Tawny Owl Strix aluco Distribution in the Urban Landscape: The Effect of Habitat, Noise and Light Pollution

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ABSTRACT

At present, the intensification of urban landcover is one of the most critical threats for biodiversity. Common side-effects of urban spawl are anthropogenic noise and artificial light at night (ALAN). Although their negative effects have often been described, little research has concerned nocturnal wildlife, especially avian predators. Here, we investigated the effect of urban and tree cover, traffic noise and ALAN on the presence of the Tawny Owl *Strix aluco*, a common night-active predator in Europe. We conducted playback surveys along an urban gradient in Turin (Italy) to detect species presence. Traffic noise was measured in the field, the cover of built-up and (semi-)natural areas was estimated using GIS and multiple measures of ALAN were acquired from a light pollution map. We modelled species presence as a function of each environmental predictor and we found a significant negative relationship with light pollution, which was the foremost urban stressor affecting Tawny Owl occurrence. Our findings suggest that Tawny Owls are more likely to be found in less artificially illuminated areas and that their distribution in urban areas is not only influenced by noise pollution and the availability of suitable habitat, but also the intensity of ALAN plays an important role. Therefore, light pollution could be a key driver of the spatial distribution of Tawny Owls and potentially other nocturnal species in urban ecosystems.

Keywords: Urbanisation, *Strix aluco*, Urban ecology, Playback survey, Owls, ALAN, Traffic noise

Short title: Tawny Owl distribution in the urban landscape

INTRODUCTION

Urbanisation is recognised as one of the most severe human-induced environmental changes of the 21st century and it is predicted that built-up areas will continue to increase until at least 2030 worldwide (Grimm et al. 2008, Seto et al. 2012). This is concomitant with UN projections that foresee that the global human population could rise to 8.5 billion by 2030 and to 9.7 billion by 2050, (United Nations 2019). The process of urbanisation is therefore a relevant ongoing phenomenon that can profoundly shape the landscape, and represents a severe threat for natural ecosystems and biodiversity (Foley et al. 2005, Aronson et al. 2014). The foremost detrimental effects are habitat loss, fragmentation and degradation, which limit the availability of suitable habitat for species and force them to move or cope with the new urban conditions (McKinney 2002, Mcdonald et al. 2008, Sushinsky et al. 2013). The maintenance of wildlife in urban landscapes is of increasing concern, and a large body of research has highlighted how urbanisation can strongly affect the survival and the diversity of several bird species (Meffert 2013, Aronson et al. 2014, Isaksson 2018).

Despite that some species can exploit human resources and are able to adapt to the urban life thanks to advantageous behavioural and physiological changes (Møller 2009, Alberti et al. 2017, Isaksson 2018), others are urban avoiders and are not able to persist in urbanised areas (Geschke et al. 2018, Isaksson 2018). The capacity to survive in human-transformed habitats is strongly connected to the species-specific degree of adaptation to urban life (Johnson & Munshi-South 2017). Moreover, urban development often proceeds with considerable increases in anthropogenic noise and artificial light at night (ALAN), two common pollutants that pose crucial challenges for species to adapt and survive in urban environments (Bermúdez-Cuamatzin et al. 2009, Proppe et al. 2013, Isaksson 2018). Both increase as a consequence of urban sprawl and human activities, and in Europe it has been estimated that more than 80% of the land is affected by light pollution at night (Falchi et al. 2016). The exposure to anthropic stressors such as noise and ALAN has revealed many bio-ecological effects, such as effects on biological clocks of birds and interference with their sensory perception, activity patterns and spatial distribution (Hölker et al. 2010, Dominoni et al. 2016, Dominoni et al. 2020, Adams et al. 2019). Species exposed to noise and light pollution have shown significant changes to their phenology and reproductive success (Senzaki et al. 2020). Traffic noise can influence the distribution of birds in the environment, lowering their occurrence in particularly noisy places (Herrera-Montes & Aide 2011), and the synergistic interaction with ALAN can also shape avian assemblages and decrease their abundance (Wilson et al. 2021). In addition, intense levels of ALAN alter the nocturnal migration of many avian species, affecting their orientation and therefore the success of their movement (Van Doren et al. 2017).

Evidence of the impacts of urbanisation comes from studies concerning mostly diurnal species, but very limited research has involved night-active resident species. Among birds, owls are the most well-known group of nocturnal species and many are top predators, having a significant influence on ecosystems (Isaac et al. 2013). Since most owls rely on a remarkable acoustic sensory capcity to locate prey, high noise levels can impair their hunting success (Mason et al. 2016, Fröhlich & Ciach 2018) and hinder these predators from colonizing urbanised areas due to higher energy costs, i.e. more vocal efforts would be required since the calls would be hampered by high noise levels (Nemeth et al. 2013, Fröhlich & Ciach 2019). Owls have also evolved to hunt efficiently in dark conditions thanks to specific anatomical and physiological eye adaptations (Beckwith-Cohen et al. 2015), but how owls are distributed and how they behave in artificially illuminated landscapes needs to be investigated much further. At present, some recent research has shed light on this topic for either beneficial (Rodríguez et al. 2021) or adverse (Scobie et al. 2016, Marín-Gómez et al. 2020, Hanmer et al. 2021) effects of ALAN. Moreover, since noise and light pollution often co-occur in the urban environment to affect species, they should be considered together to better measure the impact of urbanisation. Accounting for both of these urban stressors in addition to the density of human infrastructures (i.e. urban cover) in the landscape should provide a clearer picture of the response of species to urbanisation.

From this perspective, the goal of this study was to investigate the effect of these factors commonly related to urban landscapes on the distribution of a nocturnal avian predator. We also accounted for the availability and size of suitable habitat across our study area. To do so, we used the Tawny Owl *Strix aluco*, a common night-active predator breeding across most of Europe (Cramp & Simmons 1985, Mikkola 2013). The Tawny Owl can inhabit urban settings and is a sedentary species (Cramp & Simmons 1985, Ranazzi et al. 2000), therefore it must cope with local environmental changes, including urban-related alterations, i.e. changes in urban cover intensity, noise and light pollution. Being a predator strongly relying on hearing to hunt and with strict nocturnal habits, the Tawny Owl is an ideal model species to examine the impacts of human-induced stressors like anthropogenic noise and ALAN. Therefore, by conducting playback surveys in a (sub-)urban area, we aimed to assess the relative importance of a set of multiple factors typically occurring in the urban landscape (i.e. urban land cover, tree cover, traffic noise and ALAN) on the probability of presence of the Tawny Owl.

