height ($h_c$) offers an alternative to using observed $h_c$. Specifically, aerodynamic canopy height can be estimated using the Monin-Obukhov similarity theory definition of the log-wind profile,

$$u(z) = \frac{u_c}{K} \left[ \ln \left( \frac{z - d}{z_{0m}} \right) - \frac{\gamma}{\kappa} \right]$$

(13)

Here, $u(z)$ is wind speed at height $z$, $d$ is the zero-plane displacement height, and $\gamma$ is a stability function for momentum (Dyer and Hicks, 1970). Under near-neutral atmospheric stability (i.e., $\gamma = 0$), Eq. (13) can be re-arranged to determine a single value of $h_c$ that best predicts flux-tower measurements of $\frac{h_c}{u_c}$ using the assumptions that $d = 0.7h_c$ and $z_{0m} = 0.1h_c$,

$$\frac{ku(z)}{u_c} = \ln \left( \frac{z - 0.7h_c}{0.1h_c} \right)$$

(14)

While $d/z_{0m} = 7$ is a common assumption (Bonan, 2016), this ratio has been demonstrated to change with land-cover type, LAI, and stand density (Nakai et al., 2008). However, we maintained this assumption for our analysis, as we were primarily interested in simply understanding how $h_c$ (and hence $z_{0hm}$) changes seasonally; thus, the absolute accuracy of our $h_c$ estimates was not critical.

To quantify seasonal variability in $h_c$, we first split up the time series at each site into non-overlapping 3-day windows. Within each window, a single value of $h_c$ was optimized to minimize the mean absolute error between all observed and predicted half-hour values of $\frac{ku(z)}{u_c}$. This gave us one estimate of $h_c$ every three days. For this optimization, we used a different data filtering approach than in Section 2.2. Here, we closely followed Pennypacker and Baldocchi (2016) and Chu et al. (2018).

Additionally, we filtered for atmospheric neutrality, and this was the only part of our analysis to include this filter. In estimating $h_c$, we applied a roughness sublayer correction at forest sites (Chu et al., 2018). If the reference height ($z_f$) was less than 1.5$h_c$ ($h_c$ equal to PI reported canopy height), we included a roughness-sublayer correction factor ($\lambda_B$), optimizing using the following instead of Eq. (14):

$$\frac{ku(z)}{u_c} = \ln \left( \frac{z - 0.7h_c}{0.1h_c} \right) + \ln(\lambda_B)$$

(15)

From Chu et al. (2018), $\lambda_B = 1.25$. We did not include a roughness sublayer correction in any other part of our analysis, and we believe this would not meaningfully impact our results as Hu et al. (2020) found that including a roughness-sublayer correction did not improve predictions of turbulent fluxes. Seasonal summaries for $h_c$ for each site are provided in Fig. S4.

In addition to calculating $h_c$, we also used wind-profile data from sites recording wind speed at multiple heights to individually estimate $d$ and $z_{0hm}$. For each site, we included wind measurements at multiple heights to individually estimate $d$ and $z_{0hm}$. The reference height ($z_f$) was optimized to minimize the mean absolute error between measured and estimated $H$. This gave $z_{0hm} = \frac{z_f - d}{\exp \left( \frac{ku(z)}{u_c} \right)}$

(17)

2.7. Seasonal sensitivity to estimating $H$

While initial results indicated there was significant seasonality in both $R_{ah}$ and $k_B^{-1}$ (Figs. 2, 3, 6), it is also common to assume $k_B^{-1} = 0$ or $k_B^{-1} = c$ when predicting $H$. To understand the implications of using either of these assumptions for predicting seasonal patterns in $H$, we calculated the relative difference between estimated ($H$) and measured values of $H$ (i.e., $H/H$). The constant $c$ for each PFT was obtained from Rigden et al. (2018), and is representative of mean growing season $k_B^{-1}$. The impacts of each assumption were evaluated by visualizing time series of the relative difference between measured and estimated $H$ at a 3-day timestep.

