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# **Suivi hivernal des oiseaux communs (SHOC)**

Analysis of the common wintering birds  
in France 2014-2018

Thierry Onkelinx

INBO.be

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### **Analysis of the common wintering birds in France 2014-2018**

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## Part I

## Set-up of the analyses

# 1 METHODOLOGY

Naturaconsta provided the raw observations made during the *Suivi Hivernal des Oiseaux Communs (SHOC)*. It consists of 9445 observations during 420 visits over 73 sites and 125 species. The birds are counted during a walk along a transect. The length of the transects range from 2.62 to 6.4 km. The distance between the bird and the observer is recorded in four classes: “0-50m”, “50-100m”, “>100m” and “passing”.

## 1.1 STATISTICAL MODELS

In order to get comparable results, we fit the same set of models to each species. The model estimates the average density of birds at a given site in a given winter and period. The first period ranges for the beginning of December to mid January. The second period from mid January to the end of February.

### 1.1.1 Detection function

The first step is the estimate the detection function. The detection function gives the probability that a bird is detected based on the distance to the observer. The detection function assumes that the observer sees every bird at distance 0 m. The probability of detection decreases as the distance between bird and observer increases (fig. 1.1). We describe this detection function with a half-normal density curve with parameter  $\sigma_d$ . The parameter  $\sigma_d$  governs how fast the detectability deteriorates. The detection probability at a distance of  $1.96 \sigma_d$  is about 5%. Suppose that the detection at some distance is 50%. The observer will see only 1 out of 2 birds at that distance. So the true number of birds is twice the number of observed birds at the distance.

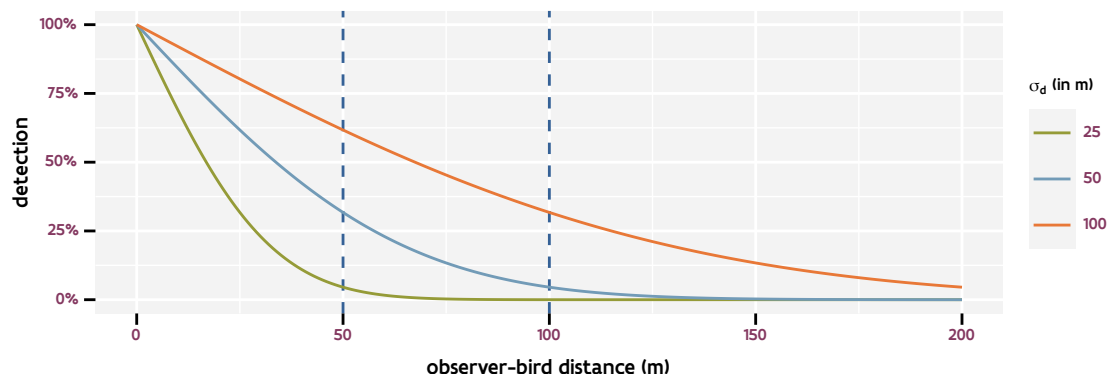


Figure 1.1: Example of two half-normal detection functions with different  $\sigma_d$

We need to estimate  $\sigma_d$  based on the data. Ideally we would have an ‘exact’ distance estimate for each observation. The available poses some challenges at this point. The class ‘passing’ is not usable as it has no associated distance. The data contains the distance classes instead of exact distances. A workaround for this problem is to work with the average detection within the distance class. This average distance is equivalent to the surface under the detection function.

We estimate this detection function by fitting a base model to the data. The base model (1.1) with a non-linear trend along winter contains following terms:

- $\beta_0$ : the overall intercept during the first period at distance 0-50m.
- $\beta_1$ : the difference between the second and the first period.
- $\beta_2$ : the difference between distance 0-50m and 50-100m.
- $\beta_3$ : the difference between distance 0-50m and >100m.
- $b_w$ : effect of winter  $w$ , modelled as a first order random walk with variance.  $\sigma_w^2$  (1.2)
- $b_s$ : effect of site  $s$ , modelled as a random intercept with variance  $\sigma_s^2$  (1.3).
- $\log(length)$  is an offset term correcting for the transect length (in km).

$$\eta_{wis} = \beta_0 + \log(length) + \beta_1 P_2 + \beta_2 D_{50-100m} + \beta_3 D_{>100m} + b_y + b_s \quad (1.1)$$

$$\Delta_{b_w} = b_w - b_{w-1} \sim \mathcal{N}(0, \sigma_w^2) \quad (1.2)$$

$$b_s \sim \mathcal{N}(0, \sigma_s^2) \quad (1.3)$$

The  $\eta_{wis}$  of the base model is linked to the observed counts  $Y_{wis}$  via either a negative binomial distribution (1.4) using the log link between  $\eta$  and  $\mu$  (1.5). The negative binomial distribution can capture overdispersion which is often present in count data of animals.

$$Y_{wis} \sim NB(\mu_{wis}, n) \quad (1.4)$$

$$\log(\mu_{wis}) = \eta_{wis} \quad (1.5)$$

The term  $e^{\beta_2}$  in the base model estimates the ratio of the area under the distance function between the distance classes 50-100 m and 0-50 m (fig. 1.2). Likewise is  $e^{\beta_3}$  an estimate for the ratio between >100 m and 0-50m. In practice, there is an upperbound to the distance  $d_{max}$  at which we can observe birds. So the distance class >100 m is actual the distance class 100- $d_{max}$  m. Next we search for an optimal  $\sigma_d$  and  $d_{max}$  value matching with these two ratios. We restrict  $\sigma_d$  to be between 20 and 200 m and  $d_{max}$  between 150 m and 1000 m.

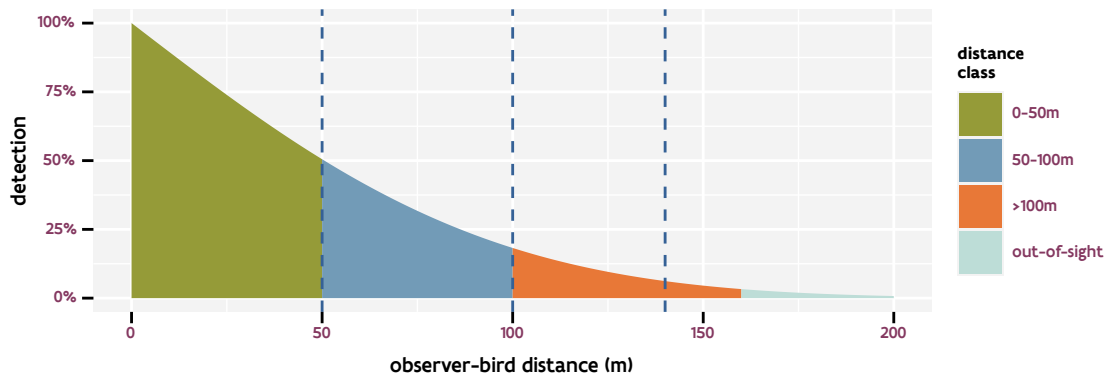


Figure 1.2: Area under the detection function for each distance class for  $\sigma_d = 75$  m and an out-of-sight distance  $d_{max}$  of 160m.

## 1.1.2 Final models

Once we know  $\sigma_d$  we can calculate the average detection probability for each of the distance classes. We replace the terms  $\beta_2$  and  $\beta_3$  in (1.1) with the calculated  $\log(detection)$  in (1.6). The log function is needed due to the log link in (1.5). The observed number of birds represents an area defined by the length of the transect and the width of the distance class. Therefore we have to replace the offset term  $\log(length)$  by  $\log(area)$ . The width of the distance classes 0-50 m and 50-100m is clear (50m). Therefore their area is 0.05 km<sup>2</sup> for ever km of transect. The width of the distance class >100 m is set to  $d_{max} - 100$  m.

$$\eta_{wis} = \beta_0 + \log(area) + \log(detection) + \beta_1 P_2 + b_w + b_s \quad (1.6)$$

We can rearrange (1.6) into (1.7). Applying the inverse link function yields (1.8) or the number of birds corrected for the sampled area and the average detection probability depends on the overall intercept  $\beta_0$ , the period effect  $\beta_1$ , the temporal trend  $b_w$  and the site effect  $b_s$ . (1.8) thus estimates the trend in density of birds (number of bird per km<sup>2</sup>).  $e^{b_w}$  estimates the relative change in bird density over time.

$$\eta_{wis} - \log(area) - \log(detection) = \beta_0 + \beta_1 P_2 + b_w + b_s \quad (1.7)$$

$$\frac{\mu_{wis}}{area \times detection} = e^{\beta_0} e^{\beta_1 P_2} e^{b_w} e^{b_s} \quad (1.8)$$

Beside (1.6), we also fit the variant with a linear trend  $\beta_4$  instead of the non-linear trend  $b_w$  (1.9).

$$\eta_{wis} = \beta_0 + \log(area) + \log(detection) + \beta_1 P_2 + \beta_4 W + b_s \quad (1.9)$$

## 1.2 FITTING THE MODEL

The models are fit the statistical software R version 3.6.1 (R Core Team, 2019) using the INLA package version 18.07.12 (Rue et al, 2017). It fits Bayesian models using Integrated Nested Laplace Approximation (INLA). Fitting Bayesian models imply select prior distributions for a number of parameters.

