### Near-term ecological forecasting for dynamic aeroconservation of migratory birds

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**Article impact statement:** Ecological forecasting can efficiently alert conservation activities to mitigate aerial hazards for in-flight migratory birds.

Abstract: Near-term ecological forecasting has potential to mitigate the negative impacts of human modifications on wildlife by directing efficient dynamic conservation action through relevant and timely predictions. We use the North American avian migration system to highlight ecological forecasting applications for aeroconservation. We use millions of observations from 143 weather surveillance radars to construct and evaluate a migration forecasting system for nocturnal bird migration over the contiguous United States. We identified the number of nights of mitigation action required to reduce risk to 50% of avian migrants passing a given area in spring and autumn based on dynamic forecasts of migration activity. We also investigated an alternative approach, employing a fixed conservation strategy using time windows that historically capture 50% of migratory passage. In practice, during both spring and autumn, dynamic forecasts required fewer action nights compared to fixed window selection at all locations (spring: mean of 7.3 more alert days; fall: mean of 12.8 more alert days). This pattern resulted in part from the pulsed nature of bird migration captured in the radar data, where the majority (53.4%) of birds move on 10% of a migration season's nights. Our results highlight the benefits of near-term ecological forecasting and the potential advantages of dynamic mitigation strategies over static ones, especially in the face of increasing risks to migrating birds from light pollution, wind energy, and collisions with structures.

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Knowing when to direct action to protect species and habitats is essential for successful conservation efforts (Wilson et al. 2005; Knight et al. 2010), and there are many examples of such campaigns (Luther et al. 2016; Liberati et al. 2019; Wilson et al. 2019; Burgess et al. 2019; Watts et al. 2020). Safeguarding highly dynamic ecological processes, such as movement and migration, poses a greater challenge (Reynolds et al. 2017). However, the spatial process of migration also creates an opportunity to reduce the amount of time during which conservation measures are necessary at any particular location. Ecological forecasting of animal movements at relevant spatial and temporal scales may provide a pathway toward real-time conservation (Dietze et al. 2018; Van Doren & Horton 2018). Days, hours, or even minutes can make the difference between successful intervention and missed opportunity when considering highly vagile species. Timely, forecasted conservation actions relevant to migrating species may include the temporary removal of terrestrial or aquatic barriers (e.g., fences, dams), aerial obstacles (e.g., wind turbines, aircraft), or point-source pollutants (e.g., light pollution, chemical pollution) (Marschall et al. 2011; Naidoo et al. 2012; Van Doren et al. 2017).

Amidst a large diversity of migratory taxa, bird movements embody these conservation challenges, both in space and time, with movements spanning weeks to months across hundreds to thousands of kilometers through diverse ecosystems (Thorup et al. 2020; Bauer et al. 2020). While a large percentage of migratory birds' annual cycles may be based in terrestrial or aquatic systems, twice annually, billions of birds fill the lower atmosphere en route to wintering or breeding grounds (Dokter et al. 2018). Spring and autumn migratory seasons often encompass multiple months, but movements are not uniformly distributed in space or time (Horton et al. 2020). During any year in a given location, the majority of migrants will pass overhead within a period of days or weeks (Horton et al. 2020), but the specific nights of the highest migration

vary across locations and years. Understanding, quantifying, and predicting this variation is essential in directing conservation action.

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Migratory birds increasingly encounter aerial threats from human development (Davy et al. 2017), some of which can be mitigated by specific conservation actions. These threats are diverse in size, shape, and their impact on migratory birds. Some of these threats induce mortality directly, for instance collisions with buildings (Loss et al. 2014a), wind turbines (Loss et al. 2013), or communication towers (Gehring et al. 2009; Loss et al. 2014b). Other threats are more diffuse in their impact. For example, light pollution may direct migrants to inhospitable urban spaces (Zuckerberg et al. 2016; La Sorte et al. 2017; Van Doren et al. 2017; Lao et al. 2020), putting those individuals at risk through diminished energy reserves, phenological delays, and susceptibility to predation or injury — each factor potentially resulting in difficult-to-measure fitness consequences. Mitigation is possible for some types of these threats, thereby enhancing safe passage of migrating birds. For example, on nights of high migratory activity, lights can be dimmed or turned off on man-made structures, or activities changed (e.g., stopping wind turbines). Predicting the specific nights on which birds will migrate has tremendous value for safeguarding aerial passage.

