Spatiotemporal variations of albedo in managed agricultural landscapes: Inferences to global warming impacts (GWI)

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Date of manuscript revision: 02/19/2020

Abstract

Context

Albedo can be used to quantify ecosystem and landscape contributions to local and global climate. Such contributions are conventionally expressed as radiative forcing (RF) and global warming impact (GWI). We contextualize our results within landscape carbon production and storage to highlight the importance of changes in albedo for landscape GWI from multiple causes, including net ecosystem production (NEP) and greenhouse gas (GHG) emissions.

Objective

To examine the spatiotemporal changes in albedo (Δα) in contrasting managed landscapes through calculations of albedo-induced RF ($RF_{\Delta\alpha}$) and GWI ($GWI_{\Delta\alpha}$) under different climatic conditions.

Methods

We selected five contrasting landscapes within the Kalamazoo River watershed in southern Michigan USA as proof of concept. The daily MCD43A3 MODIS (V006) product was used to analyze the inter- and intra-annual variations of growing season albedo. In addition, the variations of $RF_{\Delta\alpha}$ and $GWI_{\Delta\alpha}$ were computed based on landscape composition and climate.

Results

The $RF_{\Delta\alpha}$ (-5.6 W m^{-2}) and $GWI_{\Delta\alpha}$ (-1.3 CO_{2eq} ha^{-1} yr^{-1}) were high in forest-dominated landscapes, indicating cooling effects and CO_{2eq} mitigation impacts similar to crops. The CO_{2eq} mitigation of cropland-dominated landscapes was on average 52% stronger than forest-dominated landscapes. In the landscape with the highest proportion of forest, under dry and wet conditions CO_{2eq} mitigation was reduced by up to 24% and ~30%, respectively; in one cropland-dominated landscape wet conditions reduced CO_{2eq} mitigation by 23%.

Conclusions

Findings demonstrate that quantifying spatiotemporal changes in albedo in managed landscapes and under different climatic conditions is essential to understand how landscape modification affects $RF_{\Delta\alpha}$ and $GWI_{\Delta\alpha}$ and thereby contributes to ecosystem-level GWI.

Keywords: *Albedo, Land mosaics, Radiative forcing, Global warming impact, Cropland, Forest*

1. Introduction

Decoupling the causes and consequences of ecosystem functions and services at multiple spatial scales represents an important scientific frontier in landscape ecology (Raudsepp-Hearne et al. 2010; Antón et al. 2011; Chen et al. 2013; Yuan and Chen 2015; Seidl et al. 2016). Land use and land cover change (LULCC) caused by human activities (e.g., land use), natural disturbances (e.g., wildfires) and global warming directly affects regional and global climate through the exchange of energy, carbon, water, and greenhouse gases (GHGs) between the land surface and the atmosphere (Bright et al. 2015; Bonan 2016). Management activities and disturbances such as cultivation, burning, and grazing not only influence GHG emissions but also alter the surface radiation balance (Pielke et al. 2011; Shao et al. 2014). Unfortunately, little effort has been directed towards investigating resulting changes in surface radiation balance (e.g., changes in albedo) at landscape scales (Euskirchen et al. 2002; Chen et al. 2004).

Albedo — the ratio of solar radiation reflected by a surface to the total incoming solar radiation (e.g., surface radiation balance) — is a measurable physical variable that can be used to quantify ecosystem and landscape contributions to local and global climate (Dickinson 1983; Picard et al. 2012; Brovkin et al. 2013; Li et al. 2016; Storelvmo et al. 2016). Changing albedo has been proposed as one of several geoengineering options for climate change mitigation (Lenton and Vaughan 2009; Goosse 2015) and albedo is also important for understanding exchanges of energy and mass between terrestrial surfaces and the atmosphere (Merlin 2013). Albedo is in its early stages of incorporation into climate models, but it is useful for deriving different mechanisms to lower climate warming by potentially increasing the reflectance of energy back into the atmosphere (Lenton and Vaughn 2009). Although LULCC (e.g., conversions from forest to biofuel, grassland, and cropland) can significantly alter albedo (Bala et al. 2007; Cai et al. 2016), the magnitude of changes depends on vegetation type and canopy structure (see also Bennett et al. 2006; Tian et al. 2018).

Albedo is also highly correlated with leaf wetness, soil moisture, and soil water content (Henderson-Sellers & Wilson 1983; Wang et al. 2004) — which are strongly related to precipitation and its temporal distribution — and as well with plant phenology and vegetation structure (Luyssaert et al. 2014), plant or tree height (Betts, 2001), and agricultural practices (Houspanossian et al. 2017) — this last scarcely considered (Zhang et al. 2013, Jeong et al. 2014). For example, Culf et al. (1995) reported decreased albedo in forests as a function of darker leaves and darker soils under wet conditions. Berbet and Costa (2003) found that ranchlands were characterized by variable albedo throughout the entire year depending on climatic conditions (e.g., dry vs wet periods), whereas forests were characterized by higher and lower albedo in both dry and wet periods, respectively.

Changes in atmospheric conditions and land mosaics due to LULCC can affect the Earth's radiation balance (Gray 2007). Radiative forcing (RF) has been widely used to describe this imbalance as changes in the fraction of solar energy reflected by the Earth's surface (Mira et al. 2015), whether anthropogenic or natural (Lenton and Vaughan 2009). RF can thus be used to compare modifications in radiation balance due to atmospheric/surface albedo changes or due to GHG emissions. Previous studies (Betts 2000; Akbari et al. 2009) have developed methodologies to relate RF to CO_{2eq}, used to calculate ecosystem-scale contributions to global warming impacts (GWIs) — a common measure for quantifying RFs of different GHGs and other agents (Fuglestvedt et al. 2003; Forster et al. 2007; Peters et al. 2011). GWI allows us to directly relate anthropogenic activities to GHG emissions (Haines 2003; Davin et al. 2007; Cherubini et al. 2012; Robertson et al. 2017) and to understand and quantify the impact of an ecosystem on climate.

Despite escalating efforts to examine the magnitude and dynamics of albedo change due to LULCC, previous studies have focused on albedo, RF, and GWI differences among the cover types within landscapes or regions (Haas et al. 2001; Román et al. 2009; Carrer et al. 2018; Chen et al. 2019). For example, previous studies have shown that deforestation and expanding agricultural lands have played an important role in surface cooling of the northern hemisphere due to increased surface albedo and regeneration of forests after harvesting (Betts 2001; Govindasamy et al. 2001; Lee et al. 2011). Georgescu et al. (2011) simulated strong cooling effects — equivalent to a reduction in carbon emission of 78 t C ha^{-1} — by increasing the surface albedo of agricultural lands across the central United States. Loarie et al. (2011) demonstrated that introducing sugar cane production into cropland/pasture landscapes of Brazil increased albedo and evapotranspiration, which in turn appeared to cool the local climate. Importantly, to quantify the contribution of LULCC to global warming/cooling, GWI should be computed with reference to albedo due to pre-existing conditions (i.e., $\Delta\alpha$).

Here we examine the spatiotemporal changes of albedo in contrasting managed landscapes as compared to pre-existing forests through calculations of albedo-induced RF ($\Delta RF_{\Delta\alpha}$) and GWI ($\Delta GWI_{\Delta\alpha}$) under different precipitation regimes (i.e., climatic conditions). We express the relationship between landscape albedo and $GWI_{\Delta\alpha}$ (Figure 1) as:

$$[\Delta\alpha_i \times \Delta area_l \times \Delta climate_l] \rightarrow \Delta RF_{\Delta\alpha} \rightarrow \Delta GWI_{\Delta\alpha} \qquad (1)$$

where $\Delta GWI_{\Delta\alpha}$ is net landscape albedo-induced GWI, $\Delta\alpha_i$ is the difference between mean albedo at a cover type *i* and mean forest albedo (i.e., the reference), $\Delta area_l$ is variation of cover-type proportion for landscape *l,* and $\Delta climate_l$ is the variation of climatic conditions for landscape *l*. More specifically, we aim to estimate the magnitude and seasonal changes in albedo so that $\Delta GWI_{\Delta\alpha}$ can be assessed at ecosystem, landscape, and watershed scales, and included in ecosystem GWI assessments (e.g., Gelfand and Robertson 2015). We further contextualize our results within landscape carbon production and storage to highlight the importance of changes in landscape $GWI_{\Delta\alpha}$ from multiple causes, including net ecosystem production (NEP) and GHG emissions. The framework developed in this study (Equation 1, Figure 1) can be applied to any landscape to for compute landscape $GWI_{\Delta\alpha}$. To this end, we selected five contrasting landscapes in the Kalamazoo River watershed of southwestern Michigan U.S.A. as a proof of concept to investigate inter- and intra-annual variations of albedo under three different climatic conditions.