3. Results

3.1. Seasonal variability in aerodynamic resistance

There were significant seasonal patterns in $R_{ah}$ at most of our study sites, which spanned a continental-scale precipitation gradient (Fig. 2). In general, PFTs that exhibited the largest seasonal changes in leaf area (i.e., deciduous broadleaf, grassland, croplands) consistently produced strong seasonal signals in $R_{ah}$ (Fig. 2). For example, at the wettest grassland site, a restored prairie landscape in the upper Midwest (US-Ro4, MAP = 879 mm; Markland, 2019), $R_{ah}$ ranged from 44 $m^{-1}$ in the dormant season to 21 $m^{-1}$ in the growing season (Fig. 2). Likewise, at
our driest grassland site, Kendall grassland in the Walnut Gulch Experimental Watershed of southern Arizona (US-Wkg, MAP = 340 mm; Scott et al., 2010), $R_{ah}$ ranged from 75 $s \ m^{-1}$ to 48 $s \ m^{-1}$ (Fig. 2).

We further evaluated seasonal patterns by identifying the periods of the year when $R_{ah}$ values were characteristically lower (i.e., at a “minimum”) or higher (i.e., at a “maximum”). We found that in many cases maximum and minimum $R_{ah}$ values occurred in distinct and non-overlapping periods, indicating strong seasonality (Fig. 3). Specifically, we found that maximum $R_{ah}$ occurred prior to or during green-up, while minimum $R_{ah}$ occurred after green-up at most deciduous broadleaf forests, grasslands, shrublands, and agricultural sites (Figs. 2, 3, and S6). For example, at a set of three agricultural sites at the University of Nebraska Agricultural Research and Development Center (US-Ne1, US-Ne2, and US-Ne3; Suyker and Verma, 2010; Suyker and Verma, 2012), we found that maximum $R_{ah}$ occurred from 120 days prior to green-up through 20 days after green-up for corn (Zea mays L.), while minimum $R_{ah}$ ranged from 66 to 143 days after green-up. Similarly, for soybean (Glycine max [L.] Merr.), maximum $R_{ah}$ ranged from 197 days prior to green-up through 8 days after green-up (Fig. S6).

We also observed seasonality in $R_{ah}$ among some, but not all, evergreen-needleleaf and woody savanna sites. Wetter evergreen and savanna sites, as measured by mean annual precipitation (Table 1), displayed little seasonal variability in $R_{ah}$, while drier evergreen and savanna sites with lower stand density had some of the strongest seasonal patterns in $R_{ah}$. For example, US-Ho1 (MAP = 1070 mm), a sub-boreal, closed canopy site in Maine with $\approx$15–20% annual needle turnover (Hollinger et al., 1999), exhibited little seasonal variation in $R_{ah}$, $R_{am}$, or $R_{bh}$ (Fig. 3), and $R_{ah}$ had a seasonal amplitude of only 4 s
In comparison, at the lower stand density Metolius young burn site in central Oregon (US-Me6, MAP = 494 mm; Ruehr et al., 2014) or the Pinyon-Juniper woody savanna site in central New Mexico (US-Mpj, MAP = 385 mm; Anderson-Teixeira et al., 2011), we observed some of the largest seasonal changes in $R_{ah}$ among all study sites, with seasonal amplitudes of 33 and 16 s m$^{-1}$, respectively (Fig. 2). Furthermore, the timing of minimum and maximum $R_{ah}$ values at these drier evergreen needleleaf and savanna sites was opposite to the patterns found at deciduous broadleaf forests, with maximum $R_{ah}$ occurring during the growing season and minimum values more prevalent during the dormant season prior to green-up (Figs. 2, 3, and S6).

