Red Foxes in BC: an Analysis of the Spatial Point Process

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Introduction

For our Data 589 project, we have selected Red Fox (Scientific Name - Vulpes Vulpes) to do the analysis. In the GBIF database they have approximately, 610,958+ georeferences records for this species around the world, however for this project we have selected to do the analysis of the occurance of Red Fox in BC only. So with the above function we have fetched the information for British Columbia only in 127 columns and 242 number of entries.

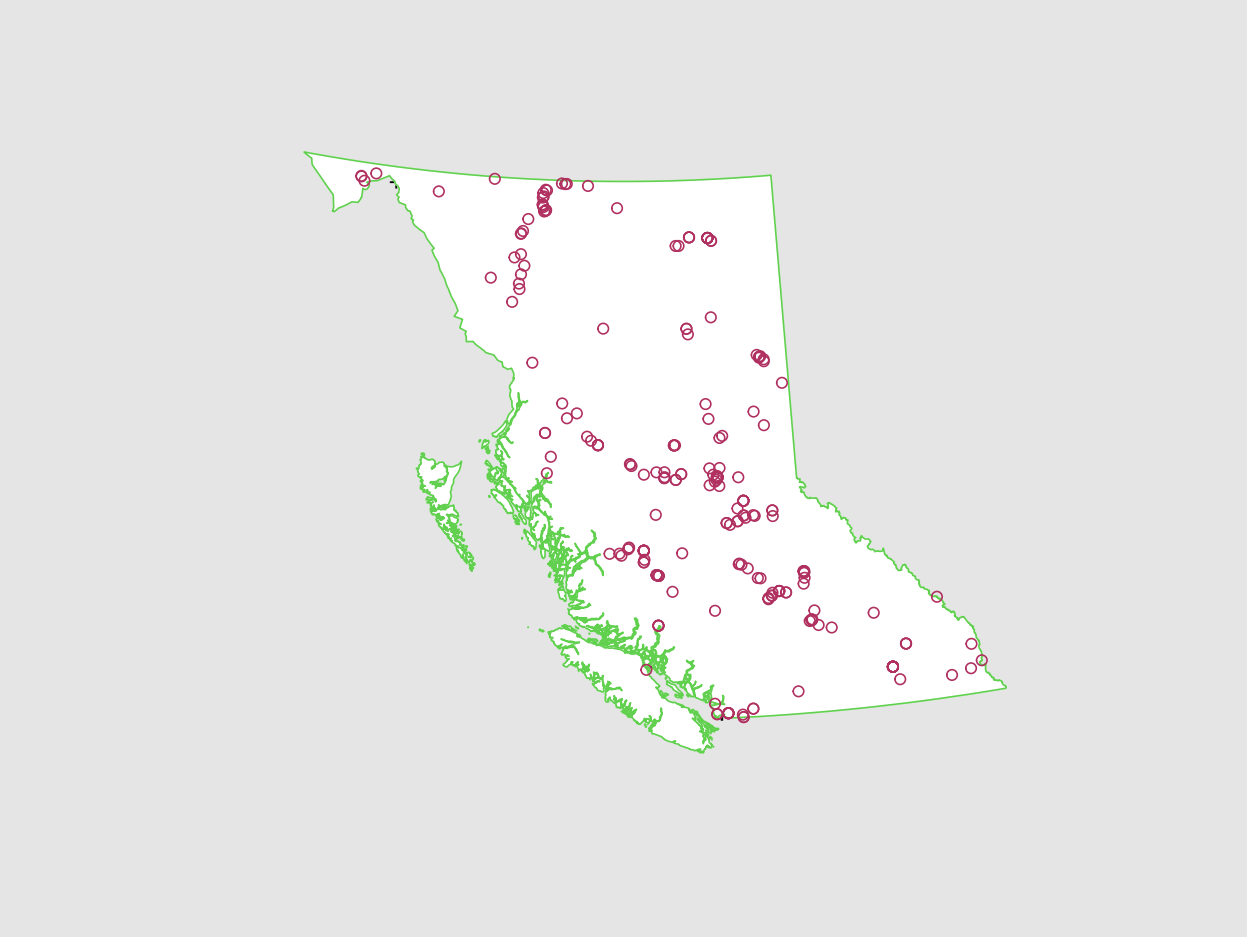


Figure 1: Occurence of Red Foxes in BC

Here we have plotted all the occurrences of Red Fox in the BC region and we can see that the species are scattered in the region specially in the upper and middle part of the province. Now we will be exploring what

is contributing to the occurrences of the species in the specific places based on various factors like elevation, close to water bodies, forests, human habitats, etc.