A significant hurdle to implementing dynamic conservation approaches is the availability of timely alerts for when action is necessary. Remote sensing tools (e.g., radar, acoustics, infrared imaging) can measure real-time nightly movements of avian migrants (Horton et al. 2015), providing invaluable information to employ toward conservation. But even such instantaneous measures are too late to prevent collisions. One approach to address this challenge is to leverage historical measures to identify the seasonal windows during which the majority of migration tends to occur (e.g., a time period that captures 50% of activity) and direct conservation action during those fixed time windows; however, migration is highly dynamic,

and the timing of migratory movements is strongly influenced by shifting atmospheric conditions (Åkesson & Hedenström 2000; Liechti 2006; Shamoun-Baranes et al. 2010). For this reason, migration shows night-to-night periodicity (Åkesson & Hedenström 2000; Deppe et al. 2015). A fixed window approach would, therefore, be apt to capture nights of both high and low migratory activity, that may lead to costly effort that has limited impact and the potential to miss important events occurring outside the fixed window. Ecological forecasts offer an alternative approach for facilitating short-term conservation actions (Clark et al. 2001; Luo et al. 2011). Forecasts, by nature, are temporally and spatially dynamic, offering lead-time for the deployment of conservation action. Van Doren and Horton (2018) built a forecasting system for predicting bird migration using radar and atmospheric conditions, however this study did not examine how to operationalize forecasts to direct conservation efforts. Analytically, this dynamic selection approach presents a modeling challenge, as large movements comprise a small fraction of the duration of a migratory season (Horton et al. 2019a). While error is an inherent property of any ecological forecast, a sufficiently accurate forecast may still capture more activity across fewer nights than a historically defined window.

To address the need for conservation solutions to mitigate hazards for nocturnally migrating birds, we examine the behavior of the dynamic and fixed approaches. We quantify the utility of a near-term forecasting system for aeroconservation (i.e., conservation of aerial habitats) using a data-intensive approach via radar remote sensing. We frame our analysis in the following context: *if* we could take actions that were 100% effective in protecting birds, on *how many nights* would we need to take action to protect 50% of all migratory birds passing through a given location? In the specific case of light pollution, there is evidence that immediate mitigation action can be effective (Van Doren et al. 2017). We address this question with both a fixed window approach using historical data and a dynamic conservation setting using near-term forecasts across the continental United States.

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### Methods:

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### (a) Weather surveillance radar data

We quantified nocturnal migration from 143 weather surveillance radar (WSR) stations across the contiguous United States from 1995 to 2018. We characterized the spring migratory period from March 1<sup>st</sup> to June 10<sup>th</sup> and autumn from August 1<sup>st</sup> to November 10<sup>th</sup>, with each season spanning a maximum of 102 nights. To capture the complete passage of migrants, radar samples were processed from sunset to sunrise at 30-minute intervals. Level-II NEXRAD data were downloaded from the Amazon Web Services (AWS) archive (https://s3.amazonaws.com/noaanexrad-level2/index.html) and processed using the WSRLIB package (Sheldon 2015). We identified signatures consistent with precipitation using MISTNET (Lin et al. 2019) and removed these from reflectivity factor (migration intensity) and radial velocity (migration speed and direction) measures. While some migration may persist through periods of light precipitation, the intersection of precipitation and migratory movements tend to be mutually exclusive, with precipitation, especially heavy precipitation, halting the movement of migrants (Richardson 1978, 1990). For both reflectivity factor and radial velocity, profiles of activity were constructed from the lowest five radar scans (0.5 to 4.5°) at 100 m vertical intervals between 0 and 3 km above ground level (Buler & Diehl 2009). We extracted data from a 5-37.5 km radius surrounding the radar. We converted reflectivity factor to reflectivity following Chilson et al. (2012), yielding units of cm<sup>2</sup>km<sup>-3</sup>, also termed η. We derived migrant ground speed (km h<sup>-1</sup>) and direction (°) from velocity azimuth displays (VADs) following Browning & Wexler (1968) and when necessary radial velocity was de-aliased following Sheldon et al. (2013). In total, just over 13 million radar scans were processed from 2,115 spring nights and 2,152 autumn nights.