- $\beta_0, \beta_1, \beta_2, \beta_3$  and  $\beta_4$  use a Gaussian prior with 0 mean and variance 1000  $\mathcal{N}(0, 1000)$
- $\sigma_w^2$  uses a PC prior with  $u = 0.25$  and  $\alpha = 0.5$
- $\sigma_s^2$  uses a PC prior with  $u = 0.6$  and  $\alpha = 0.5$
- $n$  is modelled as  $n = e^\theta$  with a  $\theta \sim \Gamma(e^{-7}, e^{-7})$

A PC (penalised complexity) prior is defined by two parameters  $u$  and  $\alpha$ .  $u$  defines a threshold value for  $\sigma$ , and  $\alpha$  defines the probability that the estimated  $\sigma$  exceeds this threshold value (1.10). The density of this prior is given in (1.11).

$$P(\sigma > u) = \alpha \quad (1.10)$$

$$\pi(\tau) = \frac{\lambda}{2} \tau^{-3/2} \exp(-\lambda \tau^{-1/2}) \quad (1.11)$$

$$\lambda = -\frac{\log(\alpha)}{y} \quad (1.12)$$



## 2 DATA EXPLORATION

This chapter explores the full dataset. We will try to estimate trends for as much species as possible. Stable models require sufficient data. Therefore, we apply a set of rules on the available data of each species. These rules are partly based on common statistical knowledge and our experience with similar data in the past. And partly based on the data analysed in this project. If a model for a given species turns out to be unstable, then we make the rules more strict. We apply the same set of rules for every species so the results are comparable among the species.

This chapter shows both the rule and the summary of the data on which the rule applies. This illustrates the available data and how the rule restricts the data. Note that these rules will remove data for some species or some sites. When volunteers collect more data in the future for such species and sites, they might have sufficient data to pass all the rules.

### 2.1 RULE 1: A SITE MUST BE SAMPLED DURING AT LEAST 3 WINTERS

The models take both a site and a winter effect into account. When a site is sampled during only one or two winters, then the model has a hard time separating the site and winter effect. This can lead to an unstable model. Therefore it is safer to restrict the data to sites with a sufficient number of visits over several winters.

Table 2.1 displays how many sites have data from 1, 2, 3, ... different winters. 37 sites have data from less than 3 different winters and are currently ignored.

Table 2.1: Number of sites with data from a number of winters.

winters	sites
1	13
2	24
3	14
4	10
5	12

## 2.2 RULE 2: USE ONLY RELEVANT SITES FOR A SPECIES

Some species are not present at every site. When a species is absent at a site, the counts are always zero. The numbers are not changing at that site, so locally there is no trend. If we would take such site into account, the overall trend will be biased towards zero.

Species that are rarely seen at a site pose a problem too. Imagine a species is only seen at the first winter with on average 10 individuals. The model tries to fit the first winter at this site as  $\log(10) = 2.303$ . All other winters at this site should be  $\log(0) = -\infty$ . This results in a strong negative local trend, which again biases the global trend.

Therefore, we require that a species is observed at a site during at least 3 different years before taking that site into account for this species. Table 2.2 is a very large table because it contains a row for each of the 107 species observed in the data. 40 species are so rare that there is not a single site at which they are observed during 3 different years.

Table 2.2: number of sites at which a species was observed split by the number of winters (columns) during which the species was observed at a site.

scientific	1	2	3	4	5	sufficient
<i>Turdus merula</i>	4	3	13	5	9	27
<i>Corvus corone</i>	3	3	12	7	8	27
<i>Alauda arvensis</i>	0	5	11	5	7	23
<i>Fringilla coelebs</i>	4	4	6	7	7	20
<i>Parus major</i>	2	4	9	4	7	20
<i>Erithacus rubecula</i>	5	3	8	5	6	19
<i>Columba palumbus</i>	7	8	9	7	3	19
<i>Cyanistes caeruleus</i>	5	6	7	2	8	17
<i>Sturnus vulgaris</i>	1	13	5	7	5	17
<i>Buteo buteo</i>	8	5	9	3	4	16
<i>Garrulus glandarius</i>	1	5	10	1	3	14
<i>Turdus viscivorus</i>	8	3	8	5	0	13
<i>Pica pica</i>	6	3	5	1	6	12
<i>Troglodytes troglodytes</i>	4	8	5	6	1	12
<i>Corvus frugilegus</i>	6	3	2	5	4	11
<i>Turdus pilaris</i>	12	5	5	2	4	11
<i>Streptopelia decaocto</i>	3	3	4	3	3	10
<i>Vanellus vanellus</i>	7	6	6	4	0	10
<i>Passer domesticus</i>	3	6	1	4	4	9
<i>Falco tinnunculus</i>	9	5	5	3	1	9
<i>Perdix perdix</i>	4	0	5	4	0	9
<i>Emberiza citrinella</i>	4	4	3	3	2	8

////////////////////////////////////



scientific	1	2	3	4	5	sufficient
<i>Larus argentatus</i>	3	2	0	0	0	0
<i>Grus grus</i>	0	2	0	0	0	0
<i>Lophophanes cristatus</i>	0	2	0	0	0	0
<i>Gallinago gallinago</i>	5	1	0	0	0	0
<i>Emberiza cirrus</i>	4	1	0	0	0	0
<i>Egretta garzetta</i>	3	1	0	0	0	0
<i>Serinus serinus</i>	3	1	0	0	0	0
<i>Saxicola rubicola</i>	2	1	0	0	0	0
<i>Emberiza calandra</i>	2	1	0	0	0	0
<i>Poecile montanus</i>	1	1	0	0	0	0
<i>Lanius excubitor</i>	1	1	0	0	0	0
<i>Corvus corax</i>	1	1	0	0	0	0
<i>Gyps fulvus</i>	0	1	0	0	0	0
<i>Dendropicos medius</i>	0	1	0	0	0	0
<i>Fringilla montifringilla</i>	9	0	0	0	0	0
<i>Circus cyaneus</i>	8	0	0	0	0	0
<i>Phylloscopus collybita</i>	6	0	0	0	0	0
<i>Anser anser</i>	2	0	0	0	0	0
<i>Anas crecca</i>	2	0	0	0	0	0
<i>Falco peregrinus</i>	2	0	0	0	0	0
<i>Scolopax rusticola</i>	2	0	0	0	0	0
<i>Dryobates minor</i>	2	0	0	0	0	0
<i>Tachybaptus ruficollis</i>	1	0	0	0	0	0
<i>Podiceps cristatus</i>	1	0	0	0	0	0
<i>Ciconia nigra</i>	1	0	0	0	0	0
<i>Milvus milvus</i>	1	0	0	0	0	0
<i>Alectoris rufa</i>	1	0	0	0	0	0
<i>Lymnocyptes minimus</i>	1	0	0	0	0	0
<i>Actitis hypoleucos</i>	1	0	0	0	0	0
<i>Strix aluco</i>	1	0	0	0	0	0
<i>Alcedo atthis</i>	1	0	0	0	0	0
<i>Anthus trivialis</i>	1	0	0	0	0	0
<i>Motacilla flava</i>	1	0	0	0	0	0
<i>Cettia cetti</i>	1	0	0	0	0	0
<i>Acanthis flammea</i>	1	0	0	0	0	0

## 2.3 RULE 3: WE NEED AT LEAST 100 OCCURRENCES PER SPECIES

An occurrence is non-zero observation at unique combination of site, year and period. For a stable model we need at least 100 occurrences.

