Supplemental Materials

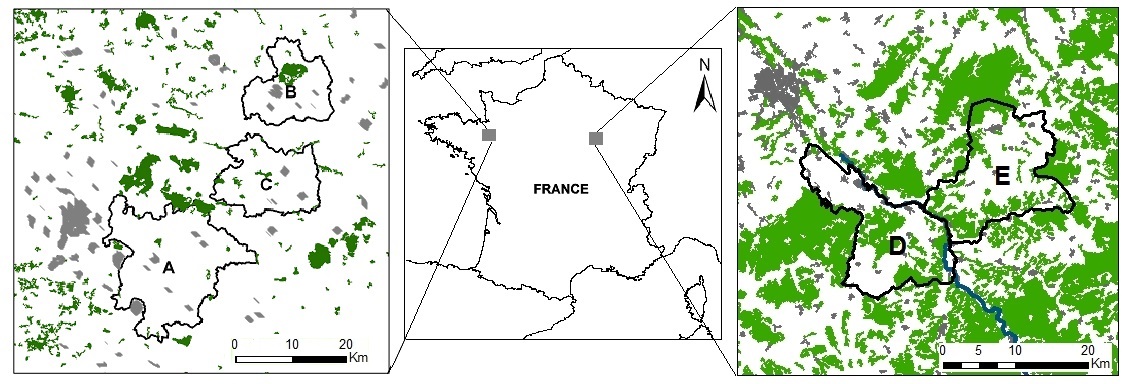
15 December 2014

Lieury et al. 2014. Compensatory Immigration challenges Predator Control: an Experimental Evidence-Based Approach Improves Management. Journal of Wildlife Management: in review

**S1. Details on Protocol Characteristics: Study Sites and Associated Predator Control.**

Table S1. Characteristics of the culling experimental protocol for each site. Annual number of killed foxes obtained from hunters and trappers and distribution of kills among the different culling methods (hunting, culling at the den, trapping and shooting) and culling periods (gestation: February-March; breeding: April-June; dispersal: July-January). Female sex ratio is also indicated in average (±SD among sites and years) and for each culling periods, given all ages or adult only.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Site** | **Year** | | | | | | |  | **Culling method** | | | |  | **Culling period** | | |
|  | *2002* | *2003* | *2004* | *2005* | *2006* | *2007* | *Total* |  | *Hunting* | *Den culling* | *Trapping* | *Shooting* |  | *Rut* | *Breeding* | *Dispersal* |
| **A** | 514 | 475 | 619 | 645 | 462 | 649 | 3364 |  | 25% | 28% | 47% | — |  | 18% | 30% | 52% |
| **B** | - | 590 | 967 | 657 | 548 | 548 | 3310 |  | 6% | 48% | 46% | — |  | 27% | 24% | 50% |
| **C** | - | 383 | 287 | 264 | 387 | 401 | 1722 |  | 4% | 63% | 33% | — |  | 17% | 51% | 33% |
| **Total** | **514** | **1448** | **1873** | **1566** | **1397** | **1598** | **8396** |  | **15%** | **42%** | **44%** | **—** |  | **21%** | **35%** | **45%** |
|  | *2006* | *2007* | *2008* | *2009* | *2010* | *2011* | *Total* |  | *Hunting* | *Den culling* | *Trapping* | *Shooting* |  | *Rut* | *Breeding* | *Dispersal* |
| **D** | 75 | 102 | 69 | 262 | 332 | 210 | 1050 |  | 19% | 3% | 51% | 27% |  | 16% | 21% | 63% |
| **E** | 314 | 284 | 233 | 122 | 104 | 107 | 1164 |  | 23% | 6% | 30% | 42% |  | 22% | 25% | 53% |
| **Total** | **389** | **386** | **302** | **384** | **436** | **317** | **2214** |  | **21%** | **4%** | **41%** | **34%** |  | **19%** | **23%** | **58%** |
| ***Female Sex Ratio in all ages*** | | | | | | | | | Average: 0.48 ± 0.04 | | | |  | 0.51 | 0.53 | 0.41 |
| ***Female Sex Ratio in adult only*** | | | | | | | | | Average: 0.50 ± 0.10 | | | |  | 0.57 | 0.44 | 0.50 |

Figure S1. Maps of the five study sites with their boundaries (black lines) and associated wooded (green) and urbanized (grey) areas. Sites A, B and C are located in the Brittany region (western France) whereas D and E are in the Champagne region (eastern France). The areas of the sites A to E are 337.4, 237.6, 238.1, 201 and 217.5 km², respectively.