MATERIALS AND METHODS

Study area

The study was conducted in the (sub-)urban area of Turin, the capital city and the most populated of the Piedmont Region (45°04’13.2’’N, 7°41’12.7’’E, northwest Italy, Fig. 1). Playback surveys were performed along an urban gradient (Fig. 2). Sample points in (semi-)natural areas were located within protected areas of the Regional Natural Park ‘Aree protette del Po Piemontese’: ‘Parco Naturale della Collina di Superga’ – located in the Turin hills and mainly dominated by oak-hornbeam formations, 'Riserva Naturale del Meisino e dell’Isolone di Bertolla’ and ‘Riserva Narturale Arrivore e Colletta’ – located within the city and mainly dominated by poplar-willow formations and oak. Sample points in urbanised areas with different levels of urban cover were located across the Turin hills.

Study design and field survey

To evaluate Tawny Owl response to urbanisation, 40 sample points within the urban landscape of Turin were surveyed using the playback technique, which is commonly employed to survey elusive and territorial birds as it improves their detection probability (Navarro et al. 2005, Worthington-Hill & Conway 2017). Sample points were randomly selected using Quantum GIS Software 3.4.5 (Quantum GIS Development Team 2020). First, the study area was divided into a grid of 1 km x 1 km plots and 40 of them were selected at random. In the next step, a multitude of points (127 in total) was randomly scattered within these plots, with a fixed distance of 500 m between them. For each 1 km square, there were from 2 to 4 points selected initially. Then, one point was selected randomly in each plot. Since the access was not free for several selected points, we relocated them along roads to define transects aimed at optimising the movements in the field, but a distance of at least 500 m between the points was always maintained.

Sample points were surveyed twice (i.e. two visits for each point) within the courtship-dispersal season, from the 21st September to the 10th November 2020. At least two weeks passed between consecutive visits to the same point. In addition to the breeding season, autumn is a favourable period to survey the Tawny Owl. A previous survey in UK showed indeed a peak time in vocal activity recorded in autumn, since in this season the owls are highly active in forming pairs and territories, and dispersing individuals are most likely to enter an established territory (Percival 1990). A second autumn survey followed later (Freeman et al. 2006) and seasonal variability in the vocal activity of some owl species was also compared and the highest response rate for the Tawny Owl was recorded in autumn (Vrezec & Bertoncelj 2018).

Playback was delivered using a handheld Bluetooth wireless speaker (Tronsmart Element, T6 Mini) positioned at chest height, c. 1.6 m above the ground. The device was designed to spread sound at 360° to ensure that vocalisations were broadcast in all directions. The call sequence consisted of territorial vocalisations of two different Tawny Owl couples (i.e. both male and female calls). Recordings of multiple pairs were used (i) to simulate a greater species density in order to increase the probability of a response, as owls will be more inclined to respond to defend their territories against many competitors nearby, and (ii) to avoid habituation to the same individual call. A fixed broadcast volume was set at a level equivalent to the sound pressure level of natural vocalizations. A sound level meter (SLM Meterk MK 09) was used to adjust the volume in order to match to the species' natural levels, i.e. 82 ± 3 dB (Vrezec & Bertoncelj 2018). Such values were obtained by positioning the SLM at a distance of 1 m from the speaker. At each sample point, the playback session lasted 13 minutes and was structured as follows:

- 2' of passive listening
- 2' of playback (1st couple broadcast)
- 2' of passive listening
- 2' of playback (2nd couple broadcast)
- 5' of passive listening

Playback was stopped as soon as an owl responded. Surveys were performed in good weather conditions, i.e. not on rainy or windy days. They were carried out five minutes after sunset and lasted generally one hour and half, depending on the time spent moving in the field between sample points and on how many were surveyed on the same night (1 to 3 points/night).

Based on a previous test of the playback methodology for the Tawny Owl and other nocturnal species (Orlando et al. 2021), we assumed that the effective detection radius was 200 m, i.e. the distance at which detectability decreases rapidly. Furthermore, this radial distance is reliable given that the average size of urban Tawny Owl territories is estimated to be around 20 ha, equivalent to an area with a c. 250 m radius (Galeotti 1994). Therefore, inferences made in an area with a 200 m radius should be quite representative of Tawny Owl territories (Orlando et al. 2021). Within the study area, there was a distance of at least 500 m between sample points, enough to avoid potential territory overlap.

Environmental variables

Different variables associated with the effects of urbanisation were considered in this study: urban cover, traffic noise, and light pollution. Urban cover was expressed as the surface area inclusive of both buildings and roads calculated with QGIS, using the most recent land-use map available for the Piedmont Region (https://www.webgis.arpa.piemonte.it). Multiple steps were followed to compute the percentage of urban cover within the 200m radius of each sample point (Appendix 1). As a measure of (semi-)natural habitat, we considered the surface area of suitable habitat, i.e. tree cover. The percentage area of tree cover within the 200 m radius of each sample point was calculated in the same way as for urban cover (Appendix 1).

Traffic noise was measured in the field with a sound level meter (SLM Meterk MK 09). At each sample point and visit, the device was kept at chest height (c. 1.6 m above the ground) and dB values were registered during the first two minutes of playback, i.e. during passive listening. Within these two minutes multiple dB values were registered, thus an averaged value of noise for each sample point and during each visit was finally calculated. Since detectability might be influenced by noise itself and therefore might affect the possibility to detect the birds, we checked whether survey visit had an effect on detectability and whether traffic noise varied between the two visits, i.e. we checked whether noise levels affected detectability differently between the two survey visits. To investigate this, when modelling species presence in relation to environmental variables we included 'survey visit' as a predictor and we compared a model using site-specific noise levels (average from the two survey visits) with a model using field-visit-specific noise levels (values specific to each visit) by using the AICc criterion (see below the details on the modelling approach).

We acquired data from https://www.lightpollutionmap.info to get detailed information on the average amount of light pollution at sample points within our study area (Falchi et al. 2016). The application of light pollution maps has previously been proved as a good method to estimate the impact of ALAN in population and behavioural studies (Ciach & Fröhlich 2017, van Hasselt et al. 2021). From the map, the impact of light pollution can be estimated as the quality of the night sky (i.e. night sky brightness) and the amount of radiance (i.e. light emitted or reflected by artificial infrastructures) on the terrestrial surface. The former parameter is computed from sky quality meter (SQM) readings, which represent an estimate to quantify artificial skyglow (night sky luminance caused by artificial lights, Falchi et al. 2016) in $mag_{SQM}/arcsec^2$, where a value of 22 is the darkest sky and <17.5 is the most illuminated sky (Sánchez de Miguel et al. 2017). Thus, a night sky with higher $mag/arcsec^2$ values will be darker. This SQM data derives from the World Atlas of artificial sky luminance, created in 2015 to quantify light pollution on a global scale (Falchi et al. 2016). The latter parameter is based on data from VIIRS (Visible Infrared Imaging Radiometer Suite), a satellite device which can be used to estimated light pollution on the Earth's surface and is equipped with a specific day/night band (DNB) sensor (Miller et al. 2013). One feature of DNB is the detection of electric lighting on the world's surface (Falchi et al. 2016, Elvidge et al. 2017). VIIRS data were available for each year from 2012, therefore we used the data for 2020, the year when we conducted the field survey. We estimated both SQM and radiance values within the 200 m radius of each sample point (Appendix 1).