58 of the 67 species have less than 100 occurrences and are thus too rare for the analysis. The final set of species is listed in table 2.3.

Table 2.3: Number of occurrences per species.

scientific	occurrences	analysis
<i>Turdus merula</i>	207	sufficient
<i>Corvus corone</i>	189	sufficient

scientific	occurrences	analysis
<i>Alauda arvensis</i>	149	sufficient
<i>Fringilla coelebs</i>	146	sufficient
<i>Parus major</i>	139	sufficient
<i>Cyanistes caeruleus</i>	127	sufficient
<i>Erithacus rubecula</i>	120	sufficient
<i>Columba palumbus</i>	113	sufficient
<i>Sturnus vulgaris</i>	112	sufficient
<i>Buteo buteo</i>	98	insufficient
<i>Garrulus glandarius</i>	88	insufficient
<i>Pica pica</i>	88	insufficient
<i>Passer domesticus</i>	70	insufficient
<i>Corvus frugilegus</i>	69	insufficient
<i>Turdus pilaris</i>	64	insufficient
<i>Troglodytes troglodytes</i>	63	insufficient
<i>Turdus viscivorus</i>	60	insufficient
<i>Streptopelia decaocto</i>	57	insufficient
<i>Emberiza citrinella</i>	46	insufficient
<i>Falco tinnunculus</i>	45	insufficient
<i>Perdix perdix</i>	41	insufficient
<i>Vanellus vanellus</i>	39	insufficient
<i>Carduelis carduelis</i>	39	insufficient
<i>Pluvialis apricaria</i>	32	insufficient
<i>Sitta europaea</i>	32	insufficient
<i>Picus viridis</i>	31	insufficient
<i>Dendrocopos major</i>	30	insufficient
<i>Anthus pratensis</i>	29	insufficient
<i>Poecile palustris</i>	29	insufficient
<i>Aegithalos caudatus</i>	24	insufficient
<i>Regulus regulus</i>	23	insufficient
<i>Turdus philomelos</i>	21	insufficient
<i>Corvus monedula</i>	21	insufficient
<i>Ardea cinerea</i>	20	insufficient
<i>Cygnus olor</i>	19	insufficient
<i>Phalacrocorax carbo</i>	17	insufficient
<i>Phasianus colchicus</i>	17	insufficient
<i>Columba livia</i>	17	insufficient
<i>Ardea alba</i>	16	insufficient
<i>Pyrrhula pyrrhula</i>	14	insufficient
<i>Fulica atra</i>	12	insufficient
<i>Numenius arquata</i>	10	insufficient
<i>Anthus spinoletta</i>	10	insufficient
<i>Turdus iliacus</i>	10	insufficient
<i>Certhia brachydactyla</i>	8	insufficient
<i>Tringa ochropus</i>	8	insufficient
<i>Coccothraustes coccothraustes</i>	8	insufficient
<i>Aythya fuligula</i>	7	insufficient
<i>Gallinula chloropus</i>	7	insufficient
<i>Prunella modularis</i>	7	insufficient
<i>Passer montanus</i>	7	insufficient
<i>Alopochen aegyptiaca</i>	6	insufficient

scientific	occurrences	analysis
<i>Anas platyrhynchos</i>	6	insufficient
<i>Dryocopus martius</i>	6	insufficient
<i>Aythya ferina</i>	5	insufficient
<i>Columba oenas</i>	5	insufficient
<i>Phoenicurus ochruros</i>	5	insufficient
<i>Ciconia ciconia</i>	4	insufficient
<i>Larus ridibundus</i>	4	insufficient
<i>Larus canus</i>	4	insufficient
<i>Chloris chloris</i>	4	insufficient
<i>Anas strepera</i>	3	insufficient
<i>Motacilla alba</i>	3	insufficient
<i>Periparus ater</i>	3	insufficient
<i>Certhia familiaris</i>	3	insufficient
<i>Spinus spinus</i>	3	insufficient
<i>Linaria cannabina</i>	3	insufficient

### 3 AVAILABLE OUTPUT

### 3.1 TABLE WITH LINEAR TRENDS

Part II starts with table 4.1 which lists the linear trend for all species. ‘model’ indicates which model is best based on Watanabe–Akaike information criterion (WAIC) (Gelman et al, 2014). Lower WAIC values imply a better model fit, while taking the model complexity into account. L indicates that the trend is linear, which implies that the change is constant. A trend is linear when the linear model has a lower WAIC than the non-linear model. NL indicates that the trend is non-linear. The change between consecutive years is not constant. Thus one should interpret the given linear change with caution. A trend is non-linear when the WAIC of the non-linear model is more than 2 units smaller than that of the linear model. When the WAIC of the non-linear model is less than 2 units smaller than the linear model, we state that the model is possibly non-linear. This is indicated as NL?. Trends of non-linear models are best interpreted based on the trend figures.

### 3.2 CREDIBLE INTERVALS

Because we apply a Bayesian model, all intervals are credible intervals. Credible intervals are conceptually different from confidence intervals. However, both indicate a similar uncertainty of an estimate. A layperson can use credible intervals as if they are confidence intervals. Therefore we will not elaborate on the difference between credible and confidence intervals. Just know that they are credible intervals, not confidence intervals.

### 3.3 TREND CLASSIFICATION

We compare the 95% credible intervals with a reference, upper and lower threshold to classify the strength of the effect into 10 classes. The change of a linear trend is converted into a change over the length of the data. The change of an index is the actual change between the two years. The reference is set to 0 (no change). The credible interval of a significant effect does not contain 0. We selected a change of -25% (3/4 of the initial value) as the lower threshold. We use the complement<sup>1</sup> of that (+33% or 4/3 of the initial value) as the upper threshold. A -25% or +33% change over 5 years is equivalent to an average yearly change of -5.6% or +5.9% in case of a linear trend.

Below are the symbols, interpretations and rules for each of the 10 classes.

- **++ strong increase:** A significant positive trend and significantly stronger than the upper threshold.
- **+~ moderate increase:** A significant positive trend and significantly weaker than the upper threshold.
- **+ increase:** A significant positive trend, not significantly different from the upper threshold.
- **~ stable:** A non-significant trend and significantly between the lower and upper threshold.
- **- increase:** A significant negative trend, not significantly different from the lower threshold.
- **~- moderate decrease:** A significant negative trend and significantly weaker than the lower threshold.

---

<sup>1</sup> $\log(3/4) = -0.2877$  and  $\log(4/3) = 0.2877$

- -- **strong decrease**: A significant negative trend and significantly stronger than the lower threshold.
- ?+ **potential increase**: A non-significant trend, significantly above the lower threshold.
- ?- **potential decrease**: A non-significant trend, significantly above the upper threshold.
- ? **unknown**: A non-significant trend, both the lower and upper threshold are probable.

One of the benefits is that we distinguish ~ (stable) and ? (unknown). Both are non-significant. The main difference between both cases is the uncertainty. We set the thresholds at important changes. If the uncertainty is large, then the credible interval contains both the lower and the upper threshold. So we have no clue what is happening, hence the unknown class. If the uncertainty is small, then the credible interval contains neither the lower nor the upper threshold. In this case we do know that the change is less extreme than the thresholds. So if there is a change, it will be smaller than important changes (the thresholds). This is informative, even though the change is not significant.

### 3.4 FIGURES

Each modelled species gets its own chapter with results. All results are display in a graphical format.

### 3.4.1 Estimated bird density

The results start with a figure showing the estimated bird density an observer would encounter at an average site during the first period. The line displays the point estimate for each winter. This is the most likely value for the average bird density. The three ribbons display the uncertainty around this point estimate. They are, from small/dark to wide/light, the 30%, 60% and 90% credible intervals. These numbers in the figure are always based on the non-linear model (1.6). The caption indicates whether the model is non-linear and how strong the linear trend is.

### 3.4.2 Indices

An index is a change compared to a baseline. This baseline is typically the estimate for some reference year. E.g we use 2013 as a baseline and compare 2015 with 2013 or 2016 with 2013. However we cannot use the figure with 2013 as baseline to compare 2015 with 2016. For that we need a figure with either 2015 or 2016 as baseline. To facilitate any pairwise comparison among years, we display one figure for every year using that year as baseline.