**S2. Summary of the Demographic Parameters and Culling Rates estimated in each Study Sites.**

Table S2. Annotations correspond to those in Fig. 1: D corresponds to fox density, Nt to adult population size in February and associated coefficient of variation CV; **λ** is the annual population growth rate; Ki measures culling bags, PB and LS the age-specific breeding probability and Litter size. Nad is the number of remaining adults Nt – KG; nJ, the estimated number of cubs and N’t = Nad+nJ. CRi are culling rates described in the Materials section.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Site | Area | Year | D | Nt | CV | λ | KG | KB | KD | sum(K) | Nad | PB(1) | PB(2-5) | PB(6-10) | LS(1) | LS(2) | LS(3-5) | LS(6-10) | nJ | N't | CR | CRG | CRB | CRD |
| A | 337 | 2002 | 0.85 | 285 | 10.3 | 1.14 | 95 | 77 | 342 | 514 | 190 | 0.89 | 0.95 | 1.00 | 4.65 | 5.06 | 5.17 | 3.71 | 421 | 611 | 0.73 | 0.3 | 0.13 | 0.56 |
| A | 337 | 2003 | 0.96 | 325 | 10.9 | 1.04 | 102 | 103 | 270 | 475 | 223 | 0.77 | 0.88 | 1.00 | 4.48 | 4.89 | 5.00 | 3.54 | 429 | 652 | 0.63 | 0.26 | 0.16 | 0.41 |
| A | 337 | 2004 | 1.00 | 339 | 13.0 | 1.00 | 106 | 242 | 271 | 619 | 233 | 0.82 | 0.91 | 1.00 | 4.84 | 5.25 | 5.36 | 3.90 | 505 | 738 | 0.73 | 0.24 | 0.33 | 0.37 |
| A | 337 | 2005 | 1.00 | 338 | 12.6 | 1.08 | 89 | 208 | 348 | 645 | 249 | 0.88 | 0.94 | 1.00 | 4.63 | 5.03 | 5.15 | 3.69 | 542 | 791 | 0.73 | 0.18 | 0.26 | 0.44 |
| A | 337 | 2006 | 1.09 | 366 | 9.9 | 1.23 | 99 | 157 | 206 | 462 | 267 | 0.87 | 0.94 | 1.00 | 4.31 | 4.71 | 4.83 | 3.37 | 539 | 806 | 0.51 | 0.22 | 0.19 | 0.26 |
| A | 337 | 2007 | 1.33 | 450 | 12.8 | 0.79 | 121 | 224 | 304 | 649 | 329 | 0.98 | 0.99 | 1.00 | 4.90 | 5.31 | 5.42 | 3.96 | 820 | 1149 | 0.51 | 0.11 | 0.19 | 0.26 |
| B | 238 | 2003 | 1.95 | 463 | 10.7 | 0.98 | 197 | 118 | 275 | 590 | 266 | 0.92 | 0.85 | 1.00 | 4.48 | 4.89 | 5.00 | 3.54 | 549 | 815 | 0.58 | 0.16 | 0.14 | 0.34 |
| B | 238 | 2004 | 1.92 | 456 | 11.0 | 1.18 | 106 | 152 | 709 | 967 | 350 | 0.94 | 0.88 | 1.00 | 4.84 | 5.25 | 5.36 | 3.90 | 801 | 1151 | 0.77 | 0.11 | 0.13 | 0.62 |
| B | 238 | 2005 | 2.27 | 540 | 10.7 | 1.02 | 147 | 170 | 340 | 657 | 393 | 0.96 | 0.92 | 1.00 | 4.63 | 5.03 | 5.15 | 3.69 | 888 | 1281 | 0.46 | 0.11 | 0.13 | 0.27 |
| B | 238 | 2006 | 2.32 | 551 | 13.0 | 1.13 | 283 | 94 | 171 | 548 | 268 | 0.96 | 0.92 | 1.00 | 4.31 | 4.71 | 4.83 | 3.37 | 563 | 831 | 0.49 | 0.15 | 0.11 | 0.21 |
| B | 238 | 2007 | 2.62 | 623 | 11.0 | 1.07 | 150 | 253 | 144 | 547 | 473 | 0.99 | 0.99 | 1.00 | 4.90 | 5.31 | 5.42 | 3.96 | 1186 | 1659 | 0.3 | 0.11 | 0.15 | 0.09 |
| C | 238 | 2003 | 0.94 | 223 | 9.9 | 1.01 | 86 | 179 | 118 | 383 | 137 | 0.74 | 0.87 | 1.00 | 4.48 | 4.89 | 5.00 | 3.54 | 258 | 395 | 0.8 | 0.17 | 0.45 | 0.3 |
| C | 238 | 2004 | 0.94 | 225 | 11.2 | 0.90 | 40 | 154 | 93 | 287 | 185 | 0.79 | 0.90 | 1.00 | 4.84 | 5.25 | 5.36 | 3.90 | 394 | 579 | 0.46 | 0.07 | 0.27 | 0.16 |
| C | 239 | 2005 | 0.85 | 203 | 13.2 | 1.26 | 46 | 134 | 84 | 264 | 157 | 0.86 | 0.93 | 1.00 | 4.63 | 5.03 | 5.15 | 3.69 | 337 | 494 | 0.49 | 0.05 | 0.27 | 0.17 |
| C | 239 | 2006 | 1.07 | 255 | 10.1 | 0.75 | 66 | 129 | 192 | 387 | 189 | 0.85 | 0.93 | 1.00 | 4.31 | 4.71 | 4.83 | 3.37 | 376 | 565 | 0.61 | 0.11 | 0.23 | 0.34 |
| C | 239 | 2007 | 0.81 | 192 | 14.4 | 1.19 | 51 | 275 | 75 | 401 | 141 | 0.98 | 0.99 | 1.00 | 4.90 | 5.31 | 5.42 | 3.96 | 351 | 492 | 0.74 | 0.14 | 0.56 | 0.15 |
| D | 201 | 2006 | 0.80 | 161 | 8.3 | 1.12 | 23 | 18 | 34 | 75 | 138 | 0.73 | 0.91 | 1.00 | 3.83 | 4.23 | 4.35 | 2.89 | 226 | 364 | 0.19 | 0.14 | 0.05 | 0.09 |
| D | 201 | 2007 | 0.90 | 181 | 7.6 | 0.75 | 23 | 20 | 59 | 102 | 158 | 0.95 | 0.99 | 1.00 | 4.42 | 4.83 | 4.94 | 3.48 | 351 | 509 | 0.19 | 0.13 | 0.04 | 0.12 |
| D | 201 | 2008 | 0.67 | 135 | 9.4 | 1.10 | 15 | 20 | 34 | 69 | 120 | 0.83 | 0.94 | 1.00 | 4.65 | 5.06 | 5.17 | 3.71 | 256 | 376 | 0.18 | 0.11 | 0.05 | 0.09 |
| D | 201 | 2009 | 0.74 | 148 | 8.5 | 0.66 | 44 | 38 | 180 | 262 | 104 | 0.76 | 0.92 | 1.00 | 3.39 | 3.80 | 3.91 | 2.45 | 155 | 259 | 0.86 | 0.3 | 0.15 | 0.69 |
| D | 201 | 2010 | 0.49 | 98 | 8.1 | 0.61 | 34 | 90 | 208 | 332 | 64 | 0.98 | 0.99 | 1.00 | 4.52 | 4.93 | 5.04 | 3.58 | 148 | 212 | 1.35 | 0.35 | 0.42 | 0.98 |
| D | 201 | 2011 | 0.30 | 60 | 11.2 | 0.82 | 29 | 35 | 146 | 210 | 31 | 0.86 | 0.96 | 1.00 | 4.00 | 4.40 | 4.52 | 3.06 | 59 | 90 | 1.76 | 0.48 | 0.39 | 1.62 |
| E | 218 | 2006 | 0.69 | 149 | 8.7 | 0.64 | 76 | 73 | 165 | 314 | 73 | 0.64 | 0.88 | 1.00 | 3.83 | 4.23 | 4.35 | 2.89 | 111 | 184 | 1.21 | 0.51 | 0.4 | 0.9 |
| E | 218 | 2007 | 0.44 | 96 | 9.3 | 0.76 | 61 | 51 | 172 | 284 | 35 | 0.93 | 0.98 | 1.00 | 4.42 | 4.83 | 4.94 | 3.48 | 77 | 112 | 1.64 | 0.64 | 0.46 | 1.54 |
| E | 218 | 2008 | 0.34 | 73 | 9.2 | 1.00 | 42 | 88 | 103 | 233 | 31 | 0.76 | 0.93 | 1.00 | 4.65 | 5.06 | 5.17 | 3.71 | 63 | 94 | 1.71 | 0.58 | 0.94 | 1.1 |
| E | 218 | 2009 | 0.34 | 73 | 9.1 | 1.14 | 24 | 41 | 57 | 122 | 49 | 0.67 | 0.89 | 1.00 | 3.39 | 3.80 | 3.91 | 2.45 | 68 | 117 | 0.87 | 0.33 | 0.35 | 0.49 |
| E | 218 | 2010 | 0.38 | 83 | 9.1 | 1.31 | 23 | 12 | 69 | 104 | 60 | 0.97 | 0.99 | 1.00 | 4.52 | 4.93 | 5.04 | 3.58 | 138 | 198 | 0.47 | 0.28 | 0.06 | 0.35 |
| E | 218 | 2011 | 0.50 | 109 | 8.9 | 0.99 | 25 | 28 | 54 | 107 | 84 | 0.80 | 0.95 | 1.00 | 4.00 | 4.40 | 4.52 | 3.06 | 153 | 237 | 0.41 | 0.23 | 0.12 | 0.23 |