2. Materials and Methods

2.1 Study area

We chose five contrasting landscapes (Figure 2) in the Kalamazoo River watershed, located in southwest Michigan, USA, for proof of concept. Within the 526,100 ha watershed, the long-term mean annual temperature is 9.9 °C and the average annual precipitation is 900 mm that is evenly distributed throughout the year (Michigan State Climatologist's Office 2013). The watershed includes portions of 10 counties: Allegan, Ottawa, Van Buren, Kent, Barry, Kalamazoo, Calhoun, Eaton, Jackson, and Hillsdale. Prior to European settlement, the watershed was dominated by forests (Brown et al. 2000) with interspersed tallgrass prairies, savannas, lakes, wetlands, and oak openings (Chapman and Brewer 2008). The watershed however has undergone significant LULCC since then. Present-day forest areas are secondary successional forests that followed their complete harvest by European settlers in the late 1800s (Brown et al. 2000). Today, the watershed consists of cultivated crops, deciduous forest stands, pasture-hay grasslands, inland lakes, wooded wetlands, and urban areas. Dominant soils of the watershed are Alfisols of medium to coarse texture that allows a continuous recharge of groundwater (Schaetzel et al. 2009).

We randomly selected five 10,000 ha landscapes (Figure 2) (Burton et al. 1998) that represent the main ecoregions of the watershed, i.e., areas characterized by similar vegetation, with the same type, quality and quantity of environmental resources (Omernik and Griffith 2014). The Kalamazoo River watershed includes three U.S. EPA ecoregions: Eastern Temperate Forest (Level I), Mixed Wood Plain (Level II), and Southern Michigan/Northern Indiana Drift Plain (Level III). At a finer scale, five Level IV ecoregions (Table S1) exist in the watershed: Battle Creek Outwash Plain (56b), Michigan Lake Plain (56d), Lake Michigan Moraines (56f), Lansing Loamy Plain (56g), and Interlobate Dead Ice Moraines (56h). (https://www.epa.gov/eco-research/ecoregion-download-files-state-region-5#pane-20). We used the five landscapes to represent the five Level IV ecoregions so that each landscape fell within an individual Level IV ecoregion.

Each landscape has different proportions of urban, cropland, barren, forest, water, wetland, and grassland cover types (Table 1). Two of the five landscapes have a higher proportion of forest (FOR_1 highest proportion of forest, and FOR_2 second highest proportion); while the remaining three landscapes are dominated by cropland ($CROP_1$, $CROP_2$, and $CROP_3$, from high to low proportion of cropland, respectively) (Table 1). Given that forest was the dominant land cover type prior to European settlement within each landscape (Brown et al. 2000), we considered the average albedo of all forest portions within each of the five landscapes during the growing season at 10:30 a.m. local time (UTC) as the reference albedo (e.g., MODIS Terra morning overpass time). Thereafter, in each landscape, changes in albedo (Δα) were obtained by calculating the difference between mean cropland and mean forest albedos, and then used to calculate $RF_{\Delta\alpha}$ and $GWI_{\Delta\alpha}$.

2.2 Landscape structure

The landscape structure of the watershed was quantified from a classified land cover map for 2011 (Figure 2) at 30×30 m spatial resolution, which was produced using the Landsat archives from the USGS Earth Explorer/GLOVIS portals (https://earthexplorer.usgs.gov/). The land cover map was obtained following the Anderson level I classification scheme and included seven land cover types: 1) urban, 2) cropland, 3) barren, 4) forest, 5) water, 6) wetland, and 7) grassland. The details of the accuracy assessment (i.e., producer and user's accuracy for each class type and the overall accuracy in an error matrix) of the classification were provided in Chen et al. (2019).

2.3 MODIS Albedo

Albedo datasets were obtained from the most recent collection (V006) of the MCD43A3 MODIS Bidirectional Reflectance Distribution Function (BRDF) product (https://doi.org/10.5067/MODIS/MCD43A3.006). MOD43A3 is a daily product at 500×500 m spatial resolution obtained by inversion of a Bidirectional Reflectance Distribution Function (the BRDF) model against a 16-day moving window of MODIS observations. The BRDF model was then used to derive the black-sky (associated to direct solar radiation) and white-sky (associated to diffuse radiation) albedos (Wang et al. 2018). We only considered snow-free, white-sky albedo at a shortwave length of 0.3-5.0 μm (hereafter, α_{SHO} and expressed in percentage). For each image, the "Albedo_WSA_shortwave" (white-sky albedo) band was selected and rescaled to 0-1. Only high-quality data were selected within the "full BRDF inversion" quality band (QA = 0). The "Snow_BRDF_Albedo" band in the MCD43A2 product was used to filter and exclude pixels with snow albedo retrievals (Chrysoulakis et al. 2018).

2.4 MODIS NDVI

Previous studies (e.g., Campbell and Norman 1998; Bonan 2008; Iqbal 2012; Liang et al. 2013; Zhao and Jackson 2014; Bright et al. 2015; Kaye and Quemada 2017; Sun et al. 2017) have thoroughly addressed the importance of snow cover on variability/uncertainty of albedo. Here, we focused on albedo change, $RF_{\Delta\alpha}$ and $GWI_{\Delta\alpha}$ only during the growing season when maximum variability of watershed crop phenology can be related with changes in climatic conditions and human disturbances at the landscape level. Therefore, for each year, we identified the "growing season" during March-October by detecting the greenness onset/offset for the entire Kalamazoo River watershed. To do so, for each year, we used a 16-day composite time series of the normalized difference vegetation index (NDVI) to detect the inflection points (i.e., dates) when the maximum and minimum change rate of NDVI occurred (Jeong et al. 2011). We obtained NDVI at a 250×250 m spatial resolution from the most recent collection (V006) of the MYD13Q1 MODIS product (https://doi.org/10.5067/MODIS/MYD13Q1.006). Finally, we divided each growing season (March-October) into three periods (hereafter, seasons) — spring, summer, and fall using astronomical season (e.g., spring equinox, summer solstice, and fall equinox).

2.5 Precipitation data

Daily precipitation data at a 4×4 km spatial resolution were obtained from the Parameter-elevation Regressions on Independent Slopes Model group (PRISM) AN81d product (http://www.prism.oregonstate.edu/) over the 2012-2017 time period. We also calculated the cumulative precipitation of the five landscapes during the growing season from March through October. For the time period considered (e.g., 2012-2017), we then identified three years as dry, normal and wet years: 2012, 2017 and 2016, respectively. The Midwest of U.S.A. experienced 6 weeks of summer drought during June-July in 2012 (Mallya et al. 2013), resulting in a growing season precipitation of <490 mm. In 2017, the watershed received over 750 mm, while this was ~700 mm (i.e., near average) for 2017. All analysis and processing of albedo, NDVI, and precipitation data were performed on the Google Earth Engine

(GEE) platform (Gorelick et al. 2017), where the MODIS products were uploaded, filtered to the date of interest, and clipped to the shape file for each of the five landscapes.

2.6 Statistical analysis

We performed analysis of variance (ANOVA) to examine the change in albedo with land cover type and landscape structure within the three-year study period and across three seasons. The following linear model was applied:

$$\alpha_{SHO} = landscape \times cover\ type \times year \times seasons \qquad (2)$$

where α_{SHO} is the snow-free white-sky albedo at the shortwave length at a daily step acquired from MODIS at 10:30 a.m. local time (UTC); landscape, cover type, year, and season are the five landscapes (FOR_1, FOR_2, $CROP_1$, $CROP_2$, $CROP_3$), the seven cover types (Table 1) at each landscape, the three years (dry, wet, and normal), and the three astronomical seasons (spring, summer, and fall), respectively. We also considered the interaction terms among the independent variables in our ANOVA.

To test the normality of our data we checked the distribution of the residuals. We then carried out ANOVA and Tukey tests for multiple comparisons using the R-package 'lsmeans' (R Core Team 2017).

2.7 Radiative forcing (RF) and global warming impact (GWI)

To quantify the potential of RF caused by changes in albedo, we referred to the direct albedo-induced RF at the top-of-atmosphere ($RF_{\Delta\alpha}$), where $\Delta\alpha$ is the change of α_{SHO} (i.e., the absolute difference between mean cropland and mean forest albedos in each of the five landscapes). We calculated $RF_{\Delta\alpha}$ (W m^{-2}) following the algorithms of Carrer et al. (2018):

$$RF_{\Delta\alpha}(t) = -\frac{1}{N}\sum_{d=1}^{N} SW_{in}\, T_a\, \Delta\alpha \qquad (3)$$

where $RF_{\Delta\alpha}$ is the mean albedo-induced radiative forcing at the top-of-atmosphere over the growing season (t), N is the number of days in the growing season, SW_{in} is the incoming solar radiation at the surface, T_a is the upward atmospheric transmittance and $\Delta\alpha$ is the albedo difference (i.e., between mean cropland and mean forest albedos). By multiplying both SW_{in} and $\Delta\alpha$ by T_a, we calculated the instantaneous amount of radiation that leaves the atmosphere at 10:30 a.m. UTC. It is worth reiterating that all the variables (i.e., SW_{in}, $\Delta\alpha$, and T_a) refer to the specific time of 10:30 a.m. UTC (e.g., MODIS Terra morning overpass time) and were considered to represent daily means. Negative values of $RF_{\Delta\alpha}$ indicate a cooling effect due to the differences between mean cropland and mean forest albedos.