Statistical analysis

Statistical analyses were carried out using R Software 3.6.3 (R Core Team 2020). To evaluate the effect of urbanisation on Tawny Owl presence, a mixed modelling approach was used, fitting a binomial generalized linear mixed model (GLMM) to determine the probability of presence in the urban environment (binomial response: 1 = present; 0 = absent). The model was fitted using the glmer function of the R package lme4 (Bates et al. 2015). Survey point identity was specified as a random effect to account for repeated observations from the same point**.** Urban cover, traffic noise, night sky quality, radiance, tree cover and survey visit were specified as fixed effects. GLMMs were first used to compare traffic noise between surveys. Therefore, we fitted a GLMM specifying traffic noise as site-specific noise and a GLMM with field-visit-specific noise and we compared these models using Akaike's information criterion (AIC). Given the small sample size (n/K ratio < 40), we used an AIC corrected for small sample sizes (AICc). With a ΔAICc ≤ 2, the difference between the models is not relevant as they have the same likelihood of being the best and can be considered equivalent in performance (Burnham & Anderson 2002). In the absence of difference between these two models, we opted to use the variable traffic noise as field-visit-specific noise in the following analysis procedure.

A multi-model inference approach was then used to identify the key variables and the best models that could best explain the variation in Tawny Owl probability of presence (Burnham & Anderson 2002). First, we built a full GLMM including all predictors, from which we got a set of candidate models and then we selected the best models (i.e. top models) using the AICc. Top models were identified with a ΔAICc ≤ 4 (Burnham & Anderson 2002) and then we calculated the Akaike weight for each candidate model, which can be described as the probability that a certain model is the best, given the data and the set of candidate models. We also calculated the relative importance (RI) for each predictor as the sum of Akaike weights (SW) from the candidate models that included the given predictor variable (Burnham & Anderson 2002). Only variables with RI > 0.7 were considered having an important effect on the model response variable, as this threshold can be generally considered statistically reliable (Galipaud et al. 2014). However, relying strictly on SW alone is argued to be restrictive when estimating variable importance (Galipaud et al. 2014, Galipaud et al. 2017). Therefore, since we also had more than one top model, we used model-averaging on the set of top models to obtain a final averaged model to determine which were the most important variables affecting Tawny Owl presence and to see if these were supportive of SW. Multi-model inference and model-averaging were performed using the MuMIn package (Barton 2020).

Before modelling, some steps were also made to ensure the quality of the analysis. Predictors were scaled, as they were measured in different measurement units. In this way, their parameter estimates were standardized and thus on a comparable scale. Then, the variance inflation factor (VIF) was used to check for potential correlation between predictor variables, where a value that exceeds 5 indicates problems of collinearity (James et al. 2014). No collinearity was found (VIF < 5 overall). Possible non-linear effects for predictors were checked adding a quadratic term in the models and a significant non-linear effect ($p < 0.05$) was found only for the variable night sky quality. Spatial autocorrelation of the binary dependent variable was also checked using Moran's test (Rangel et al. 2010), which showed no spatial autocorrelation (Moran' s I = 0.09, $p > 0.05$). Model fit was also checked for all GLMMs using the Hosmer-Lemeshow goodness of fit test (Hosmer & Lemeshow 2000), where a significant test result (as measured by the chi-squared statistic) indicates poor model fit. No poor fit was found in any model ($p > 0.05$).

RESULTS

Tawny Owls were detected 39 times (48.8 %) in total (n = 80, i.e. 40 sample points visited twice). The number of detections was essentially the same between the two visits: 19 during the first and 20 during the second. Throughout the whole survey, 56 Tawny Owls responded to playback. Among these, 32 were males, 22 were females and 2 individuals were detected only visually, so their sex was unknown.

Noise comparison between surveys

Traffic noise did not vary between surveys as we did not find a substantial informative difference between the models in the effect of site-specific and field-specific-visit noise on detectability (Table 1). Moreover, the effect of survey visit was not significant ($p > 0.05$), thus indicating the detectability was not differently affected by either the first or the second survey. In both models we found a negative but not significant effect of noise ($p > 0.05$, Table 1).

Tawny Owl response to urbanisation

Multi-model inference identified in total 14 best-fit models ($\Delta AICc \leq 4$) out of the 128 candidate models explaining the variation in Tawny Owl probability of presence (Appendix 2). All variables were included within the top models, and night sky quality and radiance were identified as the predictors with the highest relative importance in affecting the response (Table 2, Fig. 3). By averaging the regression coefficients across the 14 top models, we obtained a final averaged model inclusive of all predictors, which revealed and supported night sky quality and radiance as the predictors with the greatest and significant effects (Table 3, Fig. 4). Therefore, Tawny Owls were more likely to be found in places less artificially illuminated, i.e. higher night sky quality and lower radiance. Based on this model, we found a positive and non-linear effect of night sky quality on species presence ($\beta = 1.08 \pm 0.53$, $z = 2.02$, $p < 0.05$; Table 3) and a negative effect of radiance ($\beta = -1.07 \pm 0.54$, $z = 1.97$, $p < 0.05$; Table 3). Thus, both measures for light pollution detected an adverse effect of ALAN. The other predictors did not have a significant effect on Tawny Owl probability of presence (Table 3, Fig. 4).

DISCUSSION

The findings of this study show that the probability of presence of Tawny Owls occurring in urban environments is linked to the intensity of ALAN. We used a multivariate model and model selection to determine the most influential factors determining the presence of the Tawny Owl in urban areas. Overall, ALAN-related variables (i.e. night sky quality and radiance) had the highest relative importance among all environmental variables and emerged as the foremost influential predictors in the final averaged model. Instead, model selection did not reveal a significant effect of the remaining environmental predictors on Tawny Owl probability of presence, suggesting that this species is an urban adapter capable to tolerate moderate levels of urban intensity (Isaksson 2018). The Tawny Owl is indeed renowned for being able to inhabit urban areas, as long as suitable nest sites for breeding can be found and prey is available, including wintering birds which usually are an important component in the diet of owls inhabiting urban areas (Ranazzi et al. 2000, Solonen & Ursin 2008, Grzędzicka et al. 2013). Nevertheless, earlier studies highlighted how its occurrence in urban settings may be restrained by the lack of suitable wooded habitat and traffic noise (Ranazzi et al. 2000, Fröhlich & Ciach 2018).