**S3. Multiple-Covariate Distance Sampling Density Estimation.**

**Methods.**In the five study sites, density was estimated each winter, during the two first weeks of February, applying the Distance-Sampling methodology (Buckland *et al.* 1993) to spotlight counts of red fox (Ruette et al. 2003). Line-transect surveys were performed in western sites (A-B-C) whereas point-transect surveys were chosen in eastern sites (D- E) after a change in national road safety procedures. Both methods have been shown to give similar results when conducted simultaneously in a same site (Ruette et al. 2003). Thus, the two data sets were analysed separately using the recommended Multiple-Covariate Distance Sampling (MCDS). This method enables more relevant density estimates, taking into account additional covariates that can affect the probability detection function (Marques et al. 2007, Thomas et al. 2010). In total, 3103 red foxes were observed along 125 Line-transects (6-10 km long) with a minimum of 88 in one survey period at one site. A maximum of 193 Point-transects covered a total of 1.682 observations but only 893 (53%) with a radial distance information, and the minimum was 97 in one survey period at one site. The distance to all foxes detected was recorded by telemeter, with no distinction made between males and females. The median of observed distances in western sites was 117 m but a long tail of larger distances extended the maximal observed distance to 594 m (respectively 258m and 1000m for eastern populations). Exploratory analysis of the potential influence of covariates revealed different distance distributions among western sites, with B tending to detect foxes at lower distances (Fig. S3A). However, the survey period and site did not seem to influence distance distribution in eastern sites (Fig. S3B). Concerning the upper tail of observed distances, a truncation at 5-10% of total observations is generally recommended for line-transects (Buckland *et al.* 1993). Within this interval, we tested different estimations and compared the obtained probability of detection and confidence interval. We chose a 6.7% truncation at 300m to increase the probability of detection without decreasing the precision of estimation. After truncation, there remained 2893 observations with a minimum of 83 in any one condition. A 10% truncation is generally recommended for point-transects and we chose a 13.25% truncation at 360m that retained 670 observations in eastern sites with a minimum of 83 in any one condition. Finally, we checked the assumption of total detection close to the road. Both histograms of observed distances revealed a lack of observation in the 50 first meters which was followed by an increase of observation in the 50-120m interval (Fig. 2.C & 2.D). This seems to reflect an evasive movement prior to detection which is quite common but which led us to reject the assumption of f(0)=1. A grouping of the first intervals is recommended in such case (Buckland *et al.* 1993). For our models, we used a grouping of the 120 first meters and then 30m intervals until the largest distance.

In modelling the detection function using MCDS, the additional covariates available for analysis were site (SITE, factor covariate with population levels) and survey period (YEAR. time was entered as a factor covariate). Both site and period were assumed *a priori* to affect the detection probability. The multiple-covariate detection function was fitted to all data pooled, but when estimating density by stratum, we calculated stratum-specific detection probabilities based on the covariate values of the foxes observed in each stratum. We compared MCDS and the Conventional Distance Sampling (CDS) method, which designs a common detection function for all observations pooled. We selected the detection function within the half-normal distribution with up to two cosine series expansion terms (5 for CDS) and hazard rate distribution with up to two simple polynomial series (5 for CDS). We performed model selection using the AIC criterion. All analyses were conducted in DISTANCE 6.0 (Thomas et al. 2009). A DISTANCE project containing the data and analyses is available from the authors.

**Results.**For western sites, including SITE resulted in the largest drop in AIC, whereas YEAR did not improve the model. As a consequence, the model with both SITE and YEAR as covariates added too much complexity. The best model (MCDS SITE 2) had only two sites as covariates: A+C vs. B (Table S3A). This result confirmed the explanatory analysis that gave significantly different fox observations in B from A and C (Fig. S3A). This model had a much lower AIC than any of the CDS models. On the contrary, CDS common detection function was selected for eastern sites (Table S3B). The observed similarity between D and E (Fig.S3B) made the addition of a covariate with MCDS useless. Hazard rate distribution without adjustment terms was selected in each case. Optimal detectability in eastern sites (Figure S1.F; Estimated Sampling Width at 311m and detection probability 0.75) was 100m further that in western sites (Fig. S3E; ESW 215m and detection probability 0.717). Moreover, we observed a significant lower detectability in population B (ESW 195m and detection probability 0.65) than in A and C (ESW 233m and detection probability 0.76; Figure S3E). Despite an evidence of evasive movement prior to detection (Figure S3C and S3D), the coefficient of variation of our density estimates (derived by bootstrap; n=999) remained low (between 10 and 15% CV in the West and between 7.5 and 12% in the East) with medium good fit (GOF p value of 0.31 for the West and 0.90 for the East).