### 3.4.3 Index raster

Currently a separate index figure for each reference year is doable since the data contains only 5 years. The number of index figures will grow over the years, making it harder to interpret them. The third plot summarises the information on a raster. The x axis holds the year we want to interpret. The y axis holds the reference year. The dots given the relative change from the baseline (y axis) to the other year (x axis). Their colour indicates the strength of the change. Stronger changes have darker dots, white dots indicate no change. Red dots indicate a decrease from the baseline, blue dots an increase. A baseline with all red (blue) dots indicates the year with the largest (smallest) numbers. The shape of the dots indicates the classification of the effect. Informative dots (significant or non-significant but stable) get solid shapes.



## Part II

## Trends

## 4 LINEAR TRENDS

Table 4.1: Average yearly change

euring	scientific	french	class	model	change
10990	<i>Erithacus rubecula</i>	Rougegorge familier	++	non-linear	25.5%, (7.1%; 48.7%)
11870	<i>Turdus merula</i>	Merle noir	+	non-linear	19.0%, (5.6%; 34.4%)
16360	<i>Fringilla coelebs</i>	Pinson des arbres	?+	possibly non-linear	18.3%, (-0.8%; 41.2%)
15820	<i>Sturnus vulgaris</i>	Étourneau sansonnet	?+	possibly non-linear	18.1%, (-5.6%; 48.0%)
14640	<i>Parus major</i>	Mésange charbonnière	?+	linear	6.9%, (-3.9%; 19.1%)
6700	<i>Columba palumbus</i>	Pigeon ramier	?	possibly non-linear	3.2%, (-25.9%; 45.4%)
9760	<i>Alauda arvensis</i>	Alouette des champs	?	possibly non-linear	2.0%, (-14.5%; 21.8%)
15670	<i>Corvus corone</i>	Corneille noire	?	possibly non-linear	-0.1%, (-17.0%; 19.8%)
14620	<i>Cyanistes caeruleus</i>	Mésange bleue	?	linear	-2.1%, (-14.5%; 12.2%)

5 COLUMBA PALUMBUS (PIGEON RAMIER)

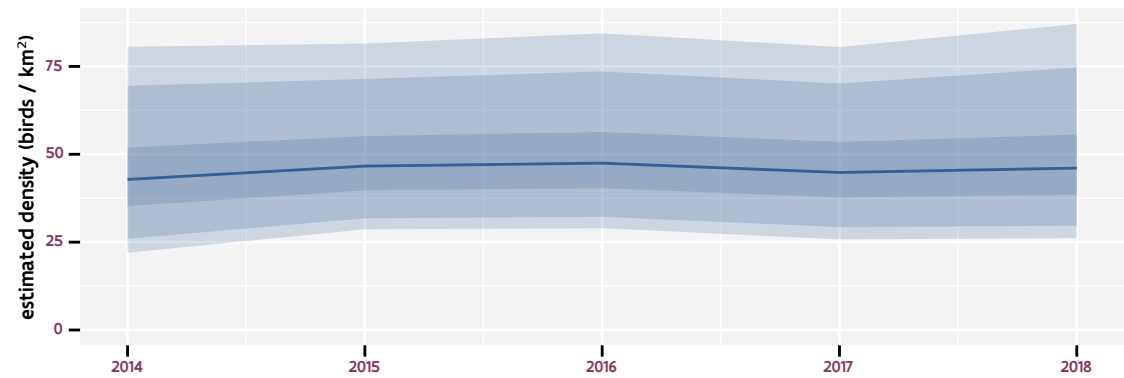


Figure 5.1: Estimated density (birds/km<sup>2</sup>) for *Columba palumbus* (Pigeon ramier) based on a non-linear model. The linear yearly change (?) is +3.2% (-25.9%; +45.4%). The trend is possibly non-linear.

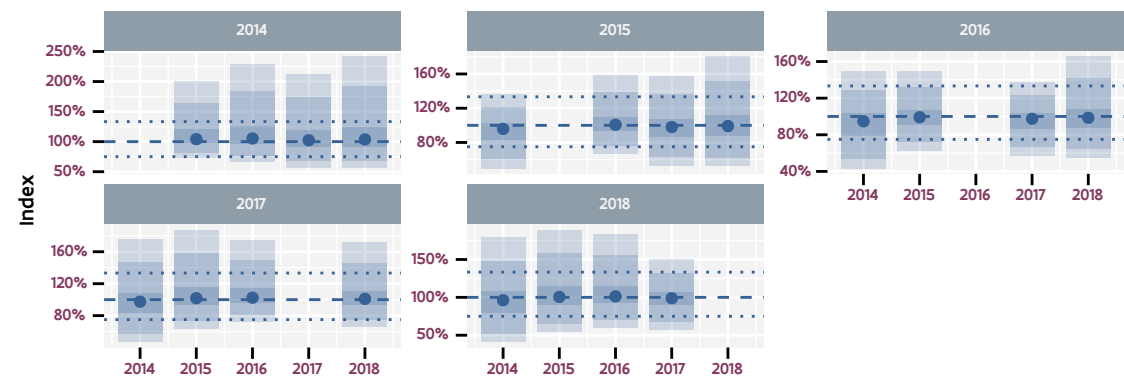


Figure 5.2: Indices for different reference years

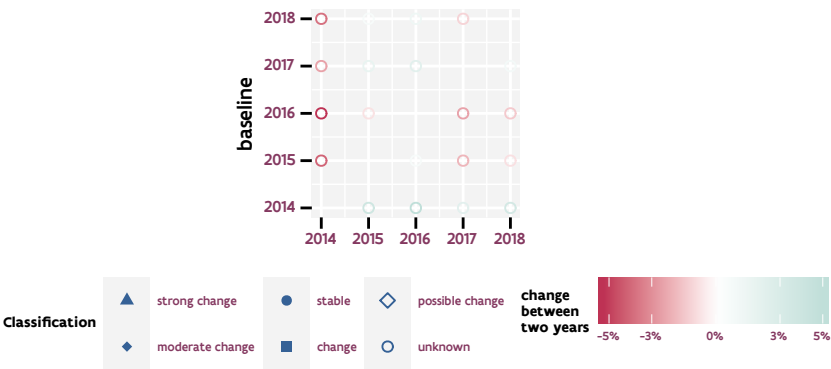


Figure 5.3: Relative change between years

## 6 *ALAUDA ARVENSIS* (ALOUETTE DES CHAMPS)

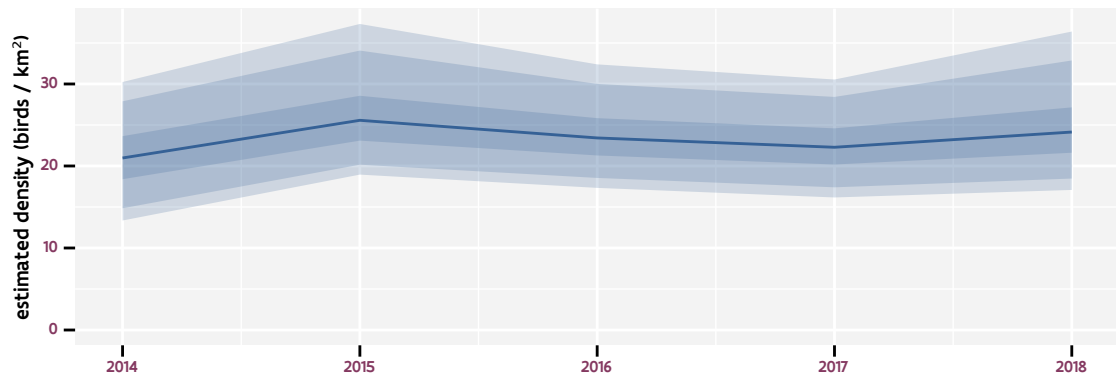


Figure 6.1: Estimated density (birds/km<sup>2</sup>) for *Alauda arvensis* (Alouette des champs) based on a non-linear model. The linear yearly change (?) is +2.0% (-14.5%; +21.8%). The trend is possibly non-linear.