Traffic noise hampers the hunting efficiency in aural-sensitive predators like owls, and therefore can influence the choice of hunting areas in the landscape. Negative effects of anthropogenic noise were previously pointed out by both experimental studies showing a decline in hunting efficiency in a noisy environment (Mason et al. 2016) and by field experiments revealing a decrease in foraging efficiency due to traffic noise (Senzaki et al. 2016). Noise pollution has also been determined as a factor able to shape the structure of owl communities in urban landscapes, limiting owl species richness when noise intensity increases (Fröhlich & Ciach 2019). Additionally, extremely noisy areas are likely to be avoided as they might require greater energy costs for communication between individuals, e.g. more efforts in vocal activity to find mates and defend territories. Nevertheless, it might be contested that noisier areas have generally lower detectability instead of being avoided by owls, i.e. noise interferes with the surveyor ability to detect owls. Though, in our study, traffic noise was not always continuous during the playback surveys even in noisier areas. So, we would have expected to hear a vocal reply if any owl was present since the duration of playback sessions was reasonably long (13 minutes), unlike in Fröhlich & Ciach 2018 which were of 5 minutes. Besides, according to our findings, the detectability of owls throughout our survey was not affected by noise since it did not vary between survey visits and no difference was found in the effect of traffic noise between the models.

As traffic noise appears to be a high relevant factor influencing the distribution of owls in urban areas (Fröhlich & Ciach 2018), in our study we would have expected to detect a significant negative relationship between traffic noise intensity and species presence. Compared to Fröhlich & Ciach 2018, both our sample size and sampling efforts were lower. This, in addition to the lack of playback surveys in inner parts of the city (e.g. public gardens closer to the city centre), might explain the low relative importance of noise that we found. However, also Shonfield & Bayne 2017 found a minimal effect of noise, by testing the impact in a boreal forest the impact of road and industrial plant noise on the distribution of three owl species and they did not find strong evidence of owls avoiding noisy areas. Nevertheless, since the industrial facilities were within the forest, the abundance of tree cover might have mitigated noise emissions (Fröhlich & Ciach 2018), thus limiting potential problems for the owls when hunting and communicating. In a similar way, in our study many sample plots were located in semi-natural areas in the Turin hills where tree cover was higher. This might have contributed to mitigate noise effect on owls.

Based on our results, Tawny Owl presence was significantly higher in less artificially illuminated areas. The negative relationship we found between Tawny Owl presence and light pollution suggests that ALAN might play a key role in the distribution of night-active owls in urban areas. This finding agrees with previous studies that found an adverse effect of artificial light at night on the occurrence of the Mottled Owl *Ciccaba virgata* (Marín-Gómez et al. 2020) and confirms the negative effect on Tawny Owl detection probability found recently by Hanmer et al. (2021). In accordance with Hanmer et al. (2021), we argue that light pollution may impair the hunting efficiency in Tawny Owls by influencing patterns of prey abundance and activity (Bird et al. 2004, Spoelstra et al. 2015). This might then reflect how the owls are distributed and how they move across the landscape. On the other hand, Rodríguez et al. (2021) suggested that ALAN aids the Burrowing Owl *Athene cunicularia* to colonize urbanised environments, as foraging efficiency was found to increase due to the attraction of its prey (mainly invertebrates) to artificial lighting sources. Species-specific trophic interactions can therefore contribute to determine the response to ALAN. Getting a better understanding of how prey is affected by light pollution could bring valuable insights into the impact of ALAN on the distribution and hunting strategies of nocturnal predators living in urban ecosystems.

In our study, we considered two parameters that measure ALAN in different ways and they both converged in detecting a negative effect on Tawny Owl presence. Night sky quality revealed a non-linear relationship, suggesting that the Tawny Owl might also occur in light-polluted areas. This might be explained by the fact that these areas were located within small protected reserves in the city ('Riserva Naturale del Meisino e dell'Isolone di Bertolla' and 'Riserva Narturale Arrivore e

Colletta') where the presence of suitable large trees like oaks may attract the owls for roosting or nesting. Suitable forest habitats are indeed vital for Tawny Owl occurrence in urban areas and thus may be good refuges even in well-lit places (Ranazzi et al. 2000, Fröhlich & Ciach 2018). However, the probability of species presence showed an increase in areas with lower night sky brightness and we did not detect a similar pattern in the relationship between species presence and radiance. Based on our data, a limited variation within night sky quality might be argued, but this specific measure of ALAN does not quantify light pollution on a wide numerical-scale (from <17.5 to 22 $mag_{SQM}/arcsec^2$, Sánchez de Miguel et al. 2017) and values of 21 and 22 are unlikely to be detected in urban landscapes where light pollution is visible. A study conducted in Italy showed that the modal estimate f the annual night sky brightness ranged between 18.0 and 21.3 at a regional scale (Bertolo et al. 2019). Moreover, based on the SQM data acquired from the light pollution map, our study area, despite not being at a regional scale, covers three different typologies of night sky quality according to the Bortle 9-level scale for night-time sky brightness (Bortle 2001): bright suburban sky (level 6), suburban-urban transition (level 7) and city sky/inner-city sky (level 8-9). Therefore, a certain degree of variation in night sky quality was available for our study area. However, further research is encouraged to look at how the distribution of nocturnal species varies across all the levels of this night sky brightness classification. According to our results, both ALAN-related variables were the best to fit the data and agreed in detecting high probabilities of presence in areas with lower intensity of ALAN. This indicates that substantial changes in the nocturnal lightscape may be additive to the changes in the soundscape in affecting the quality of the urban environment in which Tawny Owls might settle. Thus, light variations in the landscape should not be overlooked, but instead should be accounted for when assessing the distribution of night-active species occurring in urban environments.

In our study, Tawny Owls were surveyed in autumn. Survey of this species in this season are considered reliable for the peak in vocal activity and they have been also conducted on a large scale (Percival 1990, Freeman et al. 2006, Vrezec & Bertoncelj 2018). Tawny Owls' autumn territory establishment and defence is also considered less subject to short-term fluctuations than in spring (Percival 1990). Spring surveys could potentially miss the detection of some individuals, especially the birds that decided to skip breeding in a certain year (e.g. due to changes in prey availability) and this is known to occur in Tawny Owl populations (Southern 1970, Karell et al. 2009). Moreover, in our study, conducted in 2020, logistical and timing issues due to the breakout of the COVID-19 pandemic worldwide did not allow us to carry out surveys in spring. However, we address the importance that further studies are also needed during the breeding season (if not full-year monitoring studies) in addition to autumn, in order to investigate how the breeding activity and reproductive output of Tawny Owls is affected by urban stressors such as noise and ALAN.