3.2. Inferred drivers of $R_{ah}$ seasonality and linkages to spring phenology

Our findings suggested that seasonal variability in $R_{ah}$ was primarily attributable to changes in $R_{bh}$, not $R_{am}$, at most of our study sites. In general, there was strong correlation in the seasonal patterns of $R_{ah}$ and $R_{bh}$, but much lower correspondence between $R_{ah}$ and $R_{am}$ (Fig. 2). For example, at US-MMS, a 90-100 year old deciduous broadleaf forest in southern Indiana (Dragoni et al., 2011), there was a well-defined decrease in $R_{ah}$ near green-up, shifting from 23 s m$^{-1}$ to 15 s m$^{-1}$ (Fig. 2). This shift in $R_{ah}$ directly tracked $R_{bh}$, which shifted from 15 s m$^{-1}$ to 7 s m$^{-1}$. Conversely, $R_{ah}$ was anti-correlated with $R_{am}$ (Fig. 2). These patterns and linkages between $R_{ah}$ and $R_{bh}$ were reinforced by results from our attribution analysis where the total variance in $R_{ah}$ was partitioned between $R_{am}$, $R_{bh}$, and the covariance between $R_{am}$ and $R_{bh}$.
We found clear evidence among non-agricultural PFTs that the total variance in $R_{ah}$ was primarily explained by $R_{bh}$, not $R_{am}$ (Fig. 4). For example, across all deciduous broadleaf sites, variance in $R_{bh}$ explained 42-87% of the total variance in $R_{ah}$ compared to $R_{am}$ (2–36%) (Fig. 3). There were only two non-agricultural sites where we found evidence for $R_{am}$ having higher explanatory power than $R_{bh}$: CA-TP4 and US-NR1 (e.g., 63% vs 37% for CA-TP4) (Fig. 4).

Seasonal variation in $R_{bh}$ is attributable to seasonal shifts in $k_B$ rather than $u$ (Eq. (7)), as $u$ exhibits considerably less seasonal variability. We found distinct and corresponding seasonal cycles between $R_{bh}$ and $k_B$ occurring at many sites (Figs. 2, 5, and 6); $k_B^{-1}$ generally reached its highest values immediately prior to or during green-up, followed by decreases during the transition to the growing season at deciduous broadleaf, grassland, shrubland, and agricultural sites (Figs. 5 and 6). At drier evergreen needleleaf sites, such as US-Me6, we found the opposite pattern, with $k_B^{-1}$ lower during the dormant season and increasing during the growing season (Figs. 5 and 6), with strong similarity to the signal in $R_{ah}$ found at these same sites (Figs. 2

\[ \text{Var}(R_{bh}) = \text{Var}(R_{am}) + \text{Var}(R_{ah}) + 2\text{Cov}(R_{am}, R_{ah}) \]
and 3). When comparing Figs. 3 and 5, we observe that a deciduous broadleaf site (US-MMS) the timing of maximum $R_{ah}$ and $kB^{-1}$ overlapped considerably. Similar patterns can be found at the other end of the precipitation gradient; at a shrubland site in southern Arizona (US-Whs), the median day-of-year of peak $R_{ah}$ and $kB^{-1}$ were almost identical: 43 and 45 days prior to start-of-season green-up (Figs. 3 and 5). When comparing all sites, we found a strong positive linear relationship between the transition dates for $R_{ah}$ and $kB^{-1}$, with the transition dates for $R_{ah}$ and $kB^{-1}$ occurring within 30 days of each at 60% of all sites (Fig. 7a).

The timing of seasonal shifts in $R_{ah}$ and $kB^{-1}$ appeared to track green-up transition dates for some, but not all, sites (Fig. 7b,c). Linkages between green-up dates and shifts from higher to lower $R_{ah}$ and $kB^{-1}$ were notable at most deciduous broadleaf, grassland, and at least one shrubland site. For example, there were distinct decreases in $kB^{-1}$ at two deciduous forest sites (US-MMS and US-MOz) immediately after spring green-up occurred, and this response was consistent even when green-up occurred approximately 30-days earlier than normal in 2012 (Fig. 6).

This strong association between transition dates is visualized in Fig. 7b, c; transition dates between $kB^{-1}$ and $G_{cc}$ occurred within 30 days of each other for 80% of deciduous broadleaf, two out of three of grassland, and one of two of shrubland sites. By comparison, for many evergreen needleleaf forests and woody savanna ecosystems, $kB^{-1}$ transition dates generally occurred more than 120 days from green-up, if at all. In general, these patterns between $kB^{-1}$ and greenness were comparable to the patterns we found for $R_{ah}$.

