Supporting Information. C. Lisa Mahon, Gillian L. Holloway, Erin M. Bayne, and Judith D. Toms. 2019. Additive and interactive cumulative effects on boreal landbirds: winners and losers in a multi-stressor landscape. *Ecological Applications.*

Appendix S1. Additional details on avian field sampling and data compilation

Study designs

This study used data collected by Environment and Climate Change Canada (ECCC) within the Oil Sands Area under three study designs: (1) surveys targeting all representative habitats (2011-2013 sampling; habitat-based surveys), (2) surveys targeting rare and at-risk old-forest habitats (2014 sampling; habitat-based surveys), and (3) surveys targeting disturbance effects at a regional scale (2014 sampling; disturbance-based surveys). Although individual survey designs placed different emphasis on targeted habitats or stressors, they used similar sampling designs and the same field sampling methods. We grouped point-count sites (≥ nine) into survey clusters to maximize sampling efficiency and minimize safety risks for field staff. We did not sample the mineable oil sands area within the Athabasca Oil Sands Area (AOSA) due to safety concerns.

Habitat-based surveys allocated sampling effort among 41 habitat types using stratified designs. We classified habitat types (Mahon et al. 2016) into 12 vegetation communities (pine, upland black spruce, white spruce, deciduous, mixedwood, black spruce bog, larch fen, swamp, marsh, shrubland, grassland, recent harvests units, recent burns) and six structural stages (herb, shrub, pole/sapling, young forest, mature forest, old forest), and based on Alberta Vegetation Inventory data (Alberta Sustainable Resource Development 2005). We created survey clusters of point-count locations, with a minimum of 300 m spacing between adjacent point-count locations

(300 m is the maximum detection radius for most boreal songbird vocalizations; Matsuoka et al. 2012). We sampled >750 habitat-based survey clusters within the AOSA.

Disturbance-based surveys allocated sampling effort across varying levels of energy-sector disturbance using a stratified design. We combined all spatial data for energy-sector stressors (wells, industrial facilities, roads, railways, and powerlines) and estimated the average amount of disturbance within 2,500 m of all points on the landscape. We then converted the average disturbance to five disturbance classes, in approximately equal proportions from very low (<1%) to high (>10%) disturbance. We placed clusters of nine point counts on a systematic grid with 400 m spacing within each disturbance class, placing 8-14 clusters in each disturbance class. We sampled 51 disturbance-based survey clusters within the AOSA.

We followed the standard recommended protocols of Ralph et al. (1993) and Matsuoka et al. (2014). We conducted point-count surveys during suitable weather conditions between official sunrise and 4-5 hours after sunrise, from the last week of May to the first week of July. We conducted point counts for 10 minutes, using three distance bands (0-50 m, 50-100 m, and >100 m). We screened all point-count data to remove fly-overs, fly-throughs, and flocks of birds.

Data compilation

The majority of observations in a point count comprised zero or one individuals (unpublished data) of each bird species. Therefore, for this analysis, we combined bird observations from clusters of nine point counts in order to have a more finely discriminated response variable and ensure that multiple stressors would be measured. We ensured that survey clusters were separated by a minimum of 800 m.

We selected clusters from the compiled dataset to representatively capture the underlying gradients of disturbance type and intensity within the AOSA (Table 1). Disturbance is so widespread within the AOSA that representative sampling for habitat-based surveys captured gradients of both habitat and disturbance, even though these survey designs did not intentionally stratify by disturbance amount. Therefore, we supplemented the disturbance-based surveys with the habitat-based surveys. All disturbance-based surveys were selected, and habitat-based data were selected if the survey area occurred within the AOSA, included at least nine point-count locations, and was separated from other survey clusters by a minimum of 800 meters. The combined dataset of 303 survey clusters provided good coverage across the distribution of disturbances in the AOSA (Table 1).

The total area of all disturbance ranged from 0 – 60.6%, with an average of 10% area disturbed. Landscape context and forest age influenced the amount of disturbance; the percent area of disturbance in survey areas <100 years old (11%) was more than twice that found in survey areas >100 years old (5%). The most ubiquitous disturbance class was narrow linear (NL), found in 95% of survey clusters. The highest % cover of narrow linear was observed in areas with steam-assisted gravity drainage developments, which contained linear disturbance densities of 10 – 18 km/km^2. Wide linear (WL) and wells (WE) were the next most common disturbance classes at 65 and 61% respectively. These three stressors are primarily produced by bitumen, oil, and gas exploration and development, and result in small disturbance areas spread over wide geographic areas. Harvest units created by forestry were less common (40% occurrence), but result in high-disturbance areas clustered over smaller geographic areas.

Avian detection models

Our response variable was the survey cluster-level density of each landbird species (number of singing individuals per ha). Raw bird counts are an incomplete measure of abundance and need to be adjusted for species-specific detection probabilities and detection radii (Sólymos et al. 2013). To account for imperfect sampling detectability, we calculated an offset correction factor to include in our models, using the full Environment and Climate Change

Canada dataset for the OSA (>6800 point counts). The calibration factor adjusts raw counts for temporal variation in singing rate and differential detection rates in specific vegetation types, based on the effective area of detection (Matsuoka et al. 2012, Laake et al. 2015). We calculated the correction factor using multi-covariate distance sampling models using the R package “mrds”.

We stratified habitat into five categories to compute effective detection radius, following Mahon et al. (2016): (1) deciduous forest >20 years old; (2) upland conifer forest >20 years old; (3) lowland conifer forest (treed bogs and fens); (4) open lowland habitat (shrubby bogs and fens); and (5) open habitat (natural shrublands, grasslands, and recent burns and harvest units <20 years old). We used the hazard-rate key model form with simple polynomial adjustments, and used AIC to select the best multi-covariate distance sampling model from the set: (1) no covariates, (2) habitat type, (3) time since sunrise, (4) habitat type + time since sunrise.

We used the best multi-covariate distance sampling model to calculate the effective area of detection for each point-count location (Laake et al. 2015). We then summed and log-transformed the effective area of detection for each point-count location within a survey cluster (Sólymos et al. 2013) to provide a composite estimate of effective area of detection for use as an offset in statistical models.

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