While previous studies (e.g., Lenton and Vaughan 2009; Cherubini et al. 2012) used a global annual average value of 0.854 for T_a, we calculated T_a as the ratio of incoming solar radiation at the top of the atmosphere (SW_{TOA}) to that at the surface (SW_{in}) at 10:30 a.m. UTC. By assuming a same value of upward and downward atmospheric transmittances (Carrer et al. 2018), SW_{in} (W m^{-2}) was obtained from a local eddy covariance (EC) tower located at the Kellogg Biological Station Long-term Ecological Research site (42°24′N, 85°24′W) (Abraha et al. 2015), while SW_{TOA} (W m^{-2}) was calculated as:

$$SW_{TOA} = S_{po}\cos(\theta)\, d \tag{4}$$

where S_{po} is the solar constant (1,360 W m^{-2}), $cos(\theta)$ is the cosine of the solar zenith angle, obtained from the MCD43A2 (V006) MODIS BRDF Albedo Quality product (https://doi.org/10.5067/MODIS/MCD43A2.006), applying the "BRDF_Albedo_LocalSolarNoon" band, and d is the mean Earth-Sun distance. We then converted RF into the CO_2 equivalent (CO_{2eq}) by using the GWI algorithms of Bird et al. (2008) and Carrer et al. (2018):

$$GWI_{\Delta\alpha}(t) = \frac{S\, RF_{\Delta\alpha(t)}}{AF\, rf_{CO_2}}\frac{1}{TH} \tag{5}$$

where $GWI_{\Delta\alpha}$ is the CO_{2eq} (kg CO_{2eq} m^{-2} yr^{-1}) GWI due to Δα, represented by MODIS α_{SHO} acquisitions at 10:30 a.m. UTC, i.e., assuming that the values represent the mean CO_{2eq} mitigation impact of each landscape during the growing season March-October *(t)*, $RF_{\Delta\alpha}$ is the mean RF due to Δα over the growing season March-October *(t)* (Equation 3), S is cropland area (ha) for which we hypothesized the change of albedo occurred, AF is the CO_2 airborne fraction (0.48, Muñoz et al. 2010) obtained from the exponential CO_2 decay function (see Bird et al. 2008 for more details), and TH is the time horizon of potential global warming fixed at 100 years (Kaye and Quemada 2017). Lastly, the parameter rf_{CO2} — the marginal RF of

CO_2 emissions at the current atmospheric concentration — is kept as a constant (Muñoz et al. 2010; Bright et al. 2015; Carrer et al. 2018) at 0.908 W kg CO_2^{-1}.

Negative values of $GWI_{\Delta\alpha}$ indicate CO_{2eq} mitigation. We calculated the annual $GWI_{\Delta\alpha}$ as 1/100 of the total CO_{2eq} to normalize to the 100 year time horizon used in the Kyoto Protocol (Boucher et al. 2009). Notably, here we assumed that the same land mosaic in each landscape will be maintained for the duration of 100 years. Previous studies (Betts 2000; Akbari et al. 2009) have also used a constant AF as opposed to the exponential CO_2 decay function; however, the computed GWIs are similar (Bright 2015).

3. Results

Two of the five landscapes (FOR_1 and FOR_2) were dominated by forests (Table 1), with a forest coverage of 57.5% in FOR_1 and 38.4% in FOR_2. Wetlands and croplands accounted for 16.9% and 10.5% of landscape, respectively, in FOR_1 (Table 1), but only 10.1% and 26% in FOR_2 where urban land was also the highest (13.3%). Croplands were dominant in $CROP_1$, $CROP_2$, and $CROP_3$ (Table 1), with 68.1%, 64.5%, and 57.2% of area coverage, respectively. Forest cover ranked the second highest in these landscapes (14.2%, 16.7%, and 14.8%, respectively). Bare soils, grasslands, and water accounted for small portions of all five landscapes.

The entire watershed had an α_{SHO} of 15.9% during the dry (2012) and wet (2016) years and of 15.6% during the normal (2017) year (Table S2), yielding an overall average of 15.8% with a low inter-annual variation. Each cover type contributed differently to α_{SHO} at the watershed level. In particular, croplands and water bodies showed the highest (16.6%) and lowest (12.1%) α_{SHO}, respectively, with the highest values occurring in both 2012 (16.6%±1.0) and 2016 (16.6%±1.1) for croplands, and the lowest in 2017 (11.9%±3.4) for water. The other cover types showed similar α_{SHO} values, ranging 15.1-15.6% for barren and grassland, 15.2% for urban and forests and 15.4% for wetlands. At the landscape level, α_{SHO} of forest, which was considered as reference, was generally lower than that of croplands. In particular, FOR_1 and FOR_2 averaged a low α_{SHO} of 14.6% and 13.9%, respectively, whereas $CROP_1$, $CROP_2$, and $CROP_3$ recorded higher values of 16.7%, 16.4%, and 16.2%, respectively. However, FOR_1 and FOR_2

demonstrated the highest α_{SHO} in 2012 (14.7%±0.8 and 14.1%±2.3, respectively), while $CROP_1$, $CROP_2$, and $CROP_3$ demonstrated the highest α_{SHO} in different years, such as 2016 for $CROP_1$ (17.0%±0.8), 2012 and 2016 for $CROP_2$ (16.5%±0.6), and 2017 for $CROP_3$ (16.3%±1.7). In the forest-dominated landscapes, all cover types showed higher α_{SHO} during the dry year (2012). However, for FOR_2, α_{SHO} values of cropland and barren were high in the wet year (2016). In the cropland-dominated landscapes, the highest α_{SHO} value (17.1%) was observed in $CROP_3$ (±1.1) for croplands in 2017, and in $CROP_1$ for both urban (±0.6) and croplands (±0.8) in 2016.

Our ANOVA model (R^2=0.64) (Table 2) indicated that the variation of α_{SHO} was significant (p-value <0.001) among the five landscapes (i.e., ecoregions) (ω^2=26.6%) by cover type (i.e., landscape mosaics) (ω^2=11.1%) and their interactions (ω^2=5.2%), with year and its interactions explaining <1% of the variation. However, the variation from season (i.e., seasonality) (ω^2=15.9%) explained more than cover type.

Forest-dominated landscapes (FOR_1 and FOR_2) showed lower least square means (LSM) of α_{SHO} ($LSM\alpha_{SHO}$) than cropland-dominated landscapes ($CROP_1$, $CROP_2$ and $CROP_3$) (Figure 3a) over the three years. A decreasing inter-annual trend (between 2012, 2016, and 2017 growing seasons) characterized FOR_1, FOR_2, and $CROP_2$, with FOR_1 showing statistically higher $LSM\alpha_{SHO}$ in the dry (2012) year; whereas $CROP_2$ showed statistically lower $LSM\alpha_{SHO}$ in the normal (2017) year. In addition, differences in LSM between cropland and forest albedos ($LSM_{\Delta\alpha}$) appeared to be higher in FOR_1, FOR_2, and $CROP_3$ (Figure 3b), but with increasing inter-annual trends, than in $CROP_1$ and $CROP_2$. However, only FOR_2 showed statistically lower $LSM_{\Delta\alpha}$ in the dry year (2012) (Figure 3b).

Clear seasonal patterns existed in α_{SHO} and were generally lower in spring and autumn than in the summer (Figure 4). However, in $CROP_2$, the α_{SHO} of the major cover types (i.e., cropland, forest, urban, and wetland) was the highest in the spring of the dry year. The α_{SHO} of cropland and urban areas in 2017 (a normal year) was also relatively higher in both spring and summer (Figures $4c_1$-c_3). The inter-annual variability between the wet and normal years (Figures $4b_1$–b_4 and $4c_1$–c_4, respectively) appeared similar, with small differences between FOR_1 and FOR_2 (e.g., the lowest α_{SHO} occurring in spring in FOR_1 and in autumn in FOR_2).

The mean $\Delta\alpha$ ranged between 0.4% and 2% (i.e., ~1.2% mean difference between mean cropland and mean forest albedos) (Figure 4Δa–Δc); however, the intra-annual variability of $\Delta\alpha$ differed by landscape and year. We found that forest-dominated landscapes (FOR_1 and FOR_2) had higher $\Delta\alpha$ in spring each year, with the minimum in autumn (FOR_1) and summer (FOR_2) of every year. Cropland-dominated landscapes ($CROP_1$, $CROP_2$ and $CROP_3CROP_3$) showed higher $\Delta\alpha$ in spring that was more pronounced in 2016 for $CROP_1$ (Figure 4Δb), in 2016 and 2017 for $CROP_2$ (Figure 4Δb-Δc), and in 2012 for $CROP_3$ (Figure 4Δa). However, $CROP_2$ in 2012 was characterized by a different $\Delta\alpha$ trend — lower in spring and higher in autumn (Figure 4Δa). The summer $\Delta\alpha$ variability among the five landscapes was lower in the dry year (Figure 4Δa) and higher in the normal year (Figure 4Δc). Two distinct clusters characterized the summer of the wet year (Figure 4Δb), with FOR_1, FOR_2 and $CROP_3$ having an $\Delta\alpha$ of $\geq$ 1% and $CROP_1$ and $CROP_2$ of $\leq$ 0.5%.