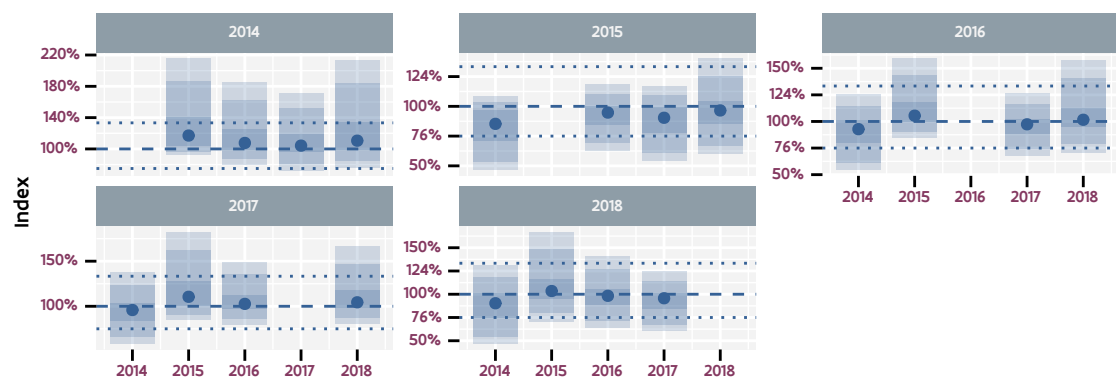


Figure 6.2: Indices for different reference years

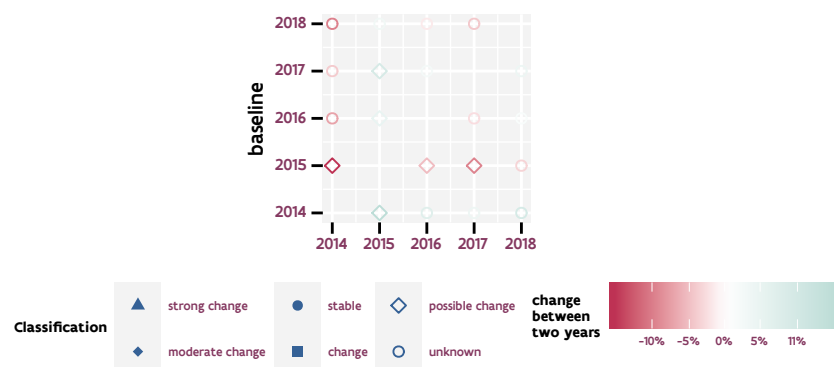


Figure 6.3: Relative change between years

## 7 *ERITHACUS RUBECULA* (ROUGE GORGE FAMILIER)

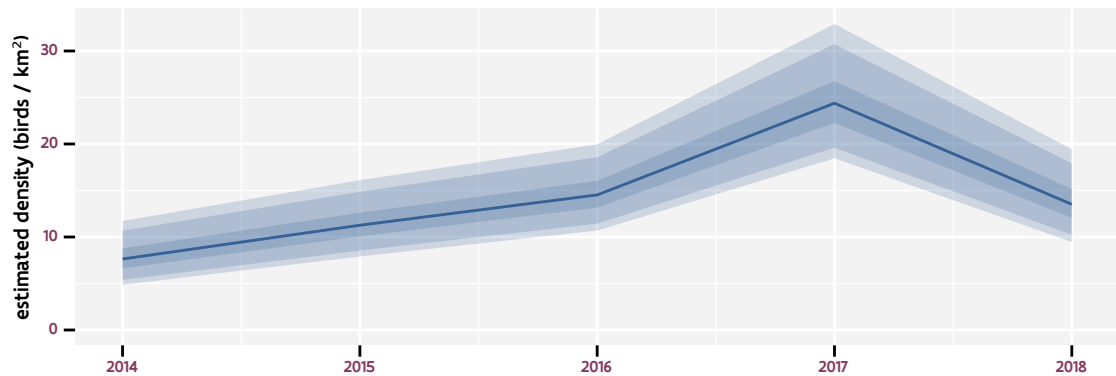


Figure 7.1: Estimated density (birds/km<sup>2</sup>) for *Erithacus rubecula* (Rougegorge familier) based on a non-linear model. The linear yearly change (++) is +25.5% (+7.1%; +48.7%). The trend is non-linear.

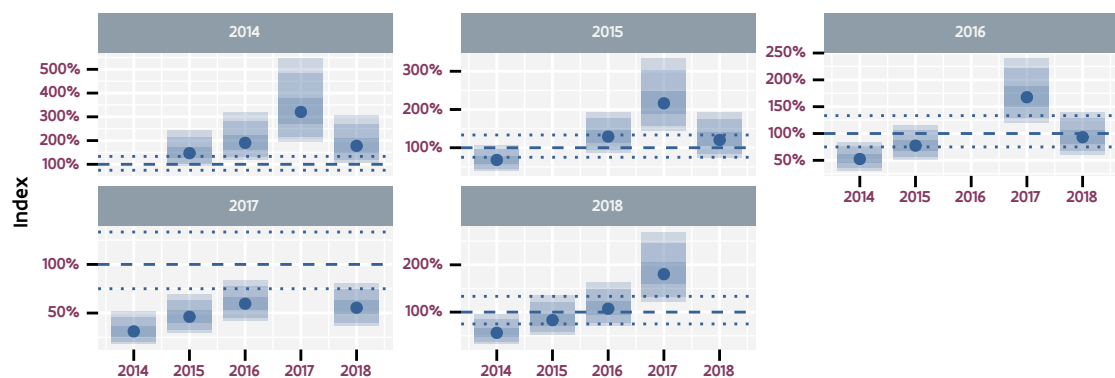


Figure 7.2: Indices for different reference years

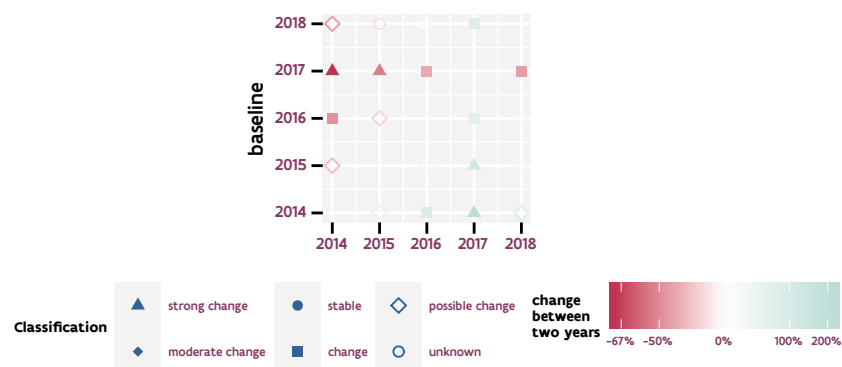


Figure 7.3: Relative change between years

# 8 *TURDUS MERULA* (MERLE NOIR)

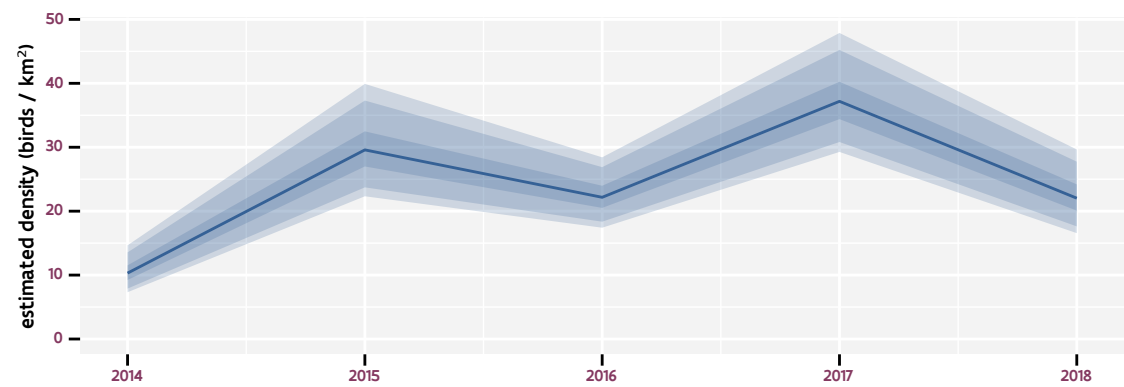


Figure 8.1: Estimated density (birds/km<sup>2</sup>) for *Turdus merula* (Merle noir) based on a non-linear model. The linear yearly change (+) is +19.0% (+5.6%; +34.4%). The trend is non-linear.