### (b) Migration forecast

We used the previously described profiles of activity to train seasonal bird migration forecast models. Our goal was to generate separate spring and autumn forecast models to predict migration traffic rate at 30-minute intervals, the same frequency as the radar measurements. To implement this, we used the product of radar reflectivity factor and groundspeed (cm<sup>2</sup>km<sup>-2</sup>hr<sup>-1</sup>) with a cube root transformation as the model's response variable. We used a gradient boosted regression tree framework (Chen & Guestrin 2016) to capture the complex spatio-temporal interactions of migratory movements as described by Van Doren & Horton (2018). We constructed models using the XGBoost package (Chen et al. 2017) in the R environment with thirteen predictors: three spatial predictors of latitude (°), longitude (°), height above ground level (m); two temporal predictors of ordinal date and hour after sunset; and eight atmospheric predictors of meridional wind (m s<sup>-1</sup>), zonal wind (m s<sup>-1</sup>), air temperature (°C), surface pressure (Pa), relative humidity (%), total cloud cover (%), visibility (m), and mean sea level pressure (Pa). Atmospheric predictors were extracted from the North American Regional Reanalysis (NARR) dataset (Mesinger et al. 2006) and linked with radar measures to align spatially (latitude, longitude, and height above ground level) and temporally (date and hour). NARR measures possess a spatial resolution of 32-km, 25 hPa vertical resolution, and 3hour temporal resolution. For variables with multiple pressure levels, we used data up to the 300 mb level. We averaged weather data within 37.5 km of each radar. We determined height above ground level by subtracting surface geopotential height from the geopotential height of each pressure level, and we linearly interpolated data at 100-m increments from 0-3000 m. Temporally, we matched radar and weather data by using the weather observation closest in time to each radar observation. We trained seasonal models using the following parameters: max\_depth = 12, eta = 0.01, gamma = 1, colsample\_bytree = 1, min\_child\_weight = 5, and subsample = 0.7. max\_depth is the maximum depth of regression trees, eta the step size

shrinkage used in updates to prevent overfitting and to make the boosting process more conservative (0.01 is a fine scale update), *colsample\_bytree* is set for subsampling of columns (no subsampling applied with a value of 1), *min\_child\_weight* corresponds to the minimum number of instances needed in each node, and *subsample* refers to the proportion of data XGBoost randomly samples from the training data prior to growing trees (Chen et al. 2017). These parameters were selected to maximize variance explained from a tuning training set which accounted for 10% of our total radar data set (see Van Doren and Horton 2018 for additional details).

To determine the seasonal utility of predictions produced by forecast models, models were iteratively trained with one year held out. For each resultant model, we made predictions of migration traffic on the held-out year using covariates from the Global Forecast System (GFS), (https://www.ncdc.noaa.gov/data-access/model-data/model-datasets/global-forcast-system-gfs). We used GFS data for this exercise, rather than NARR, because GFS data offer true meteorological forecasts, and represent the data source that would be used to generate real-time bird migration forecasts. We made 30-minute predictions of migratory activity across nine years (spring 2010 to spring 2018), with predictions aligned spatially (latitude, longitude, and height above ground level) and temporally (ordinal date, time after sunset) with radar measures derived from NEXRAD (see Methods section a). GFS predictions have a 0.5° spatial resolution and 3-hour temporal resolution that extends 384 hours (16 days) into the future. GFS predictions are updated four times daily (00, 06, 12, 18 UTC), however we only use the 0 UTC forecast that preceded the onset of nightly migration. We constrained our analyses to these nine years as a point of utility as the download of GFS data are cumbersome and require many terabytes of storage; GFS data are archived to 2004.