All five landscapes had negative $RF_{\Delta\alpha}$ (Table 3; Figure 5a). Among the cropland-dominated landscapes, $CROP_1$ and $CROP_2$ had similar lower magnitude $RF_{\Delta\alpha}$ values, with minimum and maximum values in the wet (2016) and normal (2017) years, respectively. In particular, $CROP_2$ had $RF_{\Delta\alpha}$ (W m^{-2}) of -1.2 in 2016 and -1.9 in 2017, followed by $CROP_1$ (-1.3 and -2.0) and $CROP_3$ (-2.9 and -3.7). Among the forest-dominated landscapes, FOR_1 showed a similar trend, with minimum and maximum magnitude $RF_{\Delta\alpha}$ in 2016 and 2017 (-3.9 and -5.6, respectively), while FOR_2 had the minimum and maximum magnitude $RF_{\Delta\alpha}$ in the dry (2012) and normal (2017) years (-2.7 and -2.9, respectively).

As for $RF_{\Delta\alpha}$, all five landscapes showed negative values of $GWI_{\Delta\alpha}$ (Table 3; Figure 5b), which had inter- and intra-annual trends similar to $RF_{\Delta\alpha}$ (Figure 5b). In particular, $CROP_1$ and $CROP_2$ had similar lower magnitude $GWI_{\Delta\alpha}$ (Mg CO_{2eq} ha^{-1} yr^{-1}) values, with minimum ($CROP_1$ and $CROP_2$: -0.3) and maximum ($CROP_1$: -0.5 and $CROP_2$: -0.4) values in the wet (2016) and normal (2017) years, respectively, followed by $CROP_3$ (-0.7 and -0.9, respectively). FOR_1 showed a similar trend, with minimum and maximum magnitude $GWI_{\Delta\alpha}$ in 2016 and 2017 (-0.9 and -1.3, respectively), with statistically higher

$GWI_{\Delta\alpha}$ in 2017, while FOR_2 had the minimum and maximum magnitude $GWI_{\Delta\alpha}$ in the dry (2012) and both wet and normal (2016 and 2017) years (-0.6 and -0.7, respectively) (Table 3; Figure 5b).

Taking the normal year (2017) as our baseline, the percentage changes between the normal and dry years (e.g., diff $_{2017\text{-}2012}$), and the normal and wet years (e.g., diff $_{2017\text{-}2016}$) showed reduced $\Delta\alpha$, $RF_{\Delta\alpha}$, and $GWI_{\Delta\alpha}$ values (Table 3). In particular, the decrease in $\Delta\alpha$ was higher in FOR_2, $CROP_1$ $CROP_2$ (28.5%, 9.2%, and 19.4%, respectively) for $diff_{2017\text{-}2012}$ and in $CROP_1$ and $CROP_2$ (12.6% and 34.3%, respectively) for $diff_{2017\text{-}2016}$. FOR_2 decreased the least from baseline in both $RF_{\Delta\alpha}$ and $GWI_{\Delta\alpha}$ compared to all other landscapes, which had the highest decrease in $diff_{2017\text{-}2016}$ — FOR_1 (29.9%), $CROP_1$ (32.1%), $CROP_2$ (33.4%), and $CROP_3$ (23.3%). Statistically, reductions in $\Delta\alpha$, $RF_{\Delta\alpha}$, and $GWI_{\Delta\alpha}$ values were all significant in FOR_1 (for both $diff_{2017\text{-}2012}$ and $diff_{2017\text{-}2016}$) and in $CROP_2$ (for $diff_{2017\text{-}2016}$).

4. Discussion

The main finding of our study is that $RF_{\Delta\alpha}$ and $GWI_{\Delta\alpha}$ play an important role in climate change impact due to landscape mosaics. In particular, we found that forests have lower albedo than croplands, which is in consistent with previous studies. In all five landscapes LULCC from forest to cropland showed a cooling effect with negative $RF_{\Delta\alpha}$ and $GWI_{\Delta\alpha}$ values. The results also show that the difference between mean cropland and mean forest albedos during the three years produces on average ~64%, 65%, and 28% stronger CO_{2eq} mitigation impacts in the landscape with the highest proportion of forest (FOR_1) than in cropland-dominated landscapes ($CROP_1$, $CROP_2$, and $CROP_3$, respectively), presumably due to the lower proportion in cropland (e.g., 10.5% of cropland area) in FOR_1. Additionally, dry climatic conditions in 2012 result in the highest albedo in almost all landscapes, although only significantly higher in one of the forest-dominated (FOR_1) landscapes, supporting a consensus that dry surfaces reflect more than wet surfaces. Over the growing season, albedo peaks in summer in all cover types, with lower albedo in spring and autumn due to changes in plant phenology.

4.1 Inter- and intra-annual changes in albedo

We compared α_{SHO} values among major cover types (i.e., urban, cropland, forest, and wetland), disregarding those with lower proportions (i.e., grassland, water, and barren) due to their negligible contributions to the total landscape α_{SHO}. We observed that croplands and forests had on average 7.8% higher and 0.7% lower albedo than other land covers, respectively. This is in line with previous studies that examined snow-free albedo variations among ecosystems (Jiao et al. 2017, Chen et al. 2019) and across the conterminous United States (Barnes and Roy 2010). Bonan (2008) showed that forests have lower surface albedo than other cover types, contributing to climate warming. Our study indicated that in forest-dominated landscapes (FOR_1 and FOR_2) the average of inter-annual variation of α_{SHO} was ~2.8% lower than that in cropland-dominated landscapes (Table S2; Figure 3a). Analysis of variance also revealed that the five landscapes (i.e., ecoregions), cover types (i.e., landscape mosaics), and seasons (i.e., seasonality) contributed significantly to the overall variation of α_{SHO}. Specifically, we found that besides the five landscapes, seasons (~16%) contributed by 5% more than cover type (11%) towards variation of α_{SHO} (Table 2).

Changes in α_{SHO} due to LULCC have been widely studied (Chrysoulakis et al. 2018); however, its dynamics at ecosystem-to-landscape scales remain unexplored. For example, Zheng et al. (2019) investigated how vegetation changes affect albedo trends without considering the integrated effect of both cover type and seasonality, while Matthews et al. (2003) investigated the cooling/warming effects of albedo change resulting from deforestation, but failed to consider realistic land cover change scenarios. A number of agricultural management practices are known to mitigate climate change (summarized in Smith et al. 2008 and Eagle et al. 2012), including GHG emission reductions and soil carbon storage, but the potential contribution of albedo change as an ecosystem-scale mitigation factor has not been much addressed. For example, tillage practices, harvest timing, residue management, and winter cover crops can all affect surface reflectance in annual cropping systems (Bright et al. 2015; Poeplau and Don 2015; Kaye and Quemada 2017; Robertson et al. 2017) and thus GWI.

To our knowledge, no effort has been made to understand albedo mitigation in terms of both RF and GWI in the context of landscape mosaics characterized by diverse land use type and intensity. Using the framework listed in Equation 1 and Figure 1, we were able to integrate spatial (e.g., five landscapes within ecoregions) and temporal (e.g., inter- and intra-annual) changes as main drivers of α_{SHO} variations. Regardless of land composition, cropland-dominated landscapes showed a higher intra-annual variability of α_{SHO} than forests under dry, wet, and normal climatic conditions (Figure 4 a–c), likely due to the higher disturbances that croplands experience (i.e., fragmentation, land management, crop variety, and crop seasonality). For example, α_{SHO} can be altered by the differences in leaf structure/properties (Miller et al. 2016) and leaf wetness (Luyssaert et al. 2014), by the difference in management of both perennial and annual crops and by agricultural practices (Bright et al. 2015; Kaye and Quemada 2017; Robertson et al. 2017).

The LSM multi-comparison analysis showed that dry conditions led FOR_1 to yield statistically higher α_{SHO} compared to wet and normal conditions. On the other hand, $CROP_2$ showed significantly lower α_{SHO} under normal conditions than under dry and wet conditions (Figure 3a), indicating a different albedo response of forest- and cropland-dominated landscapes to changes in climatic conditions. All other landscapes showed higher α_{SHO} in the dry year (2012) than in the normal and wet years, although not statistically different.