**Discussion.**Here, we applied Multiple Covariate Distance Sampling (Marques et al. 2007, Thomas et al. 2010) to improve the fit of detection probability and obtain unbiased and precise estimates of red fox densities in open fields. We showed that site characteristics can change the detectability of individuals. An increasing proportion of fragmented area as in B (8% relative to 3-4% in A-C) might decrease individual detectability by improving temporary refuge accessibility. However, since there is still no clear evidence of habitat selection in the red fox home range (Cavallini and Lovari 1991, Cardillo et al. 1999), we argue that our density estimates are a strong basis for studying red fox dynamics. Our selection of a more parsimonious model taking covariates of western sites into account confirms MCDS as a precious tool to add information in the detection probability and avoid potential bias without requiring several detection functions. Nevertheless, we found no real differences in density estimates between MCDS and CDS best models, except for the confidence interval (not shown). In any case, we follow Marques et al. (2007) in recommending a systemic use of MCDS when there are biological expectations on potential bias (observers, site, bad year of survey).

TABLE S3. Distance Sampling model selection of the detection probability for western Line-transects (A) and eastern Point-transects (B). Two approaches are used to fit the detection function to survey data: Conventional Distance Sampling (CDS) with a pooled detection function and Multiple-Covariate Distance Sampling (MCDS). Akaike’s Information Criterion (AIC) enables the selection among candidate models. Key functions are uniform (Uni), half normal (HN), or hazard-rate (HR). Adjustment terms are cosine (Cos) or simple polynomial (SP); (0) means that no adjustment terms were selected by AIC. Covariates for MCDS models include site (SITE) and period (YEAR) as factors. (SITE 2) covariate corresponds to SITE grouped into 2 factors for western populations: A+C and B alone. The number of parameters is shown for each model. Selected models are highlighted in bold.

Table S3A

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Key | Adjustment terms | Covariates | Number of parameters | AIC | ΔAIC |
|  |  | **CDS *f*(0) pooled** |  |  |  |
| Uni | Cos | - | 3 | 8370.79 | 36.60 |
| HN | Cos (0) | - | 1 | 8370.74 | 36.57 |
| HZ | SP (0) | - | 2 | 8367.13 | 32.96 |
|  |  | **MCDS** |  |  |  |
| HN | Cos (0) | SITE | 4 | 8338.38 | 4.21 |
| HZ | SP (0) | SITE | 4 | 8335.01 | 0.85 |
| HN | Cos (0) | SITE 2 | 3 | 8338.22 | 4.05 |
| **HZ** | **SP (0)** | **SITE 2** | **3** | **8334.17** | **0.00** |
| HN | Cos (0) | YEAR | 7 | 8368.70 | 34.54 |
| HZ | SP(0) | YEAR | 7 | 8368.09 | 33.92 |
| HN | Cos (0) | SITE YEAR | 9 | 8336.79 | 2.63 |
| HZ | SP(0) | SITE YEAR | 9 | 8338.63 | 4.47 |
| HN | Cos (0) | SITE 2 YEAR | 7 | 8335.98 | 1.81 |
| HZ | SP(0) | SITE 2 YEAR | 7 | 8338.17 | 4.00 |

Table S3B

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Key | Adjustment terms | Covariates | Number of parameters | AIC | ΔAIC |
|  |  | **CDS *f*(0) pooled** |  |  |  |
| Uni | Cos | - | 3 | 2909.12 | 2.88 |
| HN | Cos | - | 4 | 2910.39 | 4.16 |
| **HZ** | **SP (0)** | **-** | **2** | **2906.23** | **0.00** |
|  |  | **MCDS** |  |  |  |
| HN | Cos | SITE | 3 | 2915.92 | 9.69 |
| HZ | SP (0) | SITE | 3 | 2908.19 | 1.95 |
| HN | Cos | YEAR | 8 | 2916.78 | 10.55 |
| HZ | SP(0) | YEAR | 8 | 2910.97 | 4.74 |
| HN | Cos | SITE YEAR | 9 | 2916.98 | 10.74 |
| HZ | SP(0) | SITE YEAR | 9 | 2912.40 | 6.16 |

Figure S3. Distance Sampling estimations of fox density. Explanatory analyses of distance distribution are shown for western (A) and eastern (B) sites. The distribution of observed distances with associated hazard rate detection function of ungrouped and untruncated CDS is presented for western (C) and eastern (D) sites. Selected hazard rate detection functions (Table C1) of grouped and truncated observations are drawn for western Line-transects (E) and eastern Point-transects (F).

**LITTERATURE CITED**

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**S4. Model Selection of the Random Structure used for Predictions.**

Table S4. Output of the model selection of the random structure. The best random structure (in bold) is selected among a panel of intercept and slope random effects added to the full fixed model λ ~ CR + Density + CR\*Density, and taking regressive autocorrelation and heterogeneous variance structure into account. The best model maximizes the log(Likelihood) (LogLik) while limiting the degree of freedom (df). We compared multiple criteria to help selection: the Akaike’s information criterion (AIC) corrected or not for small sample size (AICc; n=28), the Bayesian information criterion (BIC) and a Likelihood Ratio Test in comparison to the null model (Likelihood Ratio and p-value). ~ 0 indicates the absence of a random effect on the intercept (~1 elsewhere). + Density | Site indicates a random effect of Site on the slope of density-dependence while + CR | Site indicates a random effect of Site on the slope of culling impact.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Model | df | logLik | AIC | AICc | BIC | LRT | P-value |
| ~ 0 | 6 | 1.47 | 9.06 | 13.06 | 16.13 | - | - |
| ~ 0 + Density | Site | 7 | 5.45 | 3.09 | 8.69 | 11.34 | 7.97 | 0.0048 |
| ~ 1 + Density | Site | 9 | 8.43 | 1.13 | 11.13 | 11.73 | 13.93 | 0.1100 |
| **~ 0 + CR | Site + Density | Site** | **9** | **10.41** | **-2.83** | **7.17** | **7.77** | **17.89** | **0.0005** |
| ~ 1 + CR | Site + Density | Site | 12 | 10.70 | 2.61 | 23.41 | 16.74 | 18.45 | 0.0052 |

**S5. Bootstrap Method for Model Selection and Prediction under Uncertainty.**

We have been confronted with the issue of performing model selection and trend prediction under the fate of uncertainty around the covariate of interest. Indeed, fox densities are estimated with appropriate uncertainty (expressed in 95% confidence interval or standard deviation). A usual method of model selection and prediction from the average of this covariable would have induced a strong bias. Despite the expected increase of imprecision, we chose to apply a bootstrap method on our model selection to avoid a possible misinterpretation of our prediction. This method assuming a normal distribution of uncertainty around the Distance Sampling estimate is explained in “The Ecological Detective” (Hilborn and Mangel 1997, Princeton University Press, UK, p168-171)