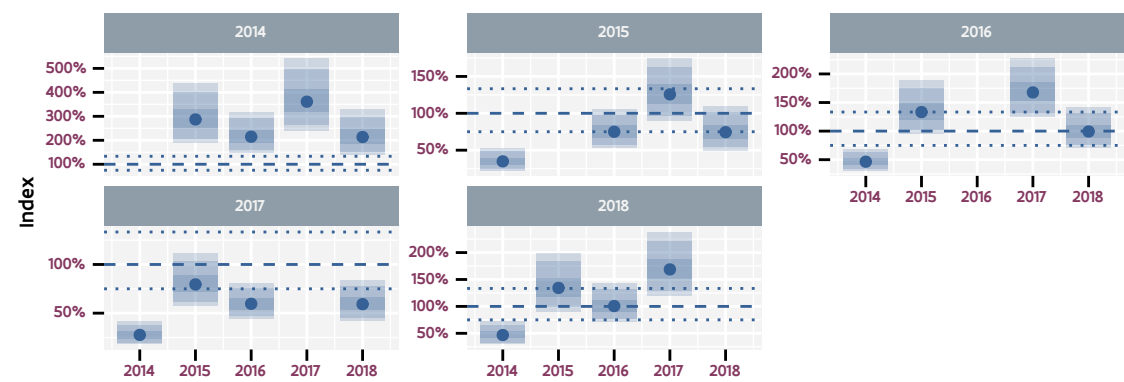


Figure 8.2: Indices for different reference years

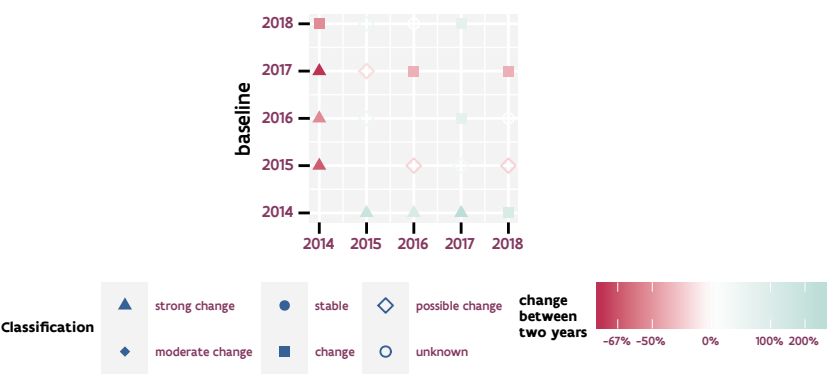


Figure 8.3: Relative change between years

9 **CYANISTES CAERULEUS (MÉSANGE BLEUE)**

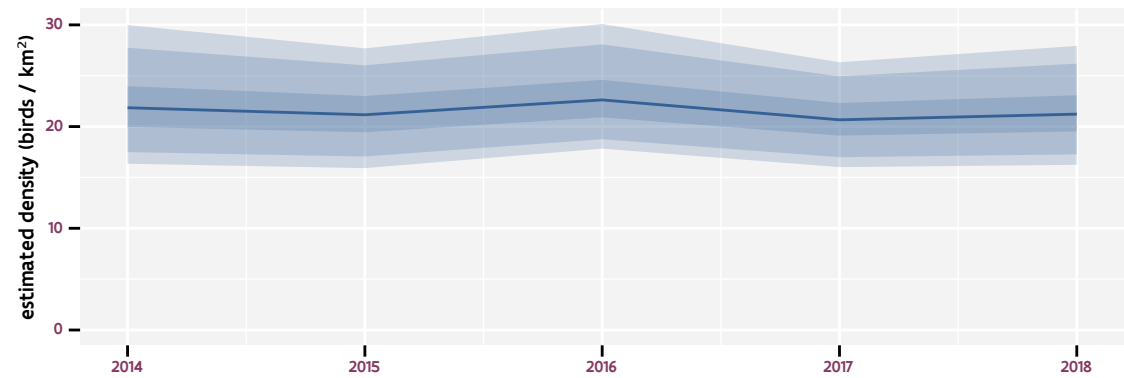


Figure 9.1: Estimated density (birds/km<sup>2</sup>) for *Cyanistes caeruleus* (Mésange bleue) based on a non-linear model. The linear yearly change (?) is -2.1% (-14.5%; +12.2%). The trend is linear.

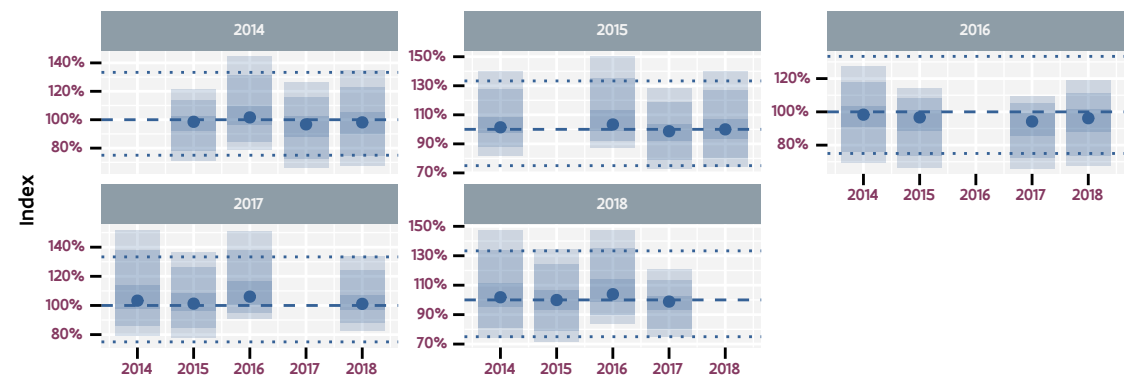


Figure 9.2: Indices for different reference years

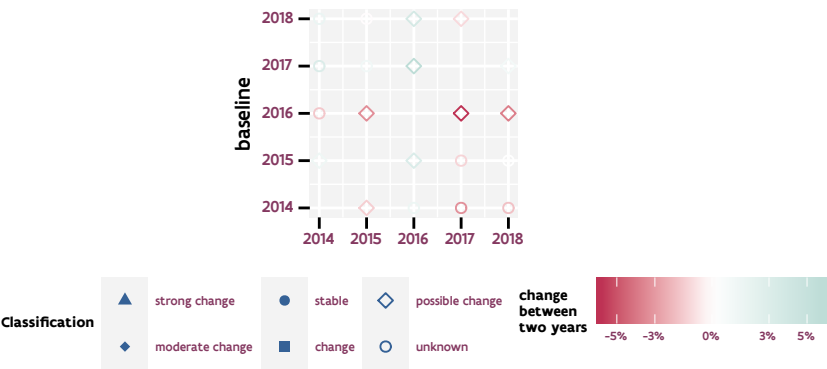


Figure 9.3: Relative change between years

10 **PARUS MAJOR (MÉSANGE CHARBONNIÈRE)**

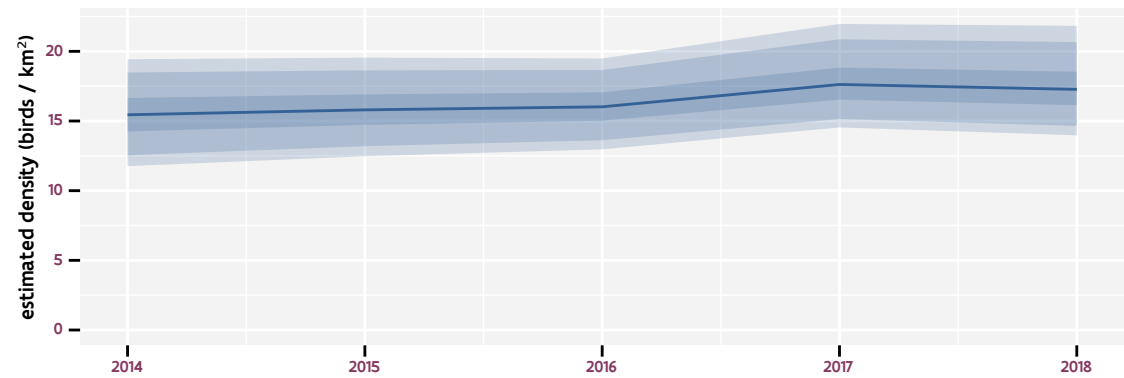


Figure 10.1: Estimated density (birds/km<sup>2</sup>) for *Parus major* (Mésange charbonnière) based on a non-linear model. The linear yearly change (??) is +6.9% (-3.9%; +19.1%). The trend is linear.