4.2 Albedo-induced radiative forcing (RFΔα) and global warming impact (GWIΔα)

We obtained $RF_{\Delta\alpha}$ (W m^{-2}) values that were more representative of the entire growing season through the years 2012, 2016, and 2017. We found that the five landscapes had a negative $RF_{\Delta\alpha}$, indicating a cooling effect. However, such effect was stronger in FOR_1 where it ranged between -3.9 W m^{-2} and -5.6 W m^{-2} (Table 3; Figure 5a), followed by $CROP_3$ (-2.9 W m^{-2} and -3.7 W m^{-2}) and FOR_2 (-2.7 W m^{-2} and -2.9 W m^{-2}), while $CROP_1$ and $CROP_2$ were almost similar (ranging between -1.2 W m^{-2} and -1.9 W m^{-2}, respectively). In other words, land mosaics in the landscape with the highest proportion of forest (e.g., FOR_1) leads to a maximum $RF_{\Delta\alpha}$ of -5.6 W m^{-2} (i.e., a cooling effect), which is similar to that hypothesized by Jiao et al. (2017) under the simulated scenario of global deforestation of evergreen broadleaf forests (local magnitude of RF_{TOA} at -5.6 W m^{-2}). Moreover, in this study we were able to investigate $RF_{\Delta\alpha}$ dynamics across three contrasting precipitation regimes — dry (2012), wet (2016), and normal (2017). The inter-annual analysis specifically showed that within each landscape, the cooling effect was lower in 2016 and higher in 2017, with the exception of FOR_2, which had a lower cooling effect in 2012 and a higher one in 2017 (e.g., slightly higher than in 2016). In sum, accurate quantification of landscape contribution to the global warming potentials needs input from both landscape composition and climate that directly regulate ecosystem properties.

The $GWI_{\Delta\alpha}$ computations enabled us to estimate the CO_{2eq} mitigation caused by the differences between mean cropland and mean forest albedos. Standardized to the same areas, the greatest contribution of albedo change to GWI occurred in the FOR_1 ($GWI_{\Delta\alpha}$ = -1.3 Mg CO_{2eq} ha^{-1} in 2017; Table 3; Figure 5b), whereas the least contribution occurred in $CROP_2$ (-0.3 Mg CO_{2eq} ha^{-1} yr^{-1}). These contributions to GWI are of the same order of magnitude as many crop management components. For example, in this same watershed a corn-soybean-wheat rotation managed with a legume cover crop had a net GWI of 0.4 - 0.6 Mg CO_{2eq} ha^{-1} yr^{-1} (Robertson et al 2000), without considering albedo change due to historical LULCC. Likewise, the net GWI of conventional and no-till cropping systems were similar in magnitude without consideration of albedo; 0.3 to 0.9 Mg CO_{2eq} ha^{-1} yr^{-1}, respectively (Gelfand et al. 2013). In several landscapes (FOR_1, FOR_2, and $CROP_3$), $GWI_{\Delta\alpha}$ was sufficient to offset the GWI costs of both N_2O emissions (0.4 Mg CO_{2eq} ha^{-1} yr^{-1}) and farming inputs for an alfalfa cropping system (~0.8 Mg CO_{2eq} ha^{-1} yr^{-1}) (Gelfand et al. 2013).

Surprisingly, the results of inter-annual variation among the three growing seasons showed that the CO_{2eq} mitigation impact between forest- and cropland-dominated (FOR_1, $CROP_3$) landscapes was statistically different in 2012 and 2016 for FOR_1 (Table 3, Figure 5a) and in 2016 for $CROP_3$, suggesting that changes in climate conditions, as seen in our study from dry to normal and from wet to normal, can affect the CO_{2eq} mitigation impacts of landscapes. Overall, in one of the forest-dominated landscapes (FOR_1) the percent decrease of CO_{2eq} mitigation due to dry and wet conditions was higher than that of the cropland-dominated landscape $CROP_3$ under wet conditions (e.g., lower albedo). Specifically, we found that both dry and wet conditions in FOR_1 could significantly reduce $CO_{2\text{-eq.}}$ mitigation by up to 24% and ~30% (i.e., percentage change), respectively; while the CO_{2eq} mitigation's decreasing in $CROP_3$ was significant under wet conditions (e.g., 23.3%), which, in both cases, is still enough to offset 11% of the total CO_{2eq} emissions of conventionally tilled corn systems in the same area and under the same climatic conditions (i.e., 2012 and 2016) (Abraha et al. 2019). Surprisingly the high decrease in $\Delta\alpha$ (e.g., FOR_1: 9% vs 6.1% and $CROP_3$: 6% vs 1%) under wet conditions did not lead to a high decrease in CO_{2eq} mitigation.

4.3 Assumptions, limitations and uncertainties

The methodology used in this study represents an analytical approach as a proof of concept of the effects of landscape patches and climatic conditions on $RF_{\Delta\alpha}$ and $GWI_{\Delta\alpha}$ in the context of forest- and cropland-dominant landscapes. However, certain assumptions can be made on the application of our approach. The first is that $RF_{\Delta\alpha}$ is related to land mosaics (e.g., patch composition) derived by land transformation (Muñoz et al. 2010). In fact, the focus of the present study is to measure the changes in $RF_{\Delta\alpha}$ and $GWI_{\Delta\alpha}$ due to conversion of forests to croplands, assuming the existing croplands were forests in the past. We then considered $\Delta\alpha$ using the baseline (forest), which is treated as a reference cover type of the five landscapes, since it was the dominant land cover type of the pre-European settlements (Brown et al. 2000).

A second assumption is related to using *in-situ* incoming radiation (SW_{in}) for the calculation of upward atmospheric transmittance (T_a). While the literature (Lenton and Vaughan 2009; Muñoz et al. 2010; Cherubini et al. 2012) refers to T_a as the annual global mean ($T_a = 0.854$) for a constant zenith angle of 60°, here we calculated T_a for a given day as the ratio SW_{in}/SW_{TOA}, with SW_{in} obtained from *in-situ* measurements within the study area (Abraha et al. 2015), specifically at the FOR_2 landscape. By avoiding such a default value for T_a (e.g., 0.845), we reduced the error by ~30%. We then assumed that SW_{in} would be the same at all five landscape locations. In fact, unlike previous studies, we calculated

$RF_{\Delta\alpha}$ and $GWI_{\Delta\alpha}$ on a relatively small area (i.e., not global/regional) for which the uncertainty error carried by a constant T_a would not have been significant.

A third assumption is related to the time horizon (TH) fixed at 100 years, which is the same time horizon used in the Kyoto Protocol (Boucher et al. 2009). By calculating the annual $GWI_{\Delta\alpha}$ as 1/100 of the total CO_{2eq}, we assumed that, in each landscape, the same land mosaic will be maintained for the duration of 100 years. This choice of TH is a limitation because short time horizons can overemphasize the impacts of albedo, while long time horizons can de-emphasize the impacts (Anderson-Teixeira et al. 2012).

Another limitation of the study is the use of a growing season (March-October) time frame for $RF_{\Delta\alpha}$ and $GWI_{\Delta\alpha}$ rather than an annual period. Previous studies (Campbell and Norman 1998; Bonan 2008; Iqbal 2012; Liang et al. 2013; Zhao and Jackson 2014; Bright et al. 2015; Kaye and Quemada 2017; Sun et al. 2017) have addressed the importance of snow cover to variability/uncertainty of albedo between forest and cropland because of the capability of forest stands of masking the snow (e.g., lowing the albedo). Nevertheless, our use of growing season values allowed to better isolate the human disturbance on the landscape through agricultural activities by focusing on the crop phenology and its relation with climatic conditions. Had we included wintertime albedo, our forest-cropland differences would have been even greater, however, since deciduous forest stands have higher wintertime albedo than cropland due to the presence of bare branches (Bonan 2008; Anderson et al. 2011) during winter. On the other hand, from the remote sensing perspective, MODIS snow-albedo retrievals have been demonstrated to be less accurate than acquisitions during the growing season (Wang et al., 2014).

There are also uncertainties associated with user-defined data (Muñoz et al. 2010), such as considering $\Delta\alpha$ as the difference between croplands and forest albedos. AF (i.e., CO_2 airborne fraction) and rf_{CO2} (the marginal RF of CO_2 emissions at the current atmospheric concentration) are estimated to embed errors of ±15% and ±10%, respectively, in the GWI estimation (Forster et al. 2007; Akbari et al. 2009). It is also worth mentioning the uncertainties related to the scale-dependency. In fact, there is a mismatch between the spatial representativeness of MODIS acquisition pixels (e.g., 500×500 m) and that of Landsat (30×30 m), which leads to intrinsic variability of the measurements (Chrysoulakis et al. 2018; Chen et al. 2019). However, as already emphasized in previous studies (Mira et al. 2015; Moustafa et al. 2017), validation techniques provide a reasonable estimate of albedo from MODIS products across homogeneous landscapes (e.g., the two forest- and the three cropland-dominated landscapes).

Lastly, we did not consider the effect of spatial autocorrelation that may affect the significance of the statistic test (Fletcher and Fortin 2018). Nevertheless, the aim of this study is not to attempt spatial predictions (Feilhauer et al. 2012) of $RF_{\Delta\alpha}$ and $GWI_{\Delta\alpha}$.