Conclusions and caveats

Our results support previous studies that enrich the body of evidence illustrating the adverse effects of urbanization on owls. Here, we advanced the knowledge on the urban ecology of the Tawny Owl by considering together, in the same study, the effect of urban cover, tree cover, noise pollution and ALAN. Being an aural-sensitive predator with strong nocturnal habits, the Tawny Owl is an ideal system to understand the impacts of noise and light pollutants on nocturnal birds, thus our research can also be used or improved to understand the ecological response of other night-active species that might occur in urban areas like the Long-eared Owl *Asio otus*, the Little Owl *Athene noctua* and the Nightjar *Caprimulgus europaeus*.

Our findings contribute to the literature on the effects of light and noise pollutants on the distribution of owls, suggesting a greater impact of ALAN rather than noise. Though, caution is needed when interpreting these results due to the methodological limitations that we discussed. Moreover, to estimate light pollution, we relied only on remote data from a light pollution map, though collecting ALAN data on the field with light-meters might allow to get valuable and more local precise information. Finally, an ideal follow-up study might use a nest-box population breeding in an urban area to examine the effect of noise and light pollution at the fitness level and on the offspring survival and then making a comparison with a population breeding in a rural area. Detailed studies of the habitat use of such populations (e.g. by tracking hunting Tawny Owls that are provisioning young) could provide an understanding of how fitness consequences are underpinned by behavioural adjustments to a noisier and lighter landscape. These approaches could overcome the limitations encountered in our study and could uncover further details regarding the current knowledge we have on the urban ecology of owls.

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TABLES

Table 1

(a) Probability of presence ~	β	SE	z	p	(b) Probability of presence ~	β	SE	z	p
(Intercept)	-1.02	0.67	-1.52	0.13	(Intercept)	-1.04	0.64	-1.62	0.10
Traffic noise (field-visit-specific)	-0.46	0.39	-1.19	0.23	**Traffic noise (site-specific)**	-0.11	0.34	-0.33	0.74
Survey visit	0.13	0.57	0.23	0.82	**Survey visit**	0.15	0.55	0.28	0.78
Radiance	-1.09	0.75	-1.46	0.14	Radiance	-1.13	0.71	-1.58	0.11
Night sky quality	-0.56	0.78	-0.72	0.48	Night sky quality	-0.46	0.72	-0.65	0.52
Night sky quality^2	0.96	0.55	1.73	0.08	Night sky quality^2	0.95	0.52	1.83	0.06
Urban cover	-0.25	0.46	-0.55	0.59	Urban cover	-0.21	0.43	-0.49	0.62
Tree cover	0.53	0.56	0.95	0.34	Tree cover	0.44	0.52	0.85	0.39
AICc: 102.2					**AICc: 103.8**				

Table 1. Model comparison between (a) field-visit-specific noise and (b) site-specific noise model. The only difference in the models consists in the ‘noise’ variable. The comparison does not show a significant difference in the effect of both noise and survey visit, and shows a ΔAICc < 2, indicating that the models can be considered equivalent in performance

Table 2

Variable	RI
Night sky quality^2	**0.81**
Radiance	**0.74**
Traffic noise	0.45
Tree cover	0.42
Urban cover	0.39
Night sky quality	0.30
Survey visit	0.24

Table 2. Sum of weights associated with the predictor variables of the candidate models obtained from the multi-model inference approach. The relative importance (RI) of each variable is given by their weight. Variables highlighted in bold with RI > 0.7 are the only ones that can be considered having an important effect on the model response. Variables with lower RI are most likely irrelevant (Galipaud et al. 2014)

Table 3

Probability of presence ~	*β*	SE	*z*	*p*
(Intercept)	-1.03	0.56	1.82	0.06
Radiance	-1.07	0.54	2.02	0.04
Night sky quality^2	1.08	0.53	2.02	0.04
Night sky quality	-0.05	0.28	0.19	0.85
Traffic noise	-0.17	0.32	0.52	0.61
Urban cover	-0.08	0.26	0.29	0.77
Tree cover	0.09	0.31	0.32	0.75
Survey visit	0.02	0.19	0.09	0.93

Table 3. Variable averaged coefficients of the final model

FIGURES

Fig. 1

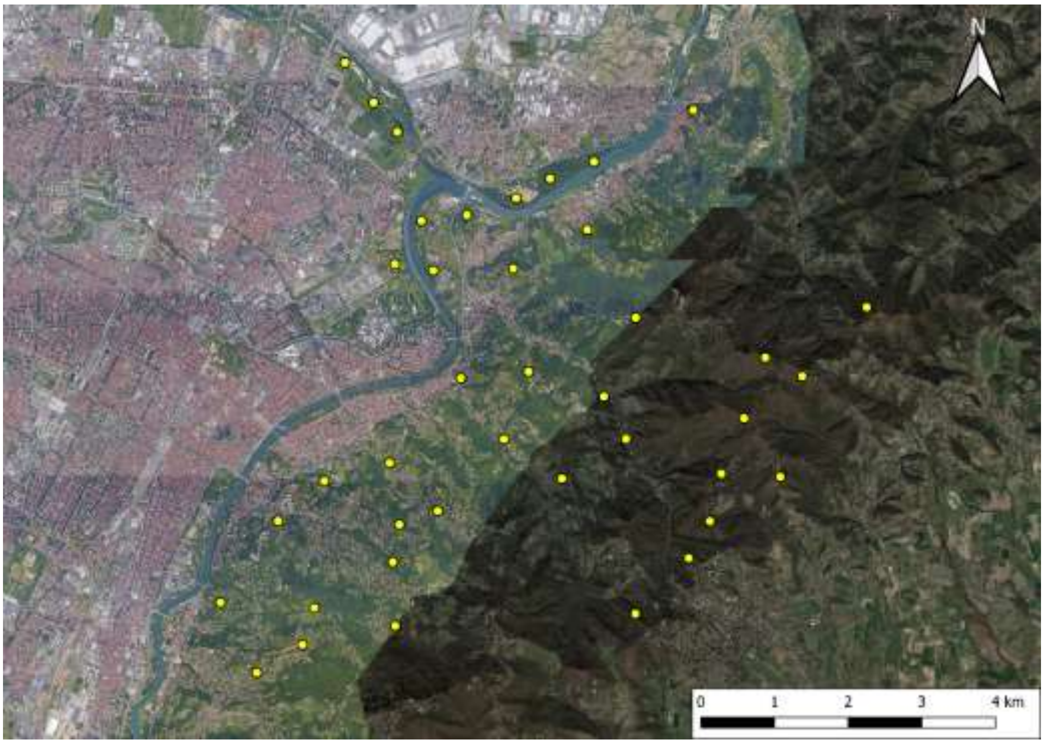
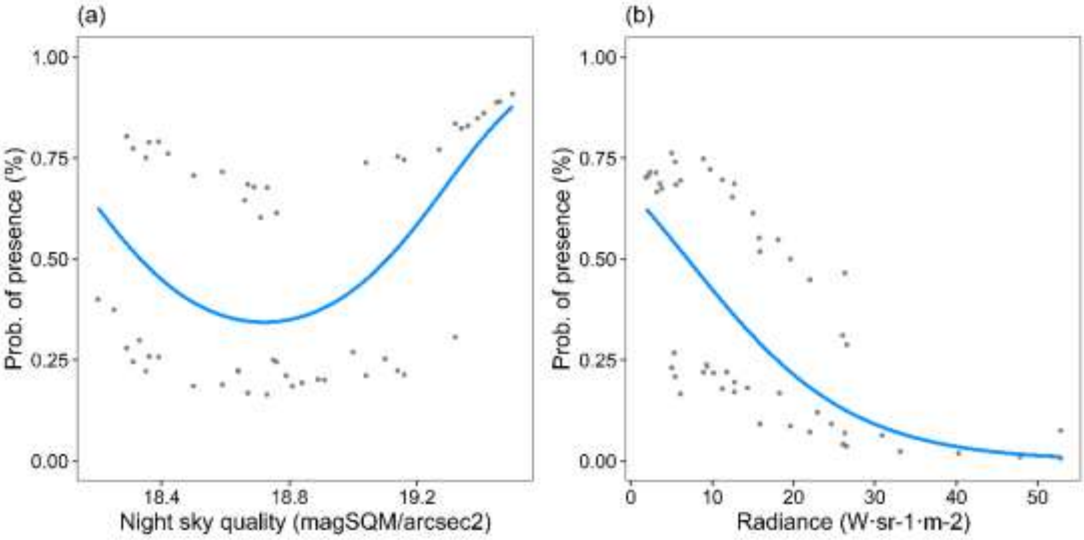