1. The explanatory variable of fox density (D) was derived from DISTANCE software with its associated Coefficient of Variation (CV) linked to standard deviation by Sd = CV \* Mean. We sampled the explanatory variable D, following a normal distribution of N[D,Sd(D)]. We derived population growth and culling rate from the sampled values.
2. We performed the same LMM selection used for the averaged variable. Selected models were averaged to extract the coefficient estimate of each effect and its confidence interval. Finally, we extracted the prediction of growth rate variation under variation of densities and culling rates, with the associated standard errors. All results were stored at each step. Bootstrap estimates are given by the arithmetic mean of estimates from each loop, and the variance of the bootstrap estimate is the sum of the square distance between the mean and each loop’s estimates, times a constant of 1/(nb -1)
3. The procedure was repeated 1000 times (nb) and we checked the significance of effects by visualizing the 95% distribution of coefficient estimates given by the loop (Figure S5). The distributions were compared to the average coefficient and its confidence interval. All analyses were run with R.2.15.1 and “AICcmodavg” package (R Developpement Core Team 2012)

Figure S5. Culling impact on red fox population growth rate. Model averaged slope estimates after bootstrap (nb=1000) of annual growth rate trends under continuous variation of a) density (DD), b) annual culling rate (CR), c) culling rate during gestation (CRG), d) culling rate during breeding (CRB) and e) culling rate during dispersal (CRD). Estimates of culling impact are calculated at Density = 1, the site-averaged situation. We compared the observed distribution of bootstrap estimates with those predicted for Density = 0.5, represented by a black point and 95% intervals in segment. Mean and Standard deviation of slope c) to e) are drawn in Fig.4 of the article.



**S6. R Script Files of the presented Statistical Analyses and Figures.**

*###########################################################################*

*#### CULLING IMPACT AND DENSITY-DEPENDENCE on RED FOX POPULATION###########*

*###########################################################################*

*# Nicolas Lieury, IMBE Aix-Marseille University, LBBE University of Lyon, #*

*#######################################################*

setwd("C: ") *# set working directory*

*### I. Import the data file from diverse information sources*

Total<-read.table("Total.txt",h=T)

*# Total.txt is Table S2 containing all information for the analysis*

attach(Total)

*### II. Figure 2 of the paper: compare density and culling rate*

par(mfrow=c(2,3),mar=c(4, 3, 1, 4),cex.axis=1.25)

plot(YEAR[GIC=="DOM"]+0.5,CR[GIC=="DOM"]\*100,axes=FALSE,ylim=c(0,300),xlim=c(2001,2008),type = "h", ylab='', xlab='', bty="n", cex=1.2,lwd=1,lty=1, col="grey")

rect(YEAR[GIC=="DOM"]+0.25,0,YEAR[GIC=="DOM"]+0.75,CR[GIC=="DOM"]\*100, col="grey" )

text(x=2002,y=290,"A",font=2,cex=1.5)

par(new=TRUE)

plot(YEAR[GIC=="DOM"],DENSITY[GIC=="DOM"],axes=FALSE, bty="n", ylim=c(0,3), xlim=c(2001,2008),type = "b", ylab = "", xlab = "", pch = 16, cex=1.5, lwd=2 )

segments(YEAR[GIC=="DOM"],DLIC[GIC=="DOM"], YEAR[GIC=="DOM"], DHIC[GIC=="DOM"] ,col="black" )

axis(2,pos=2001.7,las=1,tck=0.025,cex.lab=2)

mtext("Density (fox/km²)",2,line=1.1,cex=1,font=1)

axis(1, at = 2002:2008, labels = 2002:2008,las=1,tck=0.025)

plot(YEAR[GIC=="FOU"]+0.5,CR[GIC=="FOU"]\*100, axes=FALSE,ylim=c(0,300),xlim=c(2003,2008),type = "h", ylab='', xlab='', bty="n",cex=1.2,lwd=1,lty=1,col="grey" )

rect(YEAR[GIC=="FOU"]+0.25,0,YEAR[GIC=="FOU"]+0.75,CR[GIC=="FOU"]\*100, col="grey" )

text(x=2003,y=290,"B",font=2,cex=1.5)

par(new=TRUE)

plot(YEAR[GIC=="FOU"],DENSITY[GIC=="FOU"],axes=FALSE, bty="n", ylim=c(0,3),xlim=c(2003,2008),type = "b", ylab=" ", xlab = "", pch = 16, cex=1.5,lwd=2)

segments(YEAR[GIC=="FOU"],DLIC[GIC=="FOU"], YEAR[GIC=="FOU"], DHIC[GIC=="FOU"],col="black" )

axis(1,at = 2003:2008, labels = 2003:2008,las=1,tck=0.025)

plot(YEAR[GIC=="VEN"]+0.5,CR[GIC=="VEN"]\*100, axes=FALSE,ylim=c(0,300),xlim=c(2003,2008.5),type = "h", ylab='', xlab='', bty="n", cex=1.2,lwd=1,lty=1,col="grey" )

rect(YEAR[GIC=="VEN"]+0.25,0,YEAR[GIC=="VEN"]+0.75,CR[GIC=="VEN"]\*100, col="grey" )

axis(4,pos=2008.3,las=1,tck=0.025)

mtext("Annual Culling Rate (%)",4,cex=1,line=2,font=1,col="grey30")

text(x=2003,y=290,"C",font=2,cex=1.5)

par(new=TRUE)

plot(YEAR[GIC=="VEN"],DENSITY[GIC=="VEN"],axes=FALSE, bty="n", ylim=c(0,3),xlim=c(2003,2008.5),type = "b",ylab=" ", xlab = "", pch = 16, cex=1.5,lwd=2)

segments(YEAR[GIC=="VEN"],DLIC[GIC=="VEN"], YEAR[GIC=="VEN"], DHIC[GIC=="VEN"],col="black" )

axis(1,at = 2003:2008, labels = 2003:2008,las=1,tck=0.025)