### (c) Summing nightly migration activity

For our analyses, we used migration night as our sampling unit, and for this reason we integrated our 30-minute migration activity samples from sunset to sunrise following (Horton et al. 2020). In brief, we accounted for the flow of migrants over the sampling area (i.e., WSR-station) by multiplying cm<sup>2</sup>km<sup>-3</sup> (η) by the measured groundspeed (km h<sup>-1</sup>) and integrating through the night to account for the nightly passage using linear interpolation for area under the curve, resulting in cm<sup>2</sup>km<sup>-2</sup>night<sup>-1</sup>. We multiplied by the altitudinal resolution (0.1 km) of each profile height bin, resulting in cm<sup>2</sup>km<sup>-1</sup>night<sup>-1</sup>. We used a radar cross-section of 11cm<sup>2</sup>, which represents an average sized migratory species (Dokter et al. 2018; Horton et al. 2019b), to yield a nightly WSR-station traffic rate of birds km<sup>-1</sup>. We applied this procedure to measured and forecasted values and used these units to summarize total passage. Because some stations had missing data in the radar archive, only annual radar-season combinations with at least 100 nights were used in our analyses. During spring, this resulted in the removal of 389 radar-year replicates (of 1,119) and 467 radar-year replicates (of 1,260) during the autumn.

### (d) Quantifying migration alerts in practice

We evaluated two approaches for directing aeroconservation action: 1) dynamic selection and 2) fixed window selection. To compare these approaches, we used as a reference the number of nights needed to capture 50% of migratory activity. Under the dynamic selection scenario, we identified the minimum number of nights of conservation action (hereafter termed *action nights*) needed to capture 50% of seasonal activity. We applied dynamic selection in two ways: first, we identified nights based on the realized migration passage measured by the radars, as if we could predict the truth with complete accuracy (hereafter "*idealized dynamic* action nights"); and second, we identified nights using our migration forecast, which is

imperfect (hereafter "*forecasted dynamic* action nights"). In practice, action nights are triggered by a threshold of activity, meaning nights below the threshold receive no action and those above receive action. Thresholds are expected to vary across our coverage area.

We computed the number of forecasted dynamic action nights to capture different quantiles of migration activity as follows. First, we predicted the migration intensity for each night in the held-out year, using a seasonal model trained on the remaining years. Then, for each quantile ranging from 0.05 to 0.95 by increments of 0.05, we searched for the smallest threshold of migration activity (*t*) such that the nights with predicted intensity greater than or equal to *t* captured at least the desired fraction of total seasonal migration. For example, we define the threshold at the 90<sup>th</sup> percentile of activity for a WSR-station and subsequently determine how many forecast nights per season are captured as action nights. For those nights labeled as action nights, we also determine the percent of activity (from known historical measures) captured in those events (e.g., the 90<sup>th</sup> percentile results in 10 action nights that capture 50% of activity). We searched for thresholds using predicted migration intensities rather than measured ones, because the forecast model has high correlation between predicted and actual migration intensities (see results section B for correlation metrics), but is not perfectly calibrated in terms of magnitude, so this procedure is useful to account for any differences (Van Doren & Horton 2018). We defined the threshold from forecast predictions from all years except the year of interest.

The fixed window selection approach identifies a minimum continuous window of time that historically captures 50% of migration activity. This approach does not rely on ecological forecasting and is seasonally fixed but spatially variable. To quantify the optimal seasonal

window of time for each WSR-station, we iterated through window widths ranging from 1 to 100 nights and stepped through each combination of window width and start time (e.g., a window of 10 nights starting on April 15<sup>th</sup>). For each combination, we examined the percent of activity captured on an annual basis. We averaged the percent capture across all years and selected the optimal window that minimized duration but captured at least 50% of migratory activity. For determining the efficacy of this approach in practice, we held out the year of interest when determining the optimal window.

### **Results:**

### (a) Passage metrics from idealized dynamic and fixed window selection

Across 1,628 unique sampling nights (92,296 spring and 85,315 fall nightly samples), the majority of total migratory passage (54.3%) occurred on 10% of nights for each season (Figure 1). Under idealized dynamic selection (Figure 2A), 10.0  $\pm$  2.9 nights ( $\pm$ SD) during the spring (Figure 3A) and 10.9  $\pm$  3.8 nights ( $\pm$ SD) during autumn (Figure 3B) captured 50% of activity at each station. These nights occurred within a continuous span of 34.7  $\pm$  9.8 nights ( $\pm$ SD) during spring and 48.4  $\pm$  10.0 nights ( $\pm$ SD) during autumn. In both seasons, the majority of migration occurred on fewer nights further north (linear model showing effect of °latitude, spring, -0.27 $\pm$ 0.07, p<0.001; autumn, -0.18 $\pm$ 0.09, p<0.001) and further east (linear model showing effect of °longitude, spring, -0.05 $\pm$ 0.03, p=0.002; autumn, -0.14 $\pm$ 0.04, p<0.001).