Fig. 2

Fig. 3



(a)
(b)
Prob. of presence (%)
Night sky quality (magSQM/arcsec2)
Radiance (W·sr-1·m-2)

Fig. 4

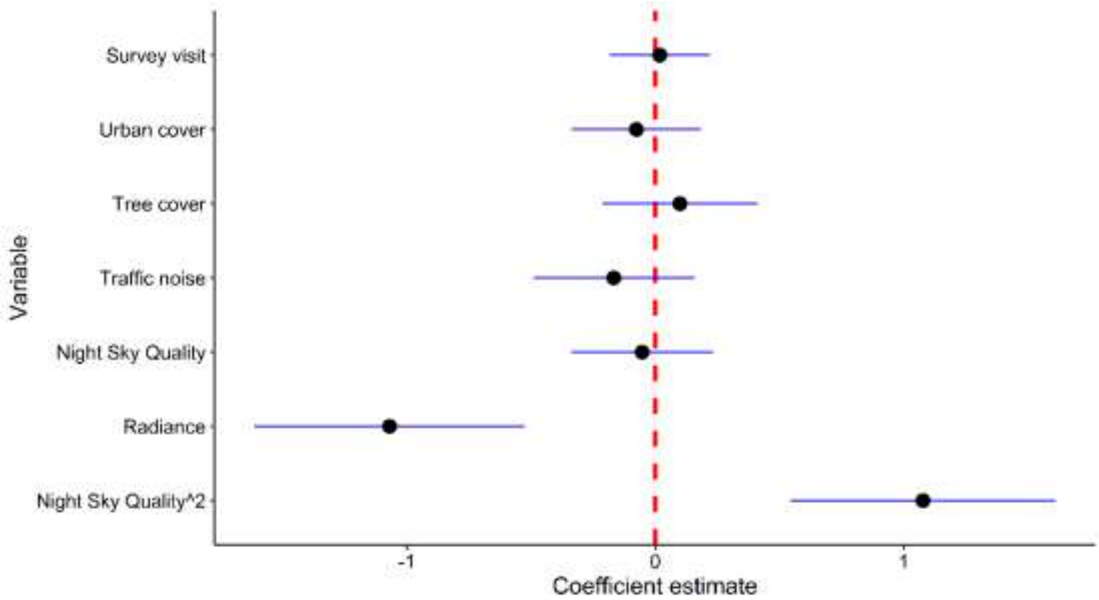

Survey visit
Urban cover
Tree cover
Traffic noise
Night Sky Quality
Radiance
Night Sky Quality^2
Variable
-1
0
1
Coefficient estimate

FIGURE CAPTIONS

Fig. 1 Study area in the urban landscape of Turin with sample points (n = 40)

Fig. 2 To give an example of the variation in urban intensity (buildings and road network), three sample points are presented here in detail. The black arrow in the first panel indicates the 200 m detectability radius, set as a threshold for the playback surveys

Fig. 3 A binomial GLMM from top models showing the effects of the most important variables on Tawny Owl probability (Prob) of presence (n = 80). The first panel (a) shows a non-linear effect of night sky quality on species presence, for which higher probabilities are more likely to be expected above 19.2 $mag_{SQM}/arcsec^2$. The second panel (b) shows instead a clear strong negative effect of radiance on species presence

Fig. 4 The graph shows the model-averaged coefficient estimates with standard error bands (blue). A significant effect was found only for radiance ($p < 0.05$) and night sky quality^2 ($p < 0.05$)

APPENDICES

Appendix 1. Details on the computation of predictor variables. The steps below were followed to compute the percentage of urban cover within the 200 m radius around each sample point, employing the most recent land-use map of the Piedmont Region available (‘Mappatura del Consumo di suolo in Piemonte 2017’, https://www.webgis.arpa.piemonte.it):

- Being a WMTS (Web Map Tile Service), the land-use map was converted in a vectorial format and overlayed on a satellite image showing the study area.

- A circular buffer zone with a 200 m radius (i.e. the detectability radius; Orlando et al. 2021) was set around all sample points to consider only the land-use within this distance.

- Each point (with its buffer) was selected, exported and saved. Then, they were all clipped individually with the vectorial land-use map, so that urban land-use could be calculated in each point separately.

- In each point, urban land-use was selected and the area calculated in m^2 using the field calculator in the layer’s attributes table. When necessary, selected urban land-use was corrected manually, by (i) adding polygons which covered buildings that were not included in the land-use map, and (ii) removing parts that were not strictly urbanised.

- The area was then converted in percentages, dividing it by the total area of the 200 m radius-buffer zone and multiplying by 100.

In the same way, tree cover was obtained by creating polygons over wooded patches, keeping the satellite image in the background. The area was calculated in the same way as for urban cover.