Methods

Briefly describe the data and what variables are included. Provide a detailed description of the analytical workflow that was applied to the data, citing any relevant literature and statistical packages employed. There should be enough information that anyone can reproduce the workflow if they had access to the data. Length: As long as necessary.

The data comes from the Global Biodiversity Information Facility (GBIF) databases. We used the package `rgbif` to access the 'Vulpes Vulpes' data from R directly, sorting by instances occuring in BC. We've extracted the longitude and latitude data from this, and converted it appropriately using the `sp` package.

Our second source of data contained the BC Window object, as well as possible covariate data: elevation, forest cover, Human Footprint Index (HFI) and distance to water.

We used the package `spatstat` to build a `ppp` object with the converted coordinates of the Red Fox locations from the GBIF data and the window from our second data source.

To conduct first moment analysis, we used functions from the aforementioned `spatstat` package. We did a quadrat test as well as hotspot analysis to gain insight into the homogeneity assumption of the point process.

For second moment analysis, we looked into Ripley's K-function and pair correlation function using functions from `spatstat`. This provides us with insight into possible clustering tendencies of the point process.

Next we looked into the relationship of the intensity with each covariate.

Results

Exploratory Analysis (First Moment till Covariates & basic individual models)

First Moment Analysis

Quadratcount

We start with investigating whether the occurence of red foxes in BC seems homogeneous, as it will inform our steps to define the intensity. We have conducted a quadrat test of homogeneity with both 5 x 5 and 10 x 10 quadrats. These quadrats are shown in Figure 2, where we can visually tell that the intensity in each quadrats are not the same. The quadrat test for both the 5 x 5 and the 10 x 10 quadrats provide a p-value of 2.2e-16, confirming that the varied intensities are not due to chance alone, but rather due to an inhomogeneous point process.

Hot spot analysis

As the next step, we investigate analyze for any hot spots in the occurences of red foxes. In Figure 3, we can see that hotspots appear scattered around the province.

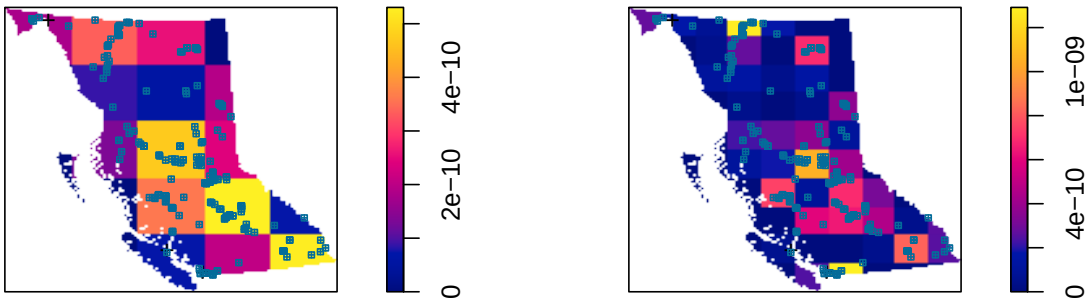


Figure 2: Intensity of Quadrat counts of Red Fox occurences, left 5x5, right 10x10