5. Conclusions

1. There are significant contributions (R^2=0.64) to the overall variation in albedo due to landscapes (i.e., ecoregions), cover types (i.e., landscape mosaics), and seasons (i.e., seasonality). Variation in seasons contributes more than landscape composition (~16% and 11%, respectively) in variations of albedo.

2. By integrating spatial (e.g., five landscapes within ecoregions) and temporal (e.g., inter- and intra-annual) patterns as main drivers of albedo variation, we found that cropland-dominated landscapes produce a higher intra-annual variability of albedo under dry, wet, and normal climatic conditions, likely due to more frequent disturbances (i.e., management activities). Forest-dominated landscapes have higher albedo in dry and wet years than that in normal years, whereas only one crop-dominated landscape shows statistically lower albedo under normal conditions than that under dry and wet ones. This indicates a different response to changes in climatic conditions from forest- and cropland-dominated landscapes.

3. The cooling effect of $RF_{\Delta\alpha}$ occurs in all landscapes but is higher in the landscape with the highest proportion of forests (FOR_1) (e.g., higher differences between mean cropland and mean forest albedos). The pattern of $GWI_{\Delta\alpha}$ across the five landscapes is similar to that of $RF_{\Delta\alpha}$, with CO_{2eq} mitigation relative to pre-existing forest vegetation higher in FOR_1 and lower in $CROP_1$ and $CROP_2$.

4. We found that in the landscape with the highest proportion of forest (FOR_1) both dry and wet conditions can significantly reduce CO_{2eq} mitigation by up to 24% and ~30%, respectively; while the

reduction of CO_{2eq} mitigation is significant only in one of the cropland-dominated landscapes ($CROP_3$) under wet conditions (e.g., 23.3% decrease).

Acknowledgements: This study was supported, in part, by the NASA Carbon Cycle & Ecosystems program (NNX17AE16G), the Great Lakes Bioenergy Research Center funded by the U.S. Department of Energy, Office of Science, Office of Biological and Environmental Research under Award Numbers DE-SC0018409 and DE-FC02-07ER64494 and the Natural Science Foundation Long-term Ecological Research Program (DEB 1637653) at the Kellogg Biological Station, the NASA Science of Terra and Aqua program (NNX14AJ32G). We wish to thank Dr. Geoffrey Henebry for helpful suggestions and comments during the post-review process. We also thank the two anonymous reviewers who helped improving the quality of our manuscript.

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Tables

Table 1 Land cover composition of the five landscapes. Bold values indicate the cover type dominating the landscape.

	Landscape				
Cover type	FOR_1	FOR_2	$CROP_1$	$CROP_2$	$CROP_3$
	ha (%)				
Urban	513 (5.2)	1330 (13.3)	545 (5.5)	1047 (10.5)	1341 (13.4)
Cropland	1035 (10.5)	2597 (26.0)	**6807 (68.1)**	**6442 (64.5)**	**5713 (57.2)**
Barren	530 (5.4)	286 (2.9)	49 (0.5)	62 (0.6)	64 (0.6)
Forest	**5672 (57.5)**	**3833 (38.4)**	1415 (14.2)	1670 (16.7)	1477 (14.8)
Water	410 (4.2)	922 (9.2)	56 (0.6)	43 (0.4)	442 (4.4)
Wetland	1669 (16.9)	1012 (10.1)	1101 (11.0)	693 (6.9)	917 (9.2)
Grassland	30 (0.3)	12 (0.1)	21 (0.2)	35 (0.4)	38 (0.4)

Table 2 Statistical results of analysis of variance (ANOVA) based on the linear model in Equation 1 (dependent variable: α_{SHO}).

Variable	DF	SS	MS	F	p	ω^2	R^2
landscape	4	1.869	0.467	3689.660	***	0.266	
seasons	2	1.118	0.559	4414.651	***	0.159	
cover type	6	0.779	0.130	1024.423	***	0.111	
landscape × cover type	24	0.371	0.015	121.891	***	0.052	
landscape × seasons	8	0.142	0.018	140.167	***	0.020	
landscape × cover type × seasons	48	0.079	0.002	12.962	***	0.011	
year × seasons	4	0.048	0.012	94.672	***	0.007	
cover type × seasons	12	0.030	0.003	19.844	***	0.004	
landscape × year	8	0.022	0.003	21.210	***	0.003	
landscape × year × seasons	16	0.020	0.001	9.684	***	0.003	
year	2	0.013	0.007	51.367	***	0.002	
landscape × cover type × year	48	0.015	0	2.505	***	0.002	
cover type × year	12	0.002	0	1.278		0	
cover type × year × seasons	24	0.003	0	1.047		0	
landscape × cover type × year × seasons	96	0.011	0	0.887		0	0.64
Residuals	19779	2.505	0				

ω^2 indicates variance in the dependent variable α_{SHO} accounted for by the independent variables landscape, cover type, year, seasons, and their interactions. Significance codes: "***" $p < 0.001$, "**" $p < 0.0.1$, "*" $p < 0.05$, "." $p < 0.1$, " " $p > 0.1$.

Table 3 Mean change of $\Delta\alpha$ (%), $RF_{\Delta\alpha}$ ($W\ m^{-2}$), and $GWI_{\Delta\alpha}$ ($Mg\ CO_{2eq}\ ha^{-1}\ yr^{-1}$) for each landscape in 2012, 2016, and 2017 growing seasons. Negative values for $RF_{\Delta\alpha}$ and $GWI_{\Delta\alpha}$ indicate cooling effects and CO_{2eq} mitigation impacts due to albedo change, respectively. Percentage changes (%) between 2017 (baseline) and the two extreme climatic years (i.e., diff $_{2017\text{-}2012}$ and diff $_{2017\text{-}1016}$, respectively) are also shown. Values with significant decrease (e.g., percent change) are highlighted in bold texts.

	2012			2016			2017			$diff_{2017\text{-}2012}$		$diff_{2017\text{-}2016}$	
	Δ_α	$RF_{\Delta\alpha}$	$GWI_{\Delta\alpha}$	Δ_α	$RF_{\Delta\alpha}$	$GWI_{\Delta\alpha}$	Δ_α	$RF_{\Delta\alpha}$	$GWI_{\Delta\alpha}$	Δ_α	$RF_{\Delta\alpha}$ / $GWI_{\Delta\alpha}$	Δ_α	$RF_{\Delta\alpha}$ / $GWI_{\Delta\alpha}$
FOR_1	1.2 (±0.8)	-4.2	-1.0	1.2 (±0.8)	-3.9	-0.9	1.3 (±0.6)	-5.6	-1.3	**9.0**	**24.0**	**6.1**	**29.9**
FOR_2	0.8 (±0.3)	-2.7	-0.6	1.0 (±0.4)	-2.9	-0.7	1.1 (±2.0)	-2.9	-0.7	28.5	9.0	7.8	1.4
$CROP_1$	0.5 (±0.2)	-1.7	-0.4	0.5 (±0.3)	-1.3	-0.3	0.5 (±0.3)	-2.0	-0.5	9.2	15.6	12.6	32.1
$CROP_2$	0.5 (±0.3)	-1.7	-0.4	0.4 (±0.2)	-1.2	-0.3	0.6 (±1.4)	-1.9	-0.4	19.4	9.9	34.3	33.4
$CROP_3$	0.9 (±0.3)	-3.2	-0.7	0.9 (±0.6)	-2.9	-0.7	0.9 (±0.5)	-3.7	-0.9	6.0	14.9	**1.0**	**23.3**

Figure captions

Fig. 1 Schematic diagram showing the relationship between landscape albedo and $GWI_{\Delta\alpha}$.

Fig. 2 Locations of the five landscapes (FOR_1, FOR_2, $CROP_1$, $CROP_2$, $CROP_3$) within the Kalamazoo River watershed in the southwest Michigan (USA). Each landscape falls within a unique Level IV ecoregion defined by the United States Environmental Protection Agency (US EPA). Basemap sources: *Esri, HERE, Garmin, USGS, Intermap, INCREMENT P, NRCAN, Esri Japan, METI, Esri China (Hong Kong), NOSTRA, © OpenStreetMap contributors, and the GIS User Community.*

Fig. 3 Least square means (LSM) multi-comparison analysis of α_{SHO} (a) and $\Delta\alpha_{SHO}$ (b) in 2012, 2016, and 2017 for each landscape. Boxes indicate the LSM; whiskers represent the lower and upper limits of the 95% family-wise confidence level of the LSM. Boxes sharing the same letters are not significantly different (intra- and inter-annual, as well as within and among the five landscapes) according to the Tukey HSD test.

Fig. 4 Mean α_{SHO} (%) by cover type and season in 2012 (a_1–a_4), 2016 (b_1–b_4), and 2017 (c_1–c_4) for the five landscapes. Mean of the difference between mean cropland and mean forest albedos ($\Delta\alpha_{SHO}$) for the same years (Δa, Δb, and Δc, respectively) is also shown.