For light pollution, we inserted the coordinates of the sample points in the light pollution map (https://www.lightpollutionmap.info) to extrapolate SQM and radiance data. It was not possible to get light data for an entire area with a 200m radius. So, to have light data more representative for our 200m radius area, for each sample point we added four points in the 200m circumference (see figure on the right) in QGIS and we got the coordinates for all of them, and then we obtained SQM and radiance data from the light pollution map. Thus, for each sample point we had in total five points with light data. Finally, we calculated the average value for each sample point.

Appendix 2. Full list of candidate models for Tawny Owl probability of presence obtained from the multi-model inference approach. The initial full model was inclusive of all predictor variables (i.e. Radiance, Night sky quality (NSQ), quadratic effect of Night sky quality (NSQ^2), Traffic noise, Tree cover, Urban cover, Survey visit). The models highlighted in bold are the top models with ΔAICc ≤ 4

Model: Tawny Owl probability of presence ~	df	logLik	AICc	ΔAICc	weight
Radiance + NSQ^2	**4**	**-43.59**	**95.71**	**0.00**	**0.12**
Radiance + NSQ^2 + Noise	**5**	**-42.91**	**96.63**	**0.93**	**0.08**
Radiance + NSQ^2 + Urban cover	**5**	**-43.41**	**97.63**	**1.92**	**0.05**
Radiance + NSQ^2 + Tree cover	**5**	**-43.44**	**97.70**	**1.99**	**0.04**
Radiance + NSQ + NSQ^2	**5**	**-43.49**	**97.79**	**2.08**	**0.04**
Radiance + NSQ^2 + Survey visit	**5**	**-43.55**	**97.91**	**2.20**	**0.04**
Radiance + NSQ^2 + Noise + Urban cover	**6**	**-42.70**	**98.54**	**2.83**	**0.03**
Radiance + NSQ^2 + Noise + Tree cover	**6**	**-42.71**	**98.57**	**2.86**	**0.03**
Radiance + NSQ + NSQ^2 + Noise	**6**	**-42.80**	**98.75**	**3.04**	**0.03**
Radiance + NSQ^2 + Noise + Survey visit	**6**	**-42.88**	**98.91**	**3.21**	**0.02**
Noise + Tree cover + Urban cover	**5**	**-44.07**	**98.96**	**3.25**	**0.02**
Radiance + NSQ + NSQ^2 + Tree cover	**6**	**-43.13**	**99.40**	**3.69**	**0.02**
Radiance + NSQ^2 + Tree cover + Urban cover	**6**	**-43.21**	**99.57**	**3.87**	**0.02**
NSQ^2 + Noise + Tree cover	**5**	**-44.45**	**99.71**	**4.00**	**0.02**
Tree cover + Urban cover	4	-45.63	99.79	4.09	0.02
Radiance + NSQ + NSQ^2 + Urban cover	6	-43.37	99.89	4.18	0.01
Radiance + NSQ^2 + Urban cover + Survey visit	6	-43.37	99.89	4.18	0.01
NSQ^2 + Noise + Tree cover + Urban cover	6	-43.37	99.90	4.19	0.01
Radiance + NSQ^2 + Tree cover + Survey visit	6	-43.41	99.96	4.26	0.01
Radiance + NSQ + NSQ^2 + Survey visit	6	-43.45	100.06	4.35	0.01
Radiance + NSQ + NSQ^2 + Noise + Tree cover	7	-42.29	100.14	4.43	0.01
Radiance + NSQ^2 + Noise + Tree cover + Urban cover	7	-42.41	100.38	4.67	0.01
NSQ^2 + Tree cover + Urban cover	5	-44.93	100.67	4.96	0.01
Noise + Tree cover	4	-46.07	100.67	4.97	0.01
NSQ^2 + Tree cover	4	-46.12	100.78	5.07	0.01
Radiance + NSQ + NSQ^2 + Noise + Urban cover	7	-42.65	100.85	5.14	0.01
Radiance + NSQ^2 + Noise + Urban cover + Survey visit	7	-42.67	100.89	5.18	0.01
Radiance + NSQ^2 + Noise + Tree cover + Survey visit	7	-42.68	100.92	5.21	0.01
Radiance + Noise + Tree cover + Urban cover	6	-43.97	101.08	5.38	0.01
Radiance + NSQ + NSQ^2 + Noise + Survey visit	7	-42.77	101.09	5.39	0.01
Radiance + Tree cover + Urban cover	5	-45.22	101.24	5.53	0.01
NSQ + NSQ^2 + Noise	5	-45.22	101.26	5.55	0.01
NSQ + NSQ^2 + Urban cover	5	-45.23	101.27	5.56	0.01
Noise + Tree cover + Urban cover + Survey visit	6	-44.06	101.27	5.56	0.01
NSQ + Noise + Tree cover + Urban cover	6	-44.07	101.29	5.58	0.01
NSQ + NSQ^2 + Noise + Urban cover	6	-44.10	101.34	5.63	0.01
NSQ + NSQ^2	4	-46.50	101.54	5.83	0.01
Radiance + NSQ + NSQ^2 + Tree cover + Urban cover	7	-43.01	101.58	5.88	0.01
NSQ + Tree cover + Urban cover	5	-45.46	101.73	6.02	0.01
Radiance + NSQ + NSQ^2 + Tree cover + Survey visit	7	-43.09	101.73	6.02	0.01
NSQ + Noise + Urban cover	5	-45.47	101.75	6.04	0.01