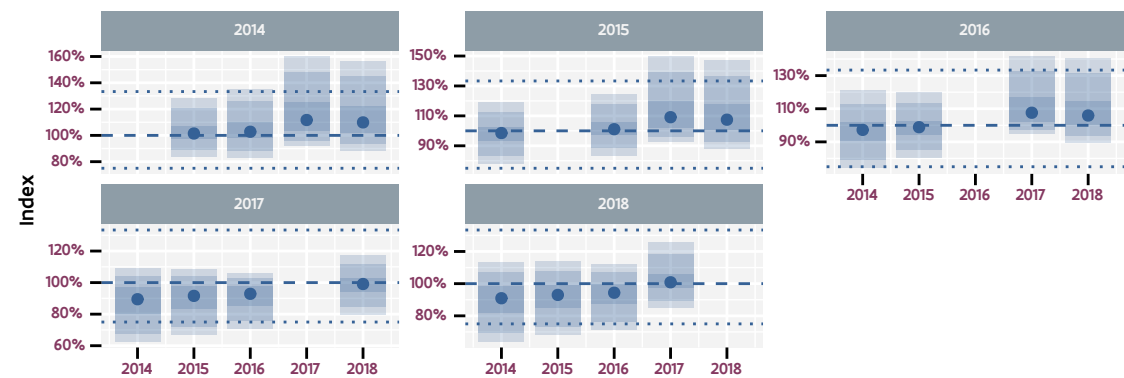


Figure 10.2: Indices for different reference years

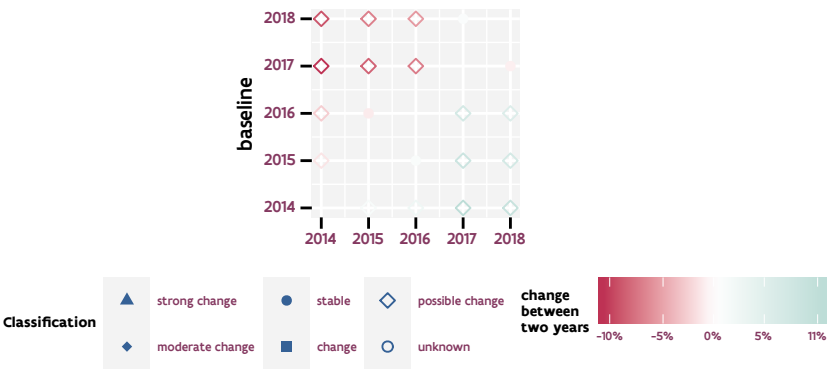


Figure 10.3: Relative change between years



11 **CORVUS CORONE (CORNEILLE NOIRE)**

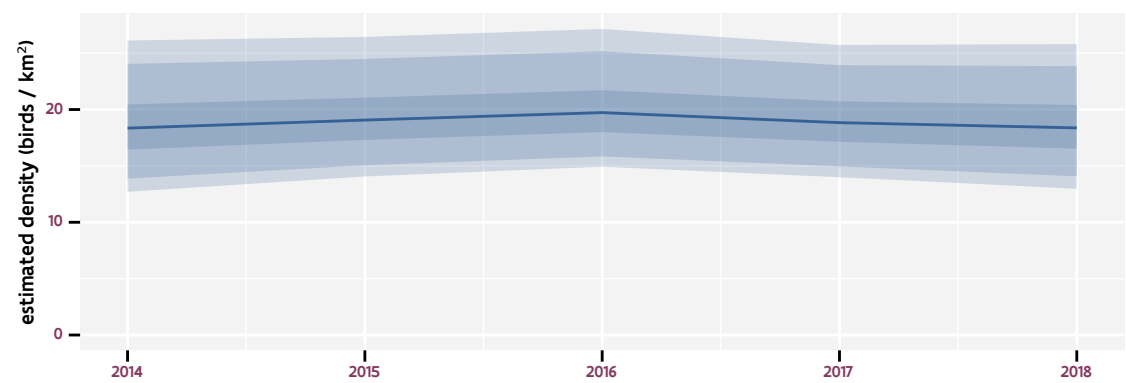


Figure 11.1: Estimated density (birds/km<sup>2</sup>) for *Corvus corone* (Corneille noire) based on a non-linear model. The linear yearly change (?) is -0.1% (-17.0%; +19.8%). The trend is possibly non-linear.

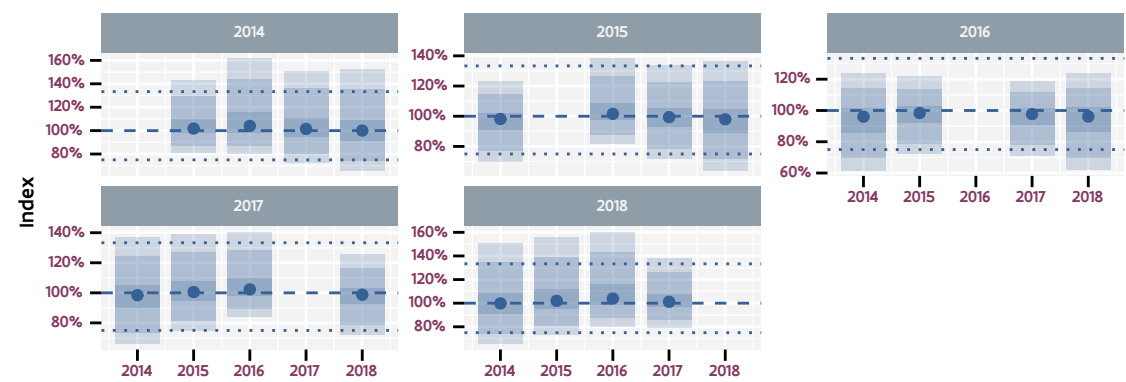


Figure 11.2: Indices for different reference years

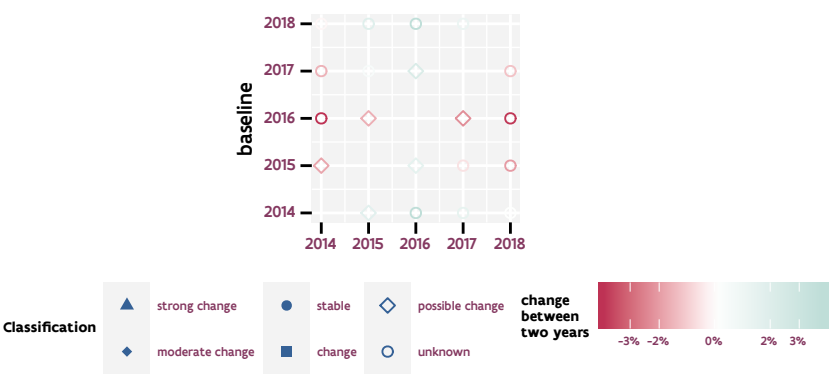


Figure 11.3: Relative change between years

12     **STURNUS VULGARIS (ÉTOURNEAU SANSONNET)**

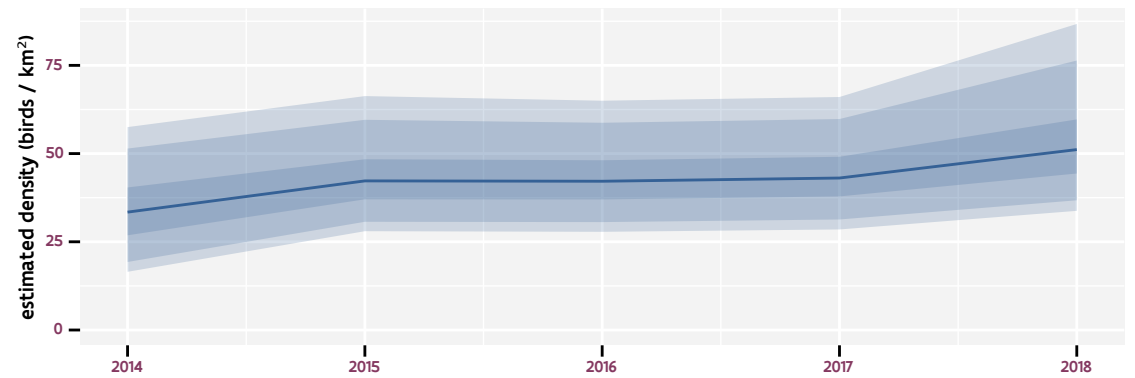


Figure 12.1: Estimated density (birds/km<sup>2</sup>) for *Sturnus vulgaris* (Étourneau sansonnet) based on a non-linear model. The linear yearly change (??) is +18.1% (-5.6%; +48.0%). The trend is possibly non-linear.