Fixed windows that captured 50% of passage (Figure 2B) spanned 19.2  $\pm$  3.9 nights ( $\pm$ SD) in spring (Figure 3C) and 26.5  $\pm$  4.6 nights ( $\pm$ SD) in autumn (Figure 3D). Window width generally decreased further north (linear model, spring, -0.08 $\pm$ 0.11,  $\pm$ CI, p=0.159; autumn, - 0.19 $\pm$ 0.13, p=0.005) and further east (linear model, spring, -0.08 $\pm$ 0.04, p<0.001; autumn, -

0.01±0.05, p=0.728); however, these linear spatial dependencies were weaker than the idealized dynamic selection trends and at times non-significant. The fixed window selection approach required significantly more time than idealized dynamic selection to capture 50% of activity (paired *t*-test, spring mean of differences 9.3 nights,  $t_{142}$ = - 36.5, *p*<0.001; autumn mean of differences 15.6 nights,  $t_{142}$ =-41.7, *p*<0.001). In both idealized dynamic and fixed window scenarios, spring periods were significantly shorter than autumn periods (paired *t*-test, mean dynamic seasonal difference 1.0 nights,  $t_{142}$ = -3.2, *p*=0.002; mean fixed-window seasonal difference 7.2 nights,  $t_{142}$ =-15.1, *p*<0.001).

### (b) Forecasted passage metrics

On average, our forecast models using NARR reanalysis data explained 73.0 % ( $\pm 0.008$  SD) of the variance of the cube-root transformed migration intensity during spring and 69.8 % ( $\pm 0.010$  CI) during autumn. Using the Global Forecast System to predict migration traffic one day in advance, our spring model explained 70.4 % ( $\pm 0.009$  SD) of the variance and 68.8 % ( $\pm 0.009$  SD) of the variance in autumn.

Because migration forecasts are imperfect, more action nights were required to capture 50% of migration activity compared to an idealized scenario (above; Figure S1). During spring, 13.7  $\pm$  3.5 ( $\pm$ SD) forecasted dynamic action nights were necessary and 15.9  $\pm$  4.6 ( $\pm$ SD) during autumn. However, this was still far fewer than with fixed selection, which required 53% more action nights in the spring (mean of 7.3 more alert days, Figure 4A) and 81% more action nights in autumn (mean of 12.8 more alert days, Figure 4B). At all WSR-stations, forecasted dynamic selection resulted in fewer action nights needed to capture 50% of migratory passage as compared to fixed window selection (Figure 4).

Our analysis used a benchmark of capturing 50% of migratory activity. We also examine the continuous gradient of migratory activity and number of action nights across the idealized dynamic, forecasted dynamic, and fixed window selection approaches (Figure 5). Consistently across our sampling space, forecasted dynamic selection captured more activity with fewer action nights as compared to fixed window selection. Lastly, we generally saw that after capturing 75% of migratory activity, the percent gain for each additional action night began to taper off (Figure 5).

### **Discussion:**

At present, conservation action often embodies a tension between society's desire to protect species and society's willingness to incur costs for that protection (Miller & Hobbs 2002; Singh et al. 2015). In the era of big data, when more tools and data are available than at any previous point in history to tackle complex ecological concerns (Luo et al. 2011), we can design strategies that provide conservation benefits for lower cost — here identifying fewer action days to reduce this tension. We show that near-term ecological forecasting can aid in realizing such a goal of dynamic and optimized action, in our case for aeroconservation, performing more efficiently than status-quo techniques and creating a path for dynamic, real-time conservation alerts that reduce society's costs of conservation. At all locations examined in this study, forecasting resulted in fewer action nights as compared to static fixed window approaches to capture comparable aerial passage and alert protective actions.