Fig. 5 Bar chart of $RF_{\Delta\alpha}$ (W m^{-2}) due to the difference between mean cropland and mean forest albedos at the top-of-atmosphere across five landscapes at 10:30 a.m. local time (UTC) during the 2012, 2016, and 2017 growing seasons (a). Panel (b) shows $GWI_{\Delta\alpha}$ (Mg CO_{2eq} ha-1 yr^{-1}) due to the difference between mean cropland and mean forest albedos. Negative values for $RF_{\Delta\alpha}$ and $GWI_{\Delta\alpha}$ indicate cooling effects and CO_{2eq} mitigation impacts, respectively. Bars sharing the same letters are not significantly different (intra- and inter-annual, as well as within and among the five landscapes) according to the Tukey HSD test.

Figures

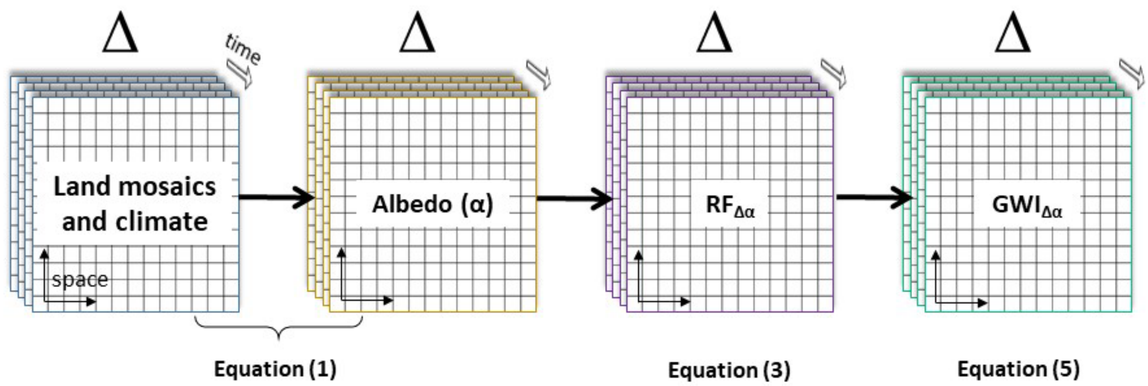


Fig. 1

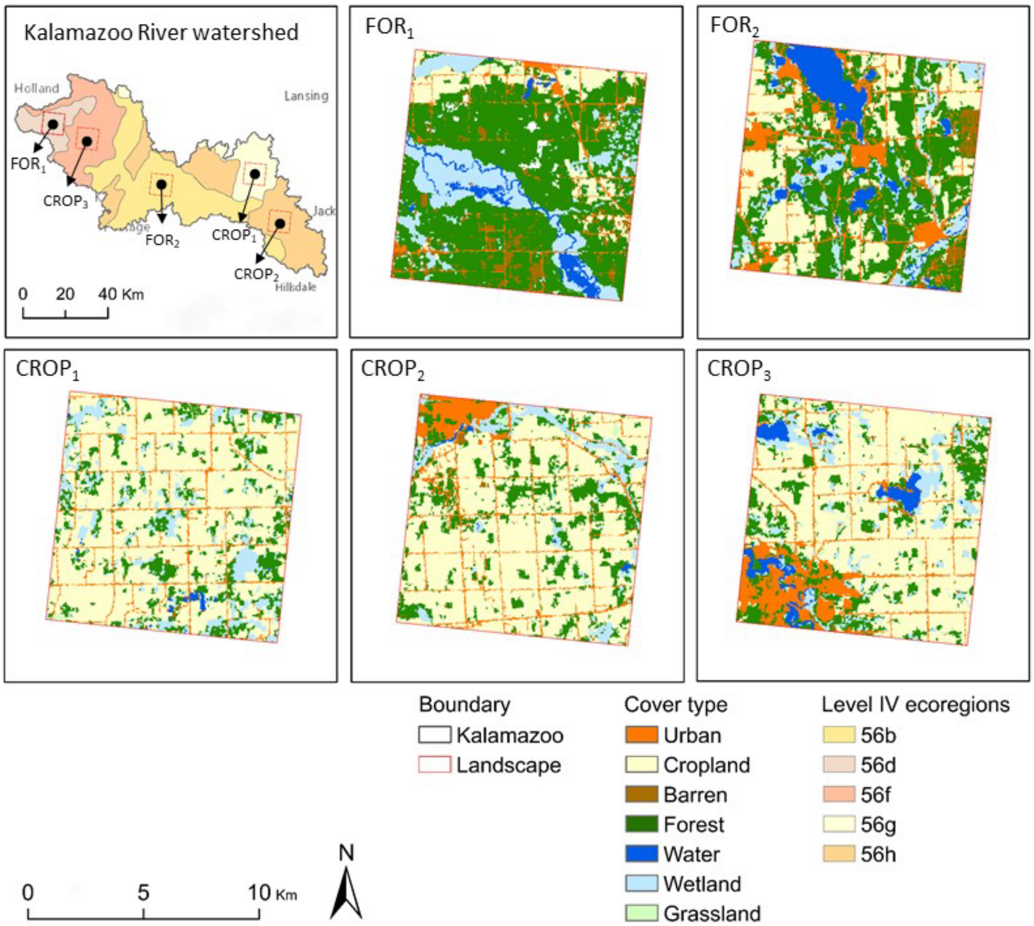

Kalamazoo River watershed
Holland
Lansing
FOR1
CROP3
FOR2
CROP1
CROP2
Hillsdale
0 20 40 Km
FOR1
FOR2
CROP1
CROP2
CROP3
Boundary
Kalamazoo
Landscape
Cover type
Urban
Cropland
Barren
Forest
Water
Wetland
Grassland
Level IV ecoregions
56b
56d
56f
56g
56h
0 5 10 Km
N