plot(YEAR[GIC=="SAR"]+0.5,CR[GIC=="SAR"]\*100,axes=FALSE, ylim=c(0,300),xlim=c(2005,2012),type = "h", ylab='', xlab='', bty="n", col="grey", lwd=1,lty=1)

rect(YEAR[GIC=="SAR"]+0.25,0,YEAR[GIC=="SAR"]+0.75,CR[GIC=="SAR"]\*100, col="grey" )

text(x=2006,y=285,"D",font=2,cex=1.5)

par(new=TRUE)

plot(c(YEAR[GIC=="SAR"],2012),c(DENSITY[GIC=="SAR"],0.25),axes=FALSE,main="", ylim=c(0,3),xlim=c(2005,2012),type = "b", ylab = "", xlab = "", pch = 16, cex=1.5,lwd=2)

segments(c(YEAR[GIC=="SAR"],2012),c(DLIC[GIC=="SAR"],0.20), c(YEAR[GIC=="SAR"],2012), c(DHIC[GIC=="SAR"],0.31),col="black" )

axis(1,at = 2006:2012, labels = 2006:2012,las=1,tck=0.025)

axis(2,pos=2005.7,las=1,tck=0.025)

mtext("Density (fox/km²)",2,line=1.1,cex=1,font=1)

plot(YEAR[GIC=="BAR"]+0.5,CR[GIC=="BAR"]\*100,axes=FALSE, ylim=c(0,300),xlim=c(2006,2013),type = "h", ylab='', xlab='', bty="n", col="grey", lwd=1,lty=1)

rect(YEAR[GIC=="BAR"]+0.25,0,YEAR[GIC=="BAR"]+0.75,CR[GIC=="BAR"]\*100, col="grey" )

axis(4,pos=2012.75,las=1,tck=0.025) ;mtext("Annual Culling Rate (%)",4,cex=1,line=2,font=1,col="grey30")

text(x=2006,y=285,"E",font=2,cex=1.5)

par(new=TRUE)

plot(c(YEAR[GIC=="BAR"],2012),c(DENSITY[GIC=="BAR"],0.5),axes=FALSE,main="", ylim=c(0,3),xlim=c(2006,2013),type = "b", ylab = "", xlab = "", pch = 16,cex=1.5,lwd=2)

segments(c(YEAR[GIC=="BAR"],2012),c(DLIC[GIC=="BAR"],0.42), c(YEAR[GIC=="BAR"],2012),c(DHIC[GIC=="BAR"],0.6),col="black" )

axis(1,at = 2006:2012, labels = 2006:2012,las=1,tck=0.025)

*### III. Linear Mixed modelling*

library(AICcmodavg)

library(mgcv)

library(nlme)

*## III.1 Data exploration*

*# Heterogeneity of variance*

par(mfrow=c(1,3))

boxplot(LAMBDA~GIC,varwidth=T, ylab="Population growth rate",xlab="Site",cex.lab=1.5,font.lab=2) *# heterogeneity of variance between GIC*

boxplot(DENSITY~GIC,varwidth=T, ylab="Pop density",xlab="Site",cex.lab=1.5,font.lab=2) *# heterogeneity of variance between GIC*

boxplot(CR~GIC,varwidth=T, ylab="Culling rate",xlab="Site",cex.lab=1.5,font.lab=2) *# heterogeneity of variance between GIC*

*#strong heterogeneity between GIC*

*# Check variable distribution and outliers*

par(mfrow=c(2,2))

dotchart(CR, main="CR")

dotchart(DENSITY,main="DENSITY")

dotchart(log(CR), main="logCR")

dotchart(log(DENSITY),main="logDENSITY")

dotchart(CR1, main="CRG")

dotchart(CR2,main="CRB")

dotchart(CR3,main="CRD")

dotchart(DENSITY,main="DENSITY")

*# Heterogeneity in explanatory variable distribution but inefficient log as weak interval*

*# Check for multicollinearity*

source("C:/Users/etu-devillard/Documents/7. LOGICIELS/R/HighstatLibV6.R") *# Source code available from Zuur et al 2009*

pairs(Total[,c(9,11,26,27,28,29)],upper.panel=panel.smooth2,lower.panel=panel.cor,cex.labels=1.5)

*# high correlation between CR variable*

library(AED)

corvif(Total[,c(11,26)]) *## VIF <3 no problem of important correlation between CR and Density*

corvif(Total[,c(11,27,28,29)]) *## CRG>3 highly correlated with other covariables*

corvif(Total[,c(11,28,29)]) *## No more issue when CRG removed*

corvif(Total[,c(11,27,28)]) *## Collinearity issue between CRG and CRD*

*## III.2 Annual culling impact: Apply model selection procedure of 5.10.1 of Zuur et al 2009*

*# III.2.1 the complete linear model*

M.lm<-lm(LAMBDA~CR+GIC+DENSITY+CR\*DENSITY,data=Total) *# both culling rate and density could influence population growth rate !*

plot(cooks.distance(M.lm),type="h")

text(cooks.distance(M.lm),labels=names(cooks.distance(M.lm)),pos=3,offset=0.1,cex=0.5)

*# strong outliers in FOU; check at the end of the process that they do not influence the result*

par(mfrow=c(2,2))

plot(M.lm) *# problem of plot repartition and indepence*

E2 <- resid(M.lm)

F2 <- fitted(M.lm)

op <- par(mfrow = c(1, 3), mar = c(4, 4, 3, 2))

MyYlab <- "Residuals"

boxplot(E2 ~ GIC, data = Total,main = "GIC", ylab = MyYlab)

*# strong heterogeneity between GIC*

plot(x = CR, y = E2, ylab = MyYlab,xlab = "Culling rate")

*# inegal repartition of explanatory variable*

abline(lm(E2~CR),lty=2)

lines(seq(min(CR),max(CR),length.out=100),predict(loess(formula=E2~CR),newdata=data.frame(CR=seq(min(CR),max(CR),length.out=100))))

plot(x = DENSITY, y = E2, ylab = MyYlab, xlab = "Fox density")

abline(lm(E2~DENSITY),lty=2)

lines(seq(min(DENSITY),max(DENSITY),length.out=100),predict(loess(formula=E2~DENSITY),newdata=data.frame(DENSITY=seq(min(DENSITY),max(DENSITY),length.out=100))))

*### GIC can be a random effect as it increase dof, we are not interested in GIC effect*

*# III.2.2 Choose the right variance structure*

library(nlme)