In our framework, we defined two important criteria: the number of action nights as a proxy for costs and our policy goal of capturing 50% of migration passage as a proxy for an important ecological benchmark. Our analysis finds a set of dates for a fixed time window and for forecasted dynamic mitigation approach(es) that can have the greatest impact per cost 13

incurred. This approach does not capture all of the costs, including opportunity costs, of each action night and does not capture all of the benefits of migratory bird conservation; instead, this approach sets the ecological goal of 50% of migration captured and asks how to minimize the action nights (costs) to achieve that goal. This cost-effectiveness approach avoids the complications of determining the socially preferred level of conservation for economic efficiency that requires a full assessment of all market and non-market costs and benefits. Using action nights as a proxy for costs corresponds to the reserve site selection literature's use of the number of sites as a cost proxy and then minimizing the number of sites chosen for a reserve network that conserves a specific number of species. That process only matches the costminimizing reserve network to achieve a level of species conservation if all land units have the same cost (Ando et al. 1998; Polasky et al. 2008); it may be possible to find a set of sites that provides the target level of conserved species for lower cost than in the site-minimizing reserve. Here, if costs are heterogenous across nights, economic cost effectiveness shifts action nights toward less costly nights, which can mean more action nights but lower cost overall. One potential next step to improving the cost effectiveness of dynamic mitigation involves assessing the heterogeneity of action night costs to take advantage of opportunities to provide collision mitigation at a lower cost.

Incorporating other economic considerations could further increase conservation per dollar through appropriate use of near-term forecasting information. First, positive correlations between higher cost action nights and numbers of migrating birds makes conservation more expensive, while negative correlations create efficiency gain opportunities (Figge 2004; Koellner & Schmitz 2006; Moore et al. 2010; Schindler et al. 2010). For example, if high wind nights pose a high opportunity cost of energy generation by turning off wind turbines but high wind also prevents many birds from migrating, the daily heterogeneity in costs can be leveraged to achieve the mitigation goal at lower cost (Hayes et al. 2019). Second, cost effectiveness relies

on the characteristics of the dynamic versus fixed window approaches' cost functions and the differences between these cost functions. Each approach's cost function likely contains a fixed cost (e.g., costs incurred to lay the groundwork to use action nights) and variable costs (e.g., costs incurred as a function of the number of action nights). Assessing the relative impact of the fixed and variable costs across the fixed window and dynamic action night choices could identify situations in which the dynamic action nights approach provides particularly large or small cost improvements over the fixed window approach. Similarly, both fixed window and forecasted dynamic conservation costs for avian conservation might include costs of the foregone energy generation of turning off wind turbines (Kennedy 2005; Cullen 2013), which interacts with energy source switching costs (Bird et al. 2016), or the costs of turning off lights in urban or energy development sites. Third, dynamic conservation may provide information that engages individuals in a positive way, which could create a social benefit that reduces the action night's social costs. Further economic efficiency analysis that addresses the specific costs of fixed window and dynamic conservation approaches, the heterogeneity of costs across space and time, and the engagement of potential participants could further improve the efficiency of conservation action decisions and provide the target level of conservation at a lower cost.

While our forecasting approach already shows improvements over static approaches, at least in terms of reducing the number of action nights, we predict that the efficiency and accuracy of this dynamic approach will continue to improve with each passing migration season through the addition of new training data, inclusion of commentary sensors, and advances in computational machinery. Methodologically, we believe our predictions will improve through additions of landscape variables (e.g., landcover, greenness), finer temporal updates (e.g., every three hours), broader spatial predictors of synoptic weather conditions, and the integration of within-season migration activity measurements. Furthermore, we expect the explicit integration of natural history data (e.g., species observations) will enhance taxonomic 15

resolution, increase the specificity of conservation decision-making, and reveal potential biases of our approach, particularly in light of stratified timing of migrant passage either by species or higher taxonomic classification (Horton et al. 2019b). While our threshold of protecting 50% activity is a subjective choice, our approach is extensible to conservation or economic priorities that may dictate different levels of protection (see Supplementary material for data on 25% and 75% thresholds).