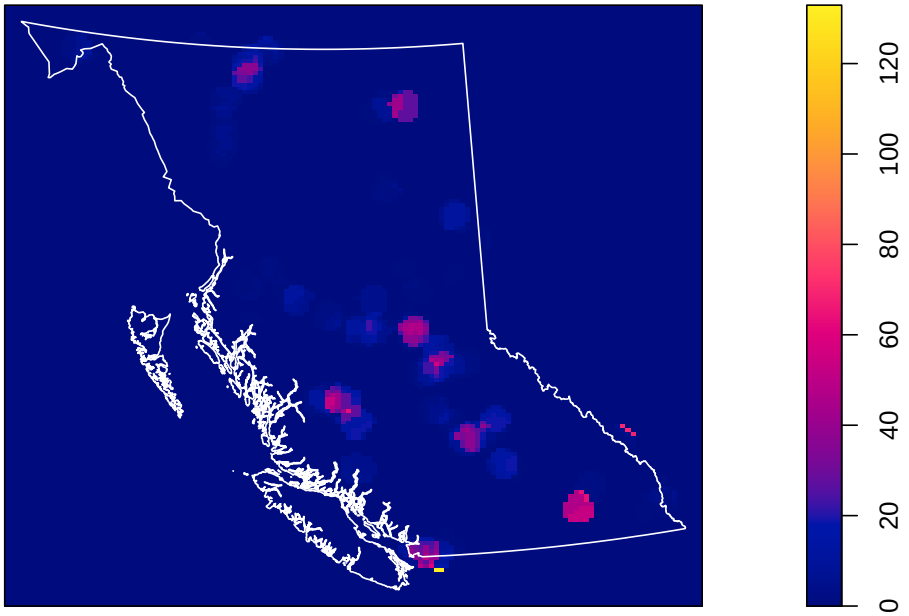


Figure 3: Hotspot of Red Foxes

2nd Moment Analysis

Ripley's K function

Ripley's K-function provides information on whether there are significant deviations from independence between points. Taking into account that the intensity of red fox occurences appear inhomogeneous, we can see in Figure 4 that there is some evidence of clustering up to a certain distance, as the black line, indicating the observed data, is separate from the 95% confidence bands of the values expected with no clustering. This suggests that the relationship between points may be due to effects between points rather than relationship with covariates. [CHECK THIS CLAIM ?]

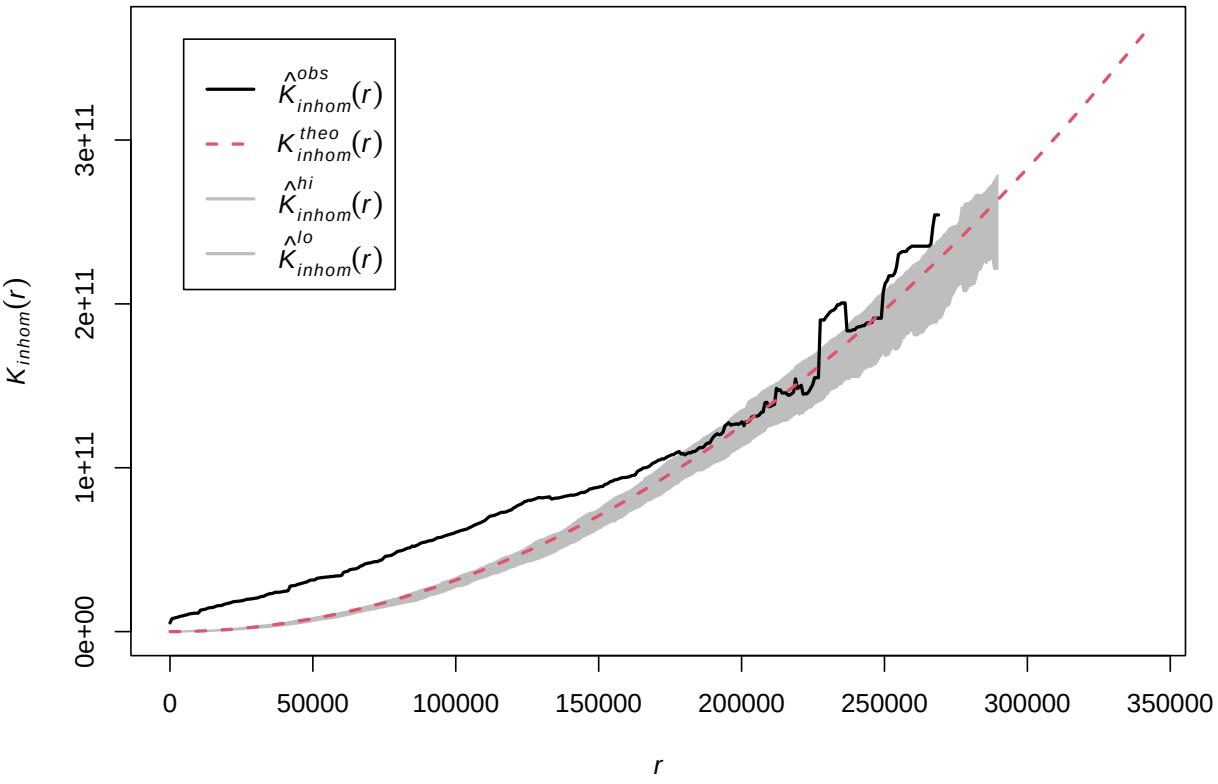


Figure 4: Ripley's K function with border correction assuming inhomogeneity

Pair correlation function

To get a sense of the distances for which clustering occurs, we used the pair correlation function. Figure 5 shows evidence for clustering at distances smaller than around 23 000m, or 23km but after that the observed values are not significantly different that those expected from a random spatial process.

```
## Generating 19 simulations by evaluating expression  ...
## 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18,  19.
##
## Done.
```