Form <- formula(LAMBDA~CR+DENSITY+GIC+CR\*DENSITY)

M.gls <- gls(Form, data = Total)

vf0 <- varIdent(form= ~ 1 | site)

M.gls0 <- gls(Form, data=Total, weights = vf0)

anova(M.gls, M.gls0) *#not better*

vf1 <- varIdent(form= ~ 1 | GIC)

M.gls1 <- gls(Form, data=Total, weights = vf1)

anova(M.gls, M.gls1) *#not better*

vf2 <- varFixed(~ CR)

M.gls2 <- gls(Form, data=Total, weights = vf2)

anova(M.gls, M.gls2) *#not better*

vf3 <- varFixed(~ DENSITY)

M.gls3 <- gls(Form, data=Total, weights = vf3)

anova(M.gls, M.gls3) *#a little better*

vf4 <- varPower(form= ~ CR | GIC)

M.gls4 <- gls(Form, data=Total, weights = vf4)

anova(M.gls, M.gls4) *#not better*

vf5 <- varPower(form= ~ DENSITY | GIC)

M.gls5 <- gls(Form, data=Total, weights = vf5)

anova(M.gls, M.gls5) *#not better*

vf6 <- varComb(varFixed(~ DENSITY) , varFixed(~ CR) )

M.gls6 <- gls(Form, data=Total, weights = vf6)

anova(M.gls, M.gls6) *#not better*

*# III.2.3 Choose the right autocorrelation structure*

M.gls<-gls(LAMBDA~CR+DENSITY+GIC+CR\*DENSITY,weights = vf3, data=Total)

E <- residuals(M.gls, type = "normalized")

par(mfrow = c(1, 5))

E1 <- E[GIC == "DOM"]

E2 <- E[GIC == "FOU"]

E3 <- E[GIC == "VEN"]

E4 <- E[GIC == "BAR"]

E5 <- E[GIC == "SAR"]

acf(E1, na.action = na.pass,main="DOM")

acf(E2, na.action = na.pass,main="FOU")

acf(E3, na.action = na.pass,main="VEN")

acf(E4, na.action = na.pass,main="BAR")

acf(E5, na.action = na.pass,main="SAR")

M.gls7 <- gls(LAMBDA~CR+DENSITY+GIC+CR\*DENSITY,data=Total,weights = vf3, correlation=corCompSymm(form=~1|GIC))

anova(M.gls, M.gls7) *#not better*

M.gls8 <- gls(LAMBDA~CR+DENSITY+GIC+CR\*DENSITY,data=Total,weights = vf3, correlation=corAR1(form=~1|GIC))

anova(M.gls, M.gls8) *# strong improve !*

*# III.2.4 Choose the right random structure: GIC as random effect !*

lmc <- lmeControl(maxIter = 50000, msMaxIter = 50000,niterEM=25000,msMaxEval=200000)

FORM <- formula(LAMBDA~CR+DENSITY+CR\*DENSITY)

MGLS<-gls(LAMBDA~CR+DENSITY+CR\*DENSITY,data=Total,method = "REML",control=lmc,weights = vf3, correlation=corAR1(form=~1|GIC))

M2.lme <- lme(FORM, random = ~ 0 + DENSITY | GIC,method = "REML", data = Total, control=lmc,weights = vf3, correlation=corAR1(form=~1|GIC))

anova(MGLS, M2.lme)

M3.lme <- lme(FORM, random = ~ 1 + DENSITY | GIC,method = "REML",data = Total, control=lmc,weights = vf3, correlation=corAR1(form=~1|GIC))

anova(MGLS, M3.lme)

M4.lme <- lme(FORM, random = ~ 0 + CR | GIC,method = "REML", data = Total, control=lmc,weights = vf3, correlation=corAR1(form=~1|GIC))

anova(MGLS, M4.lme)

M5.lme <- lme(FORM, random = ~ 1+ CR|GIC,method = "REML",data = Total, control=lmc,weights = vf3, correlation=corAR1(form=~1|GIC))

anova(MGLS, M5.lme)

M6.lme <- lme(FORM, random = ~ 0+ CR +DENSITY|GIC,method = "REML",data = Total, control=lmc,weights = vf3, correlation=corAR1(form=~1|GIC))

anova(MGLS, M6.lme)

M7.lme <- lme(FORM, random = ~ 1+ CR +DENSITY|GIC,method = "REML",data = Total, control=lmc,weights = vf3, correlation=corAR1(form=~1|GIC))

anova(MGLS, M7.lme)

anova(MGLS, M2.lme, M3.lme, M6.lme, M7.lme)

*# if we remove variance and autocorrelation structure to improve convergence:*

M6.lmeb <- lme(FORM, random = ~ 0+ CR +DENSITY|GIC,method = "REML",data = Total, control=lmc, correlation=corAR1(form=~1|GIC))

anova(M6.lme, M6.lmeb)

*# removing variance structure is not problematic and it should improve algorithm convergence*

M6.lmec <- lme(FORM, random = ~ 0+ CR +DENSITY|GIC,method = "REML",data = Total, control=lmc)

anova(M6.lme, M6.lmec)

*# removing autocorrelation structure is not a possibility*

*# III.2.5 Selected best fixed model using ML*

M.Full <- lme(LAMBDA~CR+DENSITY+CR\*DENSITY,random = ~ 0 + CR + DENSITY| GIC, method = "ML", data = Total,control=lmc, correlation=corAR1(form=~1|GIC))

M.A <- lme(LAMBDA~CR+DENSITY,random = ~ 0 + CR + DENSITY| GIC, method = "ML", data = Total, control=lmc, correlation=corAR1(form=~1|GIC))

M.B <- lme(LAMBDA~CR,random = ~ 0 + CR + DENSITY| GIC, method = "ML", data = Total, control=lmc, correlation=corAR1(form=~1|GIC))

M.C <- lme(LAMBDA~DENSITY,random = ~ 0 + CR + DENSITY| GIC, method = "ML", data = Total, control=lmc, correlation=corAR1(form=~1|GIC))

anova(M.Full,M.A)

summary(M.A)

summary(M.Full)

AIC(M.A)-AIC(M.Full)

AIC(M.B)-AIC(M.Full)

*# model validation*

par(mfrow=c(1,2))

E2 <- resid(M6.lme)

F2 <- fitted(M6.lme)