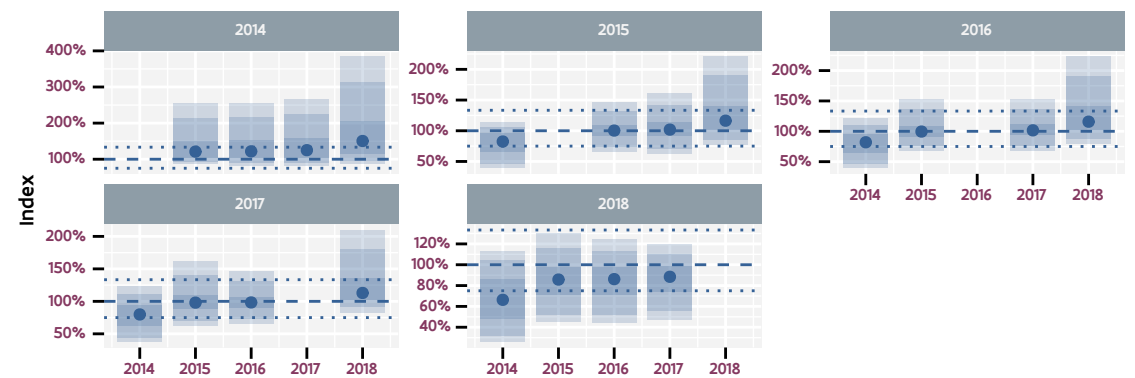


Figure 12.2: Indices for different reference years

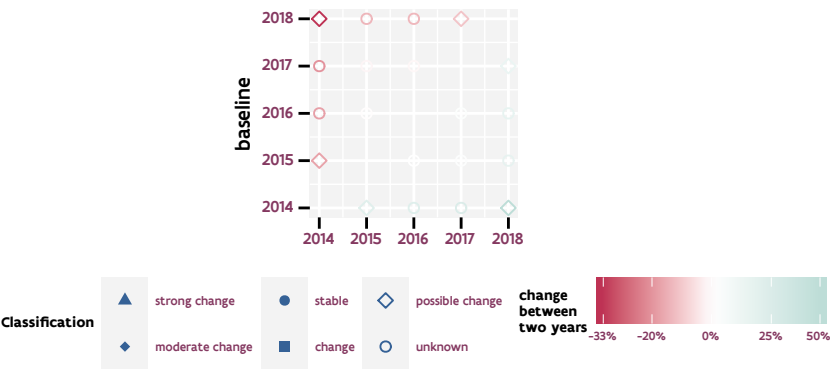


Figure 12.3: Relative change between years

13 **FRINGILLA COELEBS (PINSON DES ARBRES)**

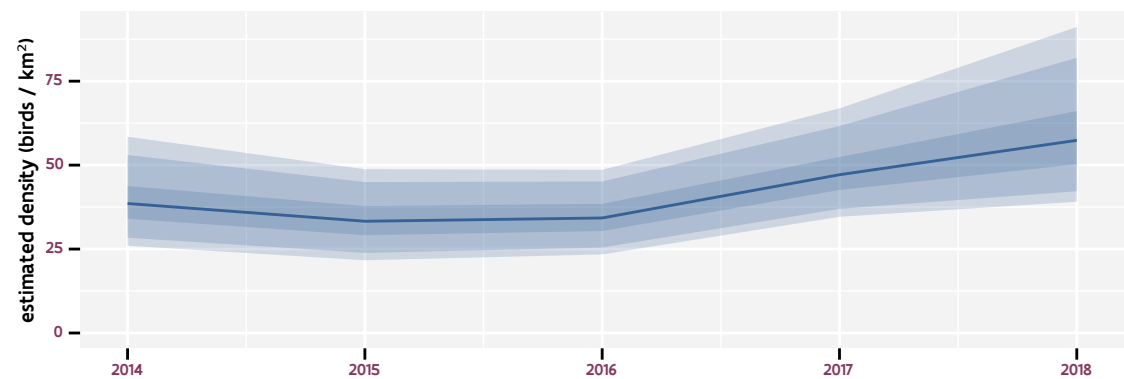


Figure 13.1: Estimated density (birds/km<sup>2</sup>) for *Fringilla coelebs* (Pinson des arbres) based on a non-linear model. The linear yearly change (?+) is +18.3% (-0.8%; +41.2%). The trend is possibly non-linear.

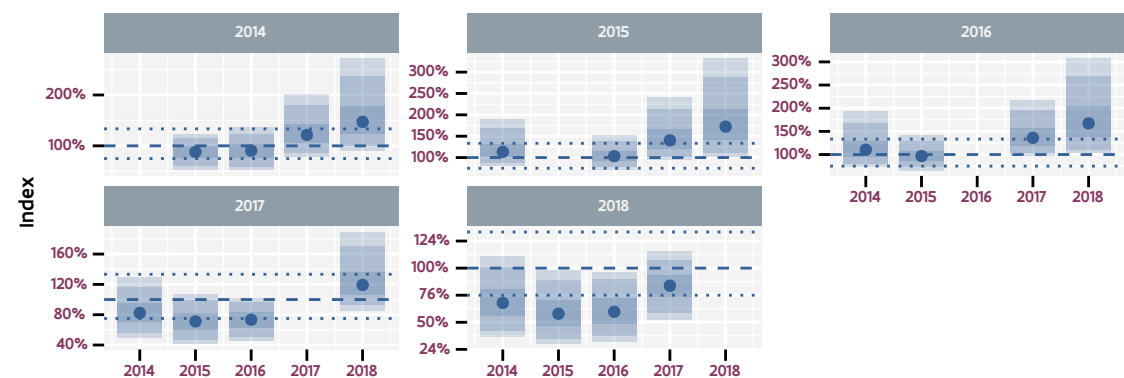


Figure 13.2: Indices for different reference years

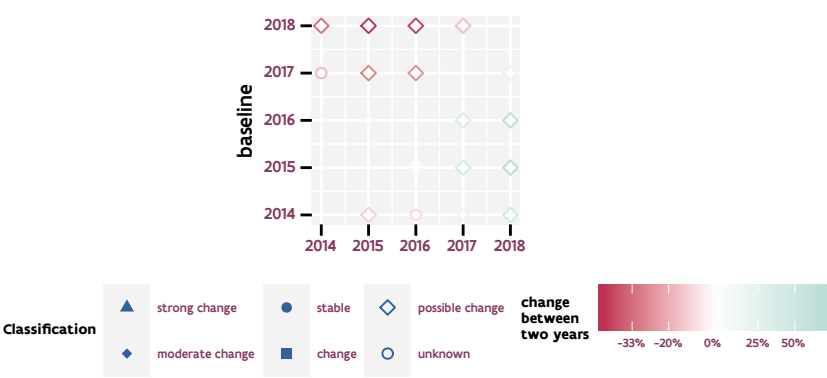


Figure 13.3: Relative change between years

## Bibliography

- Gelman, A., Hwang, J. & Vehtari, A. (2014). Understanding predictive information criteria for Bayesian models. *Statistics and Computing* 24 (6): 997–1016. ISSN 15731375. doi:10.1007/s11222-013-9416-2.
- R Core Team (2019). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria. URL <https://www.R-project.org/>.
- Rue, H., Riebler, A.I., Sørbye, S.H., Illian, J.B., Simpson, D.P. & Lindgren, F.K. (2017). Bayesian computing with INLA: A review. *Annual Reviews of Statistics and Its Applications* 4 (March): 395–421. URL <http://arxiv.org/abs/1604.00860>.