Finally, to help understand which surface roughness parameter ($z_{0m}$ or $z_{0h}$) is driving $kB^{-1}$ changes, we estimated $d$ and $z_{0m}$ through aerodynamic canopy height ($h_a$) and wind-profile data. In general, we found that $h_a$ increases during the growing season, implying $z_{0m}$ is also increasing (Fig. S4). We found a similar pattern for a cropland site with corn (US-Ne1), where there was a distinct increase in both $d$ and $z_{0m}$ during the growing season (Fig. 8). While this pattern occurred at most sites, we also found examples where $z_{0m}$ decreased during the growing season, indicating that the canopy became smoother. Specifically, at US-MMS and US-Syv, $z_{0m}$ decreased by approximately 1.5 m during the transition from spring to summer (Figs. 8 and S4).
3.3. $R_{ah}$ seasonality in croplands

There were relatively unique patterns at several of the cropland sites in our analysis, compared to other sites. Specifically, a significant proportion of the variation in $R_{ah}$ was attributable to $R_{am}$, contrasting with results at most other sites (Fig. 4). $R_{am}$ exhibited significant influence at the Nebraska corn and soybean agricultural sites (US-Ne1, US-Ne2, and US-Ne3). Our attribution analysis indicated $R_{am}$ explained a significant part of the total variance in $R_{ah}$ with $R_{am}$ explaining 37% and 52% of the variability in $R_{ah}$ for corn and soybean, respectively, compared to $R_{bh}$ which explained 47% and 48%. This similarity can be visualized in Fig. 2, as both $R_{ah}$ and $R_{am}$ closely tracked each other immediately after...
green-up in both corn and soybean sites. Seasonal patterns in $R_{bh}$ and $kB_1$ also differed notably compared to deciduous forest and grassland sites; $R_{bh}$ and $kB_1$ in cropland sites increased immediately after green-up, followed by a sudden decrease after canopy greenness reached its seasonal maximum (Figs. 2 and 6).

Strong seasonal patterns in $R_{ah}$ were also observed at weekly timescales at the alfalfa (*Medicago sativa* L.) sites in the Sacramento–San Joaquin River Delta in central California (US-Bi1 and US-Tw3), with $R_{ah}$ and $kB_1$ inversely tracking these changes in $h_a$ and greenness. Similar patterns were found at US-Tw3 (Fig. S7). The data at these sites highlight three key patterns. First, $kB_1$ was the main driver of $R_{ah}$. Second, maximum values in $R_{ah}$ and $kB_1$ occurred when canopy greenness and $z_{0m}$ were at a minimum, shortly after a harvesting event. Finally, there was little-to-no change in $R_{am}$ accompanying these patterns in $R_{ah}$. These results were comparable to the patterns observed in deciduous broadleaf, grassland, and shrubland sites; maximum and minimum values of $R_{ah}$ and $kB_1$ occurred during dormant and growing periods, respectively.

### 3.4. Implications for understanding seasonal changes in aerodynamic resistance

At many sites, we found evidence that $kB_1$ differs between the non-growing season and growing season, indicated by the clear bifurcation in $kB_1$ with higher values occurring during the non-growing season and lower values occurring during the growing season (Fig. 10). To understand how this seasonal variation in $kB_1$ may influence predictions of $H$ when compared to the assumption of static $kB_1$ (i.e., $kB_1 = 0$ or $kB_1 = c$), we estimated the full annual pattern of relative differences between estimated and measured $H$ (i.e., $\hat{H}/H$) at a 3-day timestep. We found that estimates of $H$ were quite sensitive to $kB_1 = 0$ or $kB_1 = c$; at many sites, we found that the highest relative differences generally occurred during the nongrowing season and under the assumption $kB_1 = 0$ (Fig. 11). At the arid US-Ses shrubland site, the highest values of $\hat{H}/H (> 400\%)$ occurred immediately prior to green-up (Fig. 11). We found similar seasonal patterns of $H/H$ by assuming...
$kB^{-1}$ is constant for each PFT (i.e., $kB^{-1} = c$), although the magnitude of $H/H$ was considerably reduced relative to $kB^{-1} = 0$ (Fig. 11). Furthermore, the seasonal patterns in $H/H$ observed at many sites were similar to the seasonal patterns in $R_{ah}$ (Fig. 2). In summary, these results indicated that accounting for seasonal changes in $kB^{-1}$ is critical for significantly reducing biases and errors when predicting $H$ using a “big leaf” approach.