MyYlab <- "Residuals"

plot(x = F2, y = E2, xlab = "Fitted values", ylab = MyYlab)

abline(lm(E2~F2),lty=2)

qqnorm(M6.lme, abline = c(0, 1))

*# III.2.6 Model predictions using REML: Figure 3 of the paper*

M6.lme <- lme(LAMBDA~CR+DENSITY+CR\*DENSITY, random = ~ 0+ CR +DENSITY|GIC,method = "REML",data = Total,control=lmc, correlation=corAR1(form=~1|GIC))

coef(M6.lme)

summary(M6.lme)

library(AICcmodavg)

par(mfrow=c(1,3),mar=c(5, 5, 1, 1))

xv<-seq(0,2,0.1);yv<-seq(0,3,0.1)

newdata1 <-expand.grid(CR=0,DENSITY=yv,GIC=levels(factor(GIC)))

F20 <- predictSE.lme(M6.lme,newdata1, level = 0)

F21 <- predict(M6.lme,newdata1, level = 1)

fit2<-cbind(newdata1,F20$fit,F20$se.fit,F21)

fit2$DKratio<-c(rep(4,31),rep(5,31),rep(3,31),rep(2,31),rep(1,31))

names(fit2)<-c("CR","DENSITY","GIC","F20","F20se","F21","DK")

plot(fit2$DENSITY[fit2$GIC=="DOM"], fit2$F20[fit2$GIC=="DOM"], las=1,tck=0.025,cex.lab=2,cex.axis=1.5,font.lab=1,bty="n",lwd = 5, type = "l", ylim=c(0.55,1.8),ylab = "Annual population growth rate", xlab = "Density (fox/km²)")

abline(a=1,b=0,lty=4)

for (i in 1:5){

x1 <- fit2$DENSITY[fit2$DK == i]

y1 <- fit2$F21[fit2$DK == i]

K <- order(x1)

lines(sort(x1), y1[K],lty=1,lwd=2,col=colors()[261+(i\*15)])

}

lines(fit2$DENSITY[fit2$GIC=="DOM"],fit2$F20[fit2$GIC=="DOM"]+fit2$F20se[fit2$GIC=="DOM"],lwd=3,lty=3)

lines(fit2$DENSITY[fit2$GIC=="DOM"],fit2$F20[fit2$GIC=="DOM"]-fit2$F20se[fit2$GIC=="DOM"],lwd=3,lty=3)

text(x=0,y=1.75,"a)",font=1,cex=1.5)

text(x=2.65,y=1.75,"Culling=0",font=3,cex=1.5)

text(x=2.9,y=0.7,"A",font=3,cex=1)

text(x=2.9,y=1.420,"B",font=3,cex=1)

text(x=2.8,y=0.6,"C",font=3,cex=1)

text(x=1.475,y=0.6,"D",font=3,cex=1)

text(x=1.7,y=0.6,"E",font=3,cex=1)

newdata2 <-expand.grid(CR=xv,DENSITY=mean(DENSITY),GIC=levels(factor(GIC)))

F10 <- predictSE.lme(M6.lme,newdata2, level = 0)

F11 <- predict(M6.lme,newdata2, level = 1)

fit1<-cbind(newdata2,F10$fit,F10$se.fit,F11)

fit1$K<-c(rep(4,21),rep(5,21),rep(3,21),rep(2,21),rep(1,21))

names(fit1)<-c("CR","DENSITY","GIC","F10","F10se","F11","K")

plot(fit1$CR[fit1$GIC=="DOM"]\*100, fit1$F10[fit1$GIC=="DOM"], lwd = 5, las=1,tck=0.025,cex.lab=2,cex.axis=1.5,font.lab=1,bty="n",type = "l", ylim=c(0.55,1.8),ylab = "", xlab = "Annual culling rate (%)")

abline(a=1,b=0,lty=4)

for (i in 1:5){

x1 <- fit1$CR[fit1$K == i]\*100

y1 <- fit1$F11[fit1$K == i]

K <- order(x1)

lines(sort(x1), y1[K],lty=1,lwd=2,col=colors()[261+(i\*15)])

}

lines(fit1$CR[fit1$GIC=="DOM"]\*100,fit1$F10[fit1$GIC=="DOM"]+fit1$F10se[fit1$GIC=="DOM"],lwd=3,lty=3)

lines(fit1$CR[fit1$GIC=="DOM"]\*100,fit1$F10[fit1$GIC=="DOM"]-fit1$F10se[fit1$GIC=="DOM"],lwd=3,lty=3)

text(x=0,y=1.75,"b)",font=1,cex=1.5)

text(x=172,y=1.75,"Density=1",font=3,cex=1.5)

newdata3 <-expand.grid(CR=xv,DENSITY=0.5,GIC=levels(factor(GIC)))

F30 <- predictSE.lme(M6.lme,newdata3, level = 0)

F31 <- predict(M6.lme,newdata3, level = 1)

fit3<-cbind(newdata3,F30$fit,F30$se.fit,F31)

fit3$K<-c(rep(4,21),rep(5,21),rep(3,21),rep(2,21),rep(1,21))

names(fit3)<-c("CR","DENSITY","GIC","F30","F30se","F31","K")

plot(fit3$CR[fit3$GIC=="DOM"]\*100, fit3$F30[fit3$GIC=="DOM"], lwd = 5, las=1,tck=0.025,cex.lab=2,cex.axis=1.5,font.lab=1,bty="n",type = "l", ylim=c(0.55,1.8),ylab = "", xlab = "Annual culling rate (%)")

abline(a=1,b=0,lty=4)

for (i in 1:5){

x1 <- fit3$CR[fit3$K == i]\*100

y1 <- fit3$F31[fit3$K == i]

K <- order(x1)

lines(sort(x1), y1[K],lty=1,lwd=2,col=colors()[261+(i\*15)])}

lines(fit3$CR[fit3$GIC=="DOM"]\*100,fit3$F30[fit3$GIC=="DOM"]+fit3$F30se[fit3$GIC=="DOM"],lwd=3,lty=3)

lines(fit3$CR[fit3$GIC=="DOM"]\*100,fit3$F30[fit3$GIC=="DOM"]-fit3$F30se[fit3$GIC=="DOM"],lwd=3,lty=3)

text(x=0,y=1.75,"c)",font=1,cex=1.5)

text(x=170,y=1.75,"Density=0.5",font=3,cex=1.5)

**R code for the bootstrap analysis is available from the authors.**