NSQ + Urban cover	4	-46.65	101.83	6.13	0.01
NSQ + NSQ^2 + Noise + Tree cover	6	-44.36	101.86	6.15	0.01
Radiance + NSQ^2 + Tree cover + Urban cover + Survey visit	7	-43.17	101.90	6.19	0.01
Radiance + Noise + Urban cover	5	-45.57	101.94	6.24	0.01
Tree cover + Urban cover + Survey visit	5	-45.59	102.00	6.29	0.01
NSQ^2 + Noise + Tree cover + Survey visit	6	-44.43	102.01	6.30	0.01
Radiance + Urban cover	4	-46.75	102.03	6.32	0.01
Tree cover	3	-47.88	102.07	6.36	0.00
NSQ + NSQ^2 + Noise + Tree cover + Urban cover	7	-43.31	102.17	6.46	0.00
Radiance + NSQ + NSQ^2 + Urban cover + Survey visit	7	-43.33	102.22	6.51	0.00
NSQ^2 + Noise + Tree cover + Urban cover + Survey visit	7	-43.36	102.27	6.56	0.00
Radiance + Noise + Tree cover	5	-45.73	102.27	6.56	0.00
Radiance + NSQ + NSQ^2 + Noise + Tree cover + Urban cover	8	-42.14	102.30	6.60	0.00
NSQ + NSQ^2 + Tree cover	5	-45.75	102.30	6.60	0.00
NSQ + NSQ^2 + Tree cover + Urban cover	6	-44.59	102.32	6.62	0.00
NSQ^2 + Noise + Urban cover	5	-45.80	102.41	6.70	0.00
Radiance + NSQ + NSQ^2 + Noise + Tree cover + Survey visit	8	-42.26	102.55	6.85	0.00
Radiance + Tree cover	4	-47.07	102.67	6.96	0.00
Noise + Urban cover	4	-47.12	102.78	7.07	0.00
Radiance + NSQ^2 + Noise + Tree cover + Urban cover + Survey visit	8	-42.38	102.79	7.09	0.00
Noise + Tree cover + Survey visit	5	-46.06	102.92	7.21	0.00
NSQ^2 + Tree cover + Urban cover + Survey visit	6	-44.89	102.94	7.23	0.00
NSQ + Noise + Tree cover	5	-46.07	102.95	7.24	0.00
NSQ^2 + Tree cover + Survey visit	5	-46.08	102.98	7.27	0.00
NSQ^2 + Noise	4	-47.27	103.08	7.37	0.00
Radiance + NSQ + NSQ^2 + Noise + Urban cover + Survey visit	8	-42.62	103.27	7.56	0.00
Radiance + NSQ + Noise + Tree cover + Urban cover	7	-43.92	103.40	7.70	0.00
Radiance + Noise + Tree cover + Urban cover + Survey visit	7	-43.95	103.45	7.75	0.00
Radiance + Tree cover + Urban cover + Survey visit	6	-45.18	103.51	7.80	0.00
NSQ + NSQ^2 + Urban cover + Survey visit	6	-45.19	103.53	7.82	0.00
Radiance + NSQ + Urban cover	5	-46.37	103.55	7.85	0.00
NSQ + NSQ^2 + Noise + Survey visit	6	-45.20	103.56	7.85	0.00
Radiance + NSQ + Tree cover + Urban cover	6	-45.21	103.58	7.87	0.00
Radiance + Noise	4	-47.54	103.61	7.90	0.00
NSQ + Noise + Tree cover + Urban cover + Survey visit	7	-44.05	103.66	7.95	0.00
NSQ + NSQ^2 + Noise + Urban cover + Survey visit	7	-44.07	103.70	8.00	0.00
NSQ + NSQ^2 + Survey visit	5	-46.47	103.75	8.04	0.00
Radiance + NSQ + Noise + Urban cover	6	-45.32	103.78	8.07	0.00
Radiance + NSQ + NSQ^2 + Tree cover + Urban cover + Survey visit	8	-42.98	103.98	8.27	0.00
NSQ + Tree cover	4	-47.73	103.99	8.28	0.00
NSQ + Tree cover + Urban cover + Survey visit	6	-45.42	103.99	8.28	0.00
NSQ + Urban cover + Survey visit	5	-46.61	104.04	8.33	0.00
NSQ + Noise + Urban cover + Survey visit	6	-45.45	104.05	8.34	0.00
Radiance	3	-48.91	104.13	8.42	0.00
Tree cover + Survey visit	4	-47.84	104.21	8.50	0.00
NSQ + NSQ^2 + Noise + Tree cover + Survey visit	7	-44.33	104.22	8.52	0.00

Radiance + Urban cover + Survey visit	5	-46.71	104.24	8.53	0.00
Radiance + Noise + Urban cover + Survey visit	6	-45.55	104.25	8.54	0.00
Radiance + NSQ + Noise + Tree cover	6	-45.57	104.28	8.57	0.00
NSQ + Noise	4	-48.01	104.56	8.86	0.00
NSQ + NSQ^2 + Tree cover + Survey visit	6	-45.71	104.57	8.86	0.00
Radiance + Noise + Tree cover + Survey visit	6	-45.71	104.58	8.87	0.00
NSQ + NSQ^2 + Noise + Tree cover + Urban cover + Survey visit	8	-43.29	104.60	8.89	0.00
NSQ + NSQ^2 + Tree cover + Urban cover + Survey visit	7	-44.55	104.65	8.94	0.00
NSQ^2 + Noise + Urban cover + Survey visit	6	-45.79	104.73	9.03	0.00
Radiance + NSQ + NSQ^2 + Noise + Tree cover + Urban cover + Survey visit	9	-42.11	104.79	9.09	0.00
Radiance + NSQ + Tree cover	5	-47.01	104.83	9.12	0.00
Radiance + Tree cover + Survey visit	5	-47.03	104.87	9.16	0.00
NSQ^2 + Urban cover	4	-48.23	104.99	9.28	0.00
Noise + Urban cover + Survey visit	5	-47.12	105.04	9.34	0.00
NSQ + Noise + Tree cover + Survey visit	6	-46.05	105.26	9.55	0.00
NSQ^2 + Noise + Survey visit	5	-47.27	105.34	9.63	0.00
NSQ	3	-49.55	105.41	9.70	0.00
Radiance + NSQ + Noise	5	-47.40	105.60	9.89	0.00
Radiance + NSQ	4	-48.64	105.82	10.11	0.00
Radiance + NSQ + Urban cover + Survey visit	6	-46.34	105.82	10.11	0.00
Radiance + NSQ + Noise + Tree cover + Urban cover + Survey visit	8	-43.91	105.84	10.13	0.00
Urban cover	3	-49.76	105.84	10.14	0.00
Radiance + Noise + Survey visit	5	-47.52	105.86	10.15	0.00
Radiance + NSQ + Tree cover + Urban cover + Survey visit	7	-45.18	105.91	10.20	0.00
Radiance + NSQ + Noise + Urban cover + Survey visit	7	-45.30	106.15	10.44	0.00
NSQ + Tree cover + Survey visit	5	-47.69	106.19	10.48	0.00
Radiance + Survey visit	4	-48.87	106.28	10.57	0.00
NSQ^2	3	-50.09	106.49	10.78	0.00
Radiance + NSQ + Noise + Tree cover + Survey visit	7	-45.55	106.65	10.95	0.00
NSQ + Noise + Survey visit	5	-48.00	106.81	11.11	0.00
Noise	3	-50.30	106.92	11.21	0.00
Radiance + NSQ + Tree cover + Survey visit	6	-46.97	107.10	11.39	0.00
NSQ^2 + Urban cover + Survey visit	5	-48.19	107.19	11.48	0.00
NSQ + Survey visit	4	-49.51	107.55	11.85	0.00
Radiance + NSQ + Noise + Survey visit	6	-47.38	107.91	12.20	0.00
Urban cover + Survey visit	4	-49.73	107.99	12.28	0.00
Radiance + NSQ + Survey visit	5	-48.61	108.03	12.32	0.00
NSQ^2 + Survey visit	4	-50.05	108.64	12.93	0.00
Noise + Survey visit	4	-50.30	109.13	13.42	0.00
Null	2	-53.86	111.87	16.16	0.00
Survey visit	2	53.82	113.96	18.25	0.00