### 4. Discussion

Using 190 site-years of data from the AmeriFlux and PhenoCam networks, our findings highlight how aerodynamic resistance to heat transfer ($R_{ah}$) exhibits distinct seasonal patterns among multiple plant-functional types (PFTs) and climate regimes, and how vegetation phenology may play a role governing this seasonality in certain PFTs. Specifically, PFTs that exhibit the strongest seasonal changes in canopy structure also consistently displayed strong seasonality in $R_{ah}$ and the timing of the seasonal patterns in $R_{ah}$ closely track phenological start-of-season green-up at most of these sites. Incorporating these seasonal patterns of $R_{ah}$, as well as potential linkages to spring phenology, is important for improving model-based predictions of sensible heat fluxes, and thus our understanding of how seasonal changes in the land surface more broadly impact atmospheric dynamics such as boundary layer height, vertical temperature profiles, and near-surface micro-climate.
4.1. How does aerodynamic resistance change seasonally?

The aerodynamic resistance to heat transfer ($R_{ah}$) comprises two additive resistance terms ($R_{ah} = R_{am} + R_{bh}$, Eq. (2)), and our findings provide evidence that for most sites excess resistance to heat transfer ($R_{ah}$) is a significantly stronger control over seasonal patterns of $R_{ah}$, relative to the resistance to momentum transfer ($R_{am}$) (Figs. 2–5). Recall that excess resistance ($R_{ah}$) accounts for differences between the roughness lengths for momentum ($z_{0m}$) and heat ($z_{0h}$) through the $kB^{-1}$ parameter (i.e., $k \cdot R_{bh} \cdot u_*= \ln(z_{0h}/z_{0m}) = kB^{-1}$, Eq. (7)). In this study, we found that the seasonality (Figs. 2, 3, 5, 7a) and total variance (Fig. 4) in $R_{ah}$ is best explained by $R_{ah}$ and $kB^{-1}$. Taken together, these multiple relationships linking $kB^{-1}$ to $R_{ah}$ through $R_{ah}$ imply changes in surface roughness (i.e., through $z_{0m}$ or $z_{0h}$) are a key factor determining seasonal patterns in $R_{ah}$.

At most deciduous broadleaf, grassland, and shrubland sites, $kB^{-1}$ decreases during start-of-season phenological transitions, implying the potential for a direct causal linkage between phenology and seasonal changes in $kB^{-1}$ (Figs. 6, 7 and 10). Decreasing $kB^{-1}$ in response to increasing LAI has been identified in other studies. For example, $kB^{-1}$ is commonly modeled as a function of LAI (Brutsaert, 1979; Hu et al., 2020; Kubota and Sugita, 1994; Yang and Friedl, 2003). This modeling captures decreases of $kB^{-1}$ in response to increasing LAI and provides accurate estimates of $H$ as well (Qualls and Brutsaert, 1996). Decreasing $kB^{-1}$ after green-up must be related to either $z_{0m}$ or $z_{0h}$ (Eq. (6)). Here, we conclude $z_{0h}$ is more influential than $z_{0m}$ in most cases. Specifically, we posit shifts to higher $z_{0h}$ (lower $kB^{-1}$) during start-of-season green-up are due to decreases in the fractional coverage of understory and bare soil. Landscapes dominated by bare soil or sparse vegetation exhibit $z_{0h}$ heights effectively at the soil surface, especially during warm and dry meteorological conditions where the soil is acting the primary source of heat (Verhoef et al., 1997; Yang et al., 2008). A theoretical addition of taller un-foliated roughness elements to a landscape would increase $z_{0m}$, while $z_{0h}$ would remain unchanged due to surface temperature of the understory exceeding that of the canopy temperature (Brutsaert and Sugita, 1996). During phenological transitions, such as leaf emergence in temperate deciduous forests, the canopy fills in, the coverage of bare soil and understory decreases, and transpiration increases cooling of the surface (Verhoef et al., 1997), together leading to increases in $z_{0h}$ and lowering $kB^{-1}$. Similar behavior of $kB^{-1}$ is found between PFTs that have dense and sparse canopies. Permeable-rough surfaces (e.g., deciduous broadleaf or agriculture sites) have $kB^{-1}$ values lower than bluff-rough surfaces (e.g., shrubland sites) (Brutsaert, 1982; Rigden et al., 2018). These bluff-rough surfaces, generally occurring at more arid sites, have higher proportions of land cover dominated by bare soil (Fig. S3).

While changes in $z_{0m}$ as well as $z_{0h}$ may also play a role in altering $kB^{-1}$, our results imply that observed changes in $z_{0m}$ are not driving seasonal decreases in $kB^{-1}$. Specifically, we found that $z_{0m}$ generally increases during the growing season, indicated by increasing aerodynamic canopy height ($h_{cc}$; Fig. S4) or wind-profile data (Fig. 8). All other factors being equal, increasing $z_{0m}$ by itself would lead to higher $kB^{-1}$; however, we found that $kB^{-1}$ decreases after green-up (Figs. 5, 6, 9, and 10). Therefore, we infer that increases in $z_{0h}$ offset increasing $z_{0m}$, thereby leading to decreases in $kB^{-1}$ (e.g., Fig. 1) and implying $z_{0h}$ is the more important control over $kB^{-1}$. Patterns observed at an alfalfa agricultural site (US-BII, Fig. 9) capture this dynamic. Significant decreases
in $z_{0m}$ after a harvesting event by itself should lead to decreasing $k_B^{-1}$. However, we found $k_B^{-1}$ increases after harvesting events, likely due to significant decrease in $z_{0h}$ relative to $z_{0m}$. Increases in $z_{0m}$ after green-up, while common, are not ubiquitous. Decreases in $z_{0m}$ can also occur. Specifically, functions relating $z_{0m}$ to the plant area index (i.e., PAI) exhibit non-monotonic relationship and higher leaf area and foliage density at the top of the canopy can act as a smooth surface (Blanken and Black, 2004; Shaw and Pereira, 1982). While we see such decreases in $z_{0h}$ at US-MMS, US-Syyv, and US-NR1 (Figs. 8 and S4), this likely does not outweigh the importance of $z_{0h}$ given its strong influence at other sites.

While $z_{0h}$ may have more control over seasonal changes in $R_{ah}$ relative to $z_{0m}$, this is partially due to $z_{0m}$ simply not changing as much relative to $z_{0h}$ between the non-growing and growing seasons, as the physical structure of the canopy generally remains in place even if it is defoliated (Nakai et al., 2008). Using the corn and soybean sites, we can investigate and better understand the influence of $z_{0m}$ in a system where the landscape transforms from bare soil to a full canopy within a season. Here, we found patterns in $R_{am}$ closely tracking $R_{ah}$ (Fig. 2), and $R_{am}$ explains significantly more of the observed variance in $R_{ah}$ compared to other sites (Fig. 4). This increased importance in $R_{am}$ is due to significant increases in $z_{0m}$ as the crops increase in height (Figs. 2 and 6) and the subsequent effect on the log-wind profile Eqn (13).

Phenology does not have the same level of control over $R_{ah}$ in evergreen-needleleaf sites (Figs. 2, 3 and 5). This is not surprising, given that our evergreen-needleleaf sites exhibit only minor leaf turnover each season. Where we did observe seasonal changes in $R_{ah}$ (e.g., US-Me6), these changes are also associated with changes in $R_{ah}$ and $k_B^{-1}$, comparable to other PFTs. Therefore, changes in $R_{ah}$ in evergreen-needleleaf sites are not driven by changing leaf area and the fractional cover of the forest canopy, but likely by two other interacting factors. First, increasing solar radiation and surface heating during the course of the growing season alters the temperature source height ($z_{0h}$), thereby altering $R_{ah}$ through $k_B^{-1}$, comparable to diurnal changes in $k_B^{-1}$ tracking solar radiation (Fig. 1) (Lhomme et al., 1997; Yang et al., 2008). Second, these impacts of seasonal changes in solar radiation on $k_B^{-1}$ only occur at more arid sites with taller vegetation, compared to shrublands or grasslands, and that likely have lower stand density (i.e., US-Me2, US-Me6, and US-Mpj; Figs. 2 and S3). The higher exposure of the understory or bare soil, compared to the more closed canopy sites (i.e., CA-TP4, US-Ho1, US-NR1), exacerbates the effects these changing environmental conditions have on $k_B^{-1}$. Finally, it should be noted that phenology may still play an important role in controlling seasonal patterns of $k_B^{-1}$ at lower density evergreen-needleleaf sites through the phenology of understory vegetation. However, the greenness index from PhenoCam for these sites is only derived for the canopy and does not capture the understory phenology.

From this analysis we conclude that phenology can be a key driver over observed seasonal shifts in $k_B^{-1}$ in some ecosystems, which subsequently influences $R_{ah}$ and predictions of $H$. However, the full seasonal trajectory of $k_B^{-1}$ is not explained by phenology alone; across the sites we considered, significant variations in $R_{ah}$ and $k_B^{-1}$ occurred well before and after phenological transitions (Figs. 2 and 6). For example, at a semi-arid grassland site in southern Arizona (US-Wkg), we observed distinct increases in $k_B^{-1}$ beginning in January of each year, which continued throughout the dormant season prior to green-up (Fig. 6). These shifts in $k_B^{-1}$ occurred well after senescence and before spring green-up, and such shifts are likely influenced by other environmental or meteorological factors, including evaportranspiration, net radiation, wind speed, and surface temperature (e.g., Blyth and Dolman, 1995; Lhomme et al., 1997). As a brief supplementary analysis, we conducted a multiple linear regression at US-Wkg that related $k_B^{-1}$ to a list of meteorological factors: $R_n$, surface temperature ($T_s$), latent heat flux, soil water content, wind speed, and cumulative 10-day precipitation. We found that $T_s$ emerged as the most important among these variables at seasonal time scales ($p < 0.001$ and partial correlation = 0.437, Table S2), having a strong positive relationship with $k_B^{-1}$ (Fig. S8).
The influence of $T_s$ is likely due to progressively warmer soil conditions that occur from January-June under increasing $R_{ns}$, with the soil thereby acting as the primary source of heat exchange, relative to the canopy, and resulting in $z_{0h}$ to be at the height of the soil surface. As monsoonal precipitation begins in late-June or July and green-up occurs, the soil temperature shifts and begins to cool and is therefore less sensitive to continued increases in $R_{ns}$ that occur during the remainder of the summer. While this analysis is admittedly brief, it does indicate that there are other potential drivers of seasonality in $k_B^{-1}$. In general, quantifying the influence of these factors on $k_B^{-1}$ – as well as how they interact with each other and phenology – is crucial for developing accurate models of $k_B^{-1}$.

4.2. How does changing aerodynamic resistance influence predictions of $H$?

Substantial differences between estimated ($\hat{H}$) and measured $H$ occurred when $k_B^{-1}$ is assumed constant or equal to 0 (Fig. 11). These results have important implications for modeling of the land-surface energy balance using “big leaf” energy balance equations (e.g., Eq. (1)). First, simplified assumptions of a static $k_B^{-1}$ (i.e., $k_B^{-1} = 0$ or $k_B^{-1}$ is constant) are insufficient to accurately model the complete seasonal trajectory of $H$. Assuming $z_{0m} = z_{0h}$ (i.e., $k_B^{-1} = 0$) appears to be invalid for vegetated surfaces, a result agreeing well with the literature (Yang et al., 2008). Similarly, assuming a constant value for each PFT, while helping to reduce biases (i.e., $\hat{H}/H$) relative to the assumption $k_B^{-1} = 0$, still resulted in significant seasonal deviations from measured $H$ at many sites. These results demonstrate that including a time-varying estimate of $k_B^{-1}$ that accounts for changes can eliminate seasonal patterns in $\hat{H}/H$ compared to assuming $k_B^{-1} = 0$ or $k_B^{-1} = c$, implying that anticipating how and why surface roughness changes is important for understanding seasonal dynamics in land-atmosphere interactions (Blythe and Dolman, 1994; Kustas et al., 1989).