Fig. 2

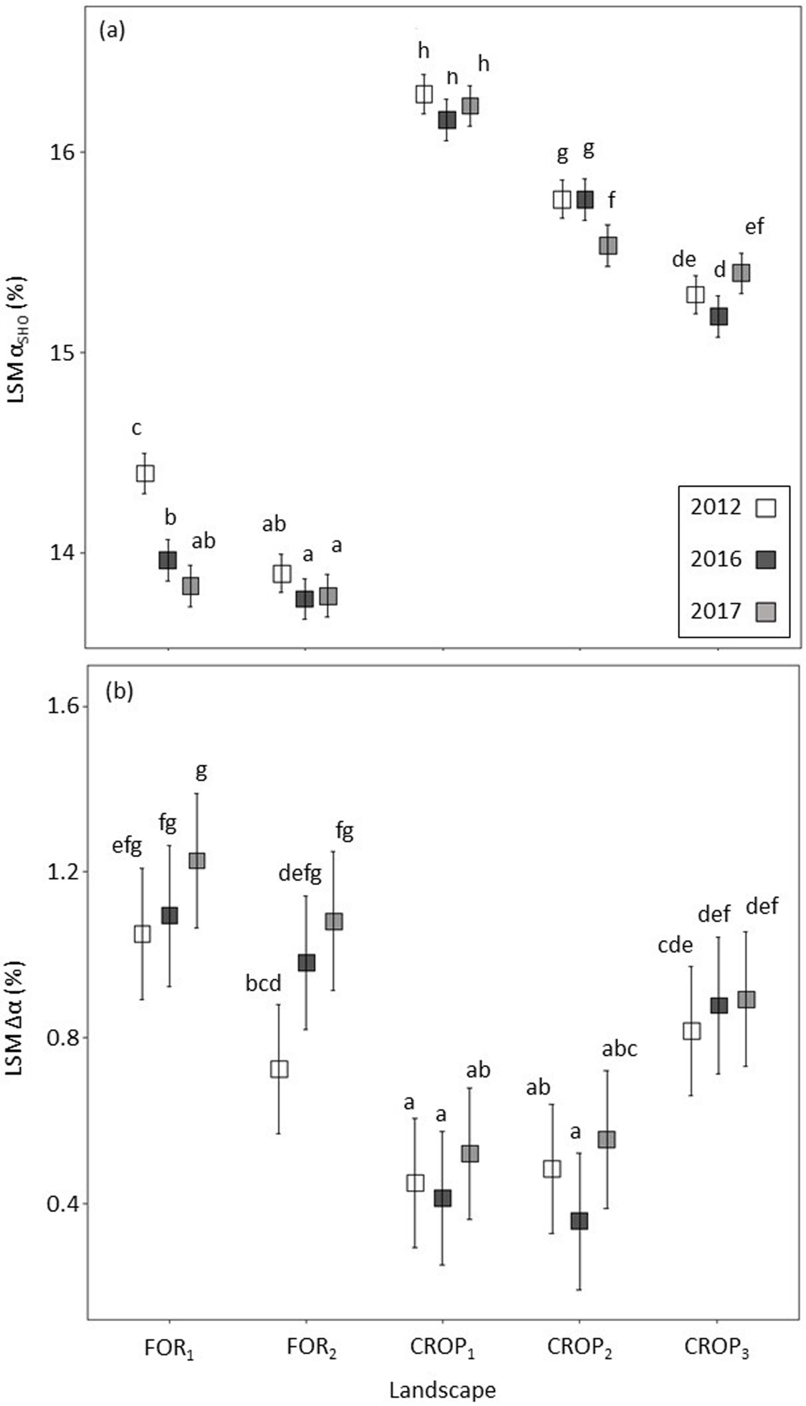
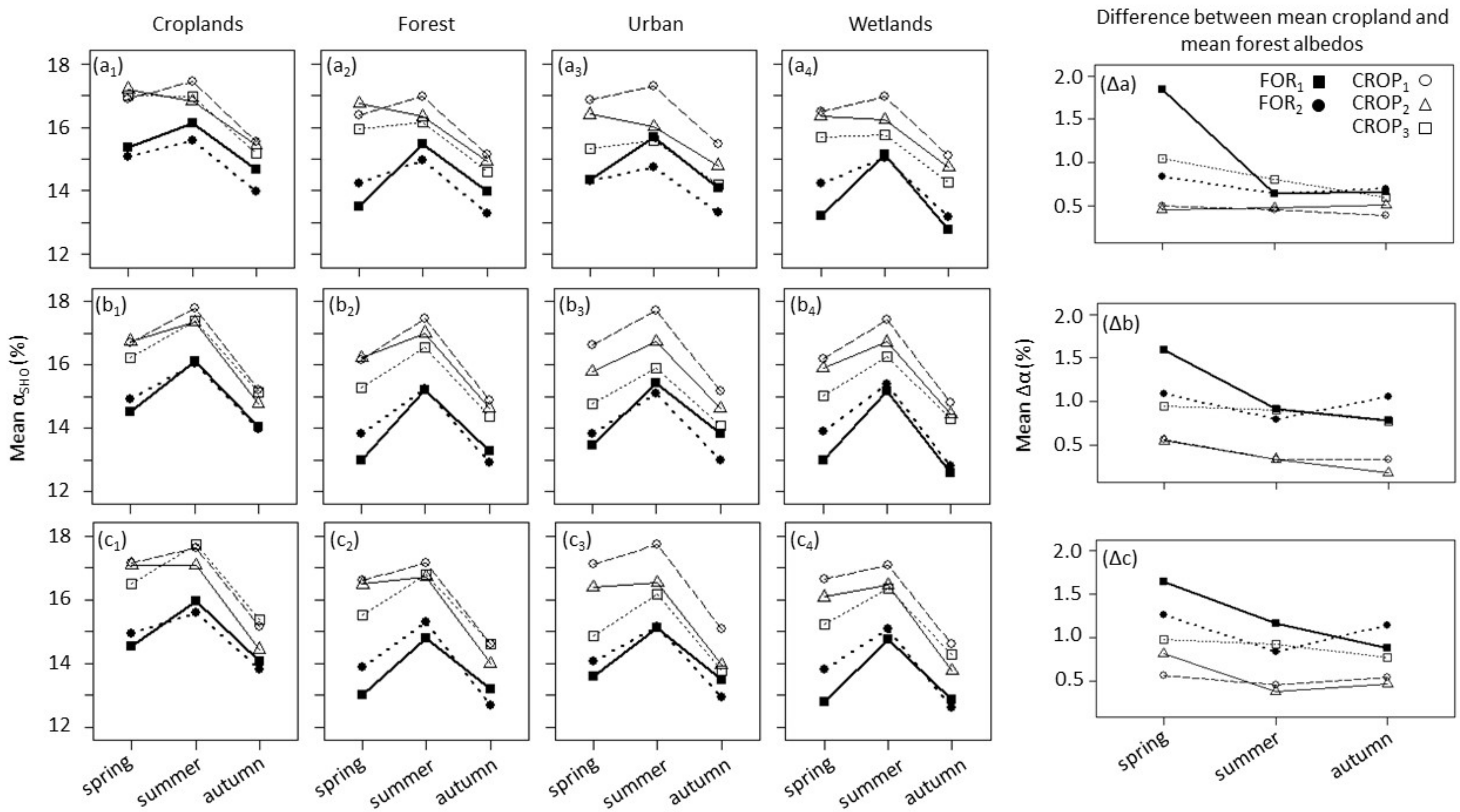

(a)
LSM α_SHO (%)
16
15
14
h
n
h
g
g
f
de
d
ef
c
b
ab
ab
a
a
2012
2016
2017
(b)
LSM Δα (%)
1.6
1.2
0.8
0.4
efg
fg
g
bcd
defg
fg
a
a
ab
ab
a
abc
cde
def
def
FOR1
FOR2
CROP1
CROP2
CROP3
Landscape

Fig. 3



Croplands
Forest
Urban
Wetlands
Difference between mean cropland and mean forest albedos
(a1)
(a2)
(a3)
(a4)
(b1)
(b2)
(b3)
(b4)
(c1)
(c2)
(c3)
(c4)
(Δa)
(Δb)
(Δc)
FOR1
FOR2
CROP1
CROP2
CROP3
Mean α SHO (%)
Mean Δα (%)
spring
summer
autumn

789

790 **Fig. 4**

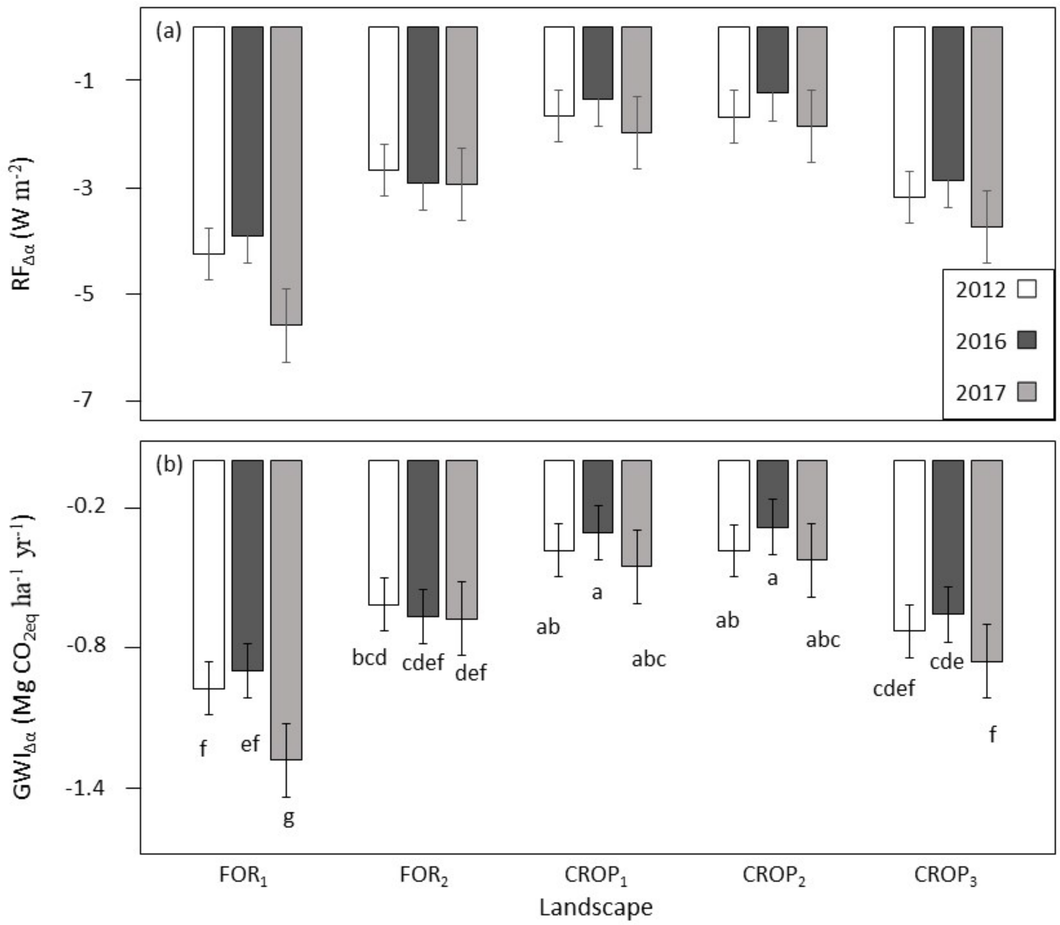

(a)
-1
-3
-5
-7
RF$_{\Delta\alpha}$ (W m^{-2})
2012
2016
2017
(b)
-0.2
-0.8
-1.4
GWI$_{\Delta\alpha}$ (Mg CO$_{2eq}$ ha^{-1} yr^{-1})
f
ef
g
bcd
cdef
def
ab
a
abc
ab
a
abc
cdef
cde
f
FOR$_1$
FOR$_2$
CROP$_1$
CROP$_2$
CROP$_3$
Landscape

Fig. 5