We recognize that spatial heterogeneity exists in the geographic distribution of action nights in spring and autumn. For example, California and the Desert Southwest required larger numbers of action nights for both idealized dynamic and fixed window selection relative to the rest of the U.S., reflecting more protracted migration passage through those regions (Figure 3). Additional anomalies during spring were evident in Texas and portions of the southeastern U.S. While forecasted dynamic selection yielded fewer action nights than fixed-window selection, deviations between forecasted and idealized dynamic selection were still high in some regions of the contiguous U.S. (Figure S1). It is likely that the complexities of topographic features, such as coastlines and terrain (e.g., Rocky Mountains), are not sufficiently captured by our model and highlight the challenge of forecasting movements in these regions. Additionally, differences between forecasted and idealized selection were higher during autumn as compared to spring. Variability of autumn movements may be larger due to age-specific departure and flight strategies (Mitchell et al. 2015) and elevated selection of weather events to promote southward flights (Horton et al. 2016), manifesting in large flights over a wider range of time (Figure 3). Capturing these spatial patterns is both important from a conservation standpoint and in the context of economic cost effectiveness, wherein action nights may have differing inherent value.

We have demonstrated that near-term ecological forecasting can address conservation challenges that evolve rapidly in space and time. Our approach uses volumes of data gathered to

learn associations of avian migration and atmospheric conditions (Van Doren & Horton 2018). We believe these tools, both in forecasting and alerting, directly translate to areas with existing radar infrastructure and archives. These approaches may encompass whole continents, e.g., Europe, Asia, or Australia, but are applicable at smaller spatial scales, requiring only a small number of radar installations. Big data analytics have arrived, particularly in wildlife ecology through large data collection efforts founded on sensor networks (e.g., radar, community science). These applications reinforce the power of these growing repositories for building new and better performing forecasts. Ecological forecasting lends itself to many conservation challenges, ranging across a wide variety of taxa and scales. For instance, predicting the emergence of ephemeral insects blooms (Stepanian et al. 2020), nesting returns of sea turtles (Van Houtan & Halley 2011), or movements of terrestrial migrants through fragmented and shifting landscapes (Fischer & Lindenmayer 2007; Lendrum et al. 2013; Geremia et al. 2020). Each of these examples are integrally linked with shifting climate, seasonal weather, and landscape and oceanic variability, requiring models that adapt to current conditions. Rethinking conservation goals in this dynamic framework opens new opportunities in the face of the growing intersection between humans and wildlife.

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**Figure 1:** Mean percent of migration activity captured across four percentile categories: bottom 50% of nights (purple), top 50% to 30% of nights (blue), top 30% to 10% of nights (green), and top 10% of nights (yellow). Small, hollow circles denote number of nights per season in each category. Large, solid activity circles are scaled by summed percent of activity in each category and are the average of spring and autumn seasons across all WSR-stations.

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**Nrticl**é Accepted



**Figure 2:** (A) Idealized dynamic and (B) fixed window selection scenarios for Brownsville, Texas during spring 2018. Idealized dynamic selection (A) shows 13 nights that tally 50.5 % of total passage across a window of 30 nights. Fixed window selection (B) shows a historically defined window of peak activity and for 2018, this window captures 52.1% of activity. **Itticl** Accepte



**Figure 3:** (A) Spring and (B) autumn mean number of nights required to dynamically capture 50% of activity in an idealized setting. Spring (C) and autumn (D) mean fixed window width that historically captures 50% of activity. Note, color scales of A-D vary.



**Figure 4:** (A) Spring and (B) autumn differences between number of action nights between forecasted dynamic selection and fixed window selection. The number of action nights for both methods is that needed to capture 50% of activity. Note, in all cases, fixed window required *more* nights than forecasted dynamic.



Percent increase

**Figure 5:** Spring (left) and autumn (right) relationship between number of action nights and activity captured for idealized dynamic, forecasted dynamic, and fixed window selection. Gray, green, and blue lines show the annual cumulative migration traffic rates for individual WSR-stations from spring of 2010 to spring of 2018. Each method has been fit with a generalized additive model and the line shading signifies the rate of increase in percent activity captured.

# **Inticl** Accepted

## A Spring



**Figure S1:** (A) Spring and (B) autumn differences between number of action nights between forecasted and idealized dynamic selection. The number of action nights for both methods is that needed to capture 50% of activity.