4.3. Implications and directions for future work

The sensitivity of $H$ to seasonal variations in $k_B^{-1}$ is unexpected when compared to inferences from past studies. Increasing $z_{0m}$ under...
land-cover shifts from grasslands to aerodynamically rougher forests leads to increased turbulence and decreasing resistance, subsequently impacting surface temperature (Burakowski et al., 2018; Lee et al., 2011). Such mechanisms have been suggested to occur during pheno-logical transitions; increases in $z_{0m}$ during green-up could decrease aerodynamic resistance to momentum transfer (Peiuelas et al., 2009). Conversely, phenology may only play a minor role controlling aerodynamic resistance. For example, in deciduous broadleaf forests, observed increases in $R_{8m}$ during phenological transitions have been attributed to decreasing synoptic-scale wind speed, and not $z_{0m}$ (Moon et al., 2020). Overall, our findings provide important new insight into the role of seasonally changing surface roughness, which in many cases appears to be associated with phenology, as a control on $H$. Perhaps more consequential, the significant seasonal biases observed under the assumption of constant $kb^{-1}$ implies the behavior for both $z_{0m}$ and $z_{0b}$ represents a key source of uncertainty for modeling land-atmosphere interactions.

Resolving uncertainty in the behavior of $z_{0m}$ and $z_{0b}$ at seasonal time scales is not only important for model improvement, but also critical for understanding how seasonal changes in $H$ may impact atmospheric dynamics, such as boundary layer height, temperature profiles, and micro-climate (Helbig et al., 2020). For example, due to the exponential nature of $kb^{-1}$ (Eq. (6)), small increases in $z_{0b}$ would reduce $R_{8b}$ leading to increased $H$ and potentially decreasing aerodynamic surface temperature and near-surface air temperature (Novick and Katul, 2020). Understanding such dynamics will likely be important for anticipating ecosystem impacts as phenology responds to a changing climate (Richardson et al., 2013). To reduce this uncertainty, developing prognostic models of $kb^{-1}$ as a function of different environmental factors – including phenology – is a key next step. Other studies have modeled differences in $kb^{-1}$ among different PFTs, for example as a function of $u_*$ or $Re_{c}$ (e.g., Rigden et al., 2018). Expanding on such models to capture the seasonal shifts and bifurcation of $kb^{-1}$ would lead to a stronger understanding of how the horizontal and vertical structure of surface roughness elements impacts $H$ (Garratt and Hicks, 1973; Maurer et al., 2013). Finally, while more complex land-surface models such as CLM or a multi-layer approach do not rely on $kb^{-1}$, our work motivates the need for investigations into how seasonal changes in land-surface properties might impact predictions from these systems-based models.

Conclusions

Through a continental-scale synthesis integrating AmeriFlux and PhenoCam data and applying Monin–Obukhov similarity theory, we find that seasonal variability in aerodynamic resistance to heat transfer is pervasive across a range of ecosystems. We found evidence that the mechanisms underlying this variation in aerodynamic resistance are likely linked to vegetation phenology in deciduous broadleaf forests, grasslands, croplands, and shrublands. Specifically, shifts to a larger leaf area led to $z_{0b}$ increases during green-up, leading to decreases in $kb^{-1}$ and in the overall total aerodynamic resistance to heat transfer. By comparison, the role of changing surface roughness to momentum transfer ($z_{0m}$) appeared to be minimal compared to $z_{0b}$. The total impact of seasonal variation in $kb^{-1}$ on model-based estimates of sensible-heat flux is important; large biases in $(H/H)$ occurred when assuming $kb^{-1}$ is constant. Predicting the full seasonal trajectory of sensible heat flux using simple one-layer land-surface energy balance models requires prognostic models and parametrizations that account for seasonal changes in $kb^{-1}$ in response to phenology and other environmental and meteorological factors. In conclusion, we found evidence vegetation phenology can influence surface-roughness at relatively fine temporal scales, directly impacting seasonal variability in aerodynamic resistance to heat transfer across a range of North American ecosystems. Because this variation in aerodynamic resistance also influences the land-surface energy balance, our findings provide insight into how land-atmosphere interactions operate at seasonal time scales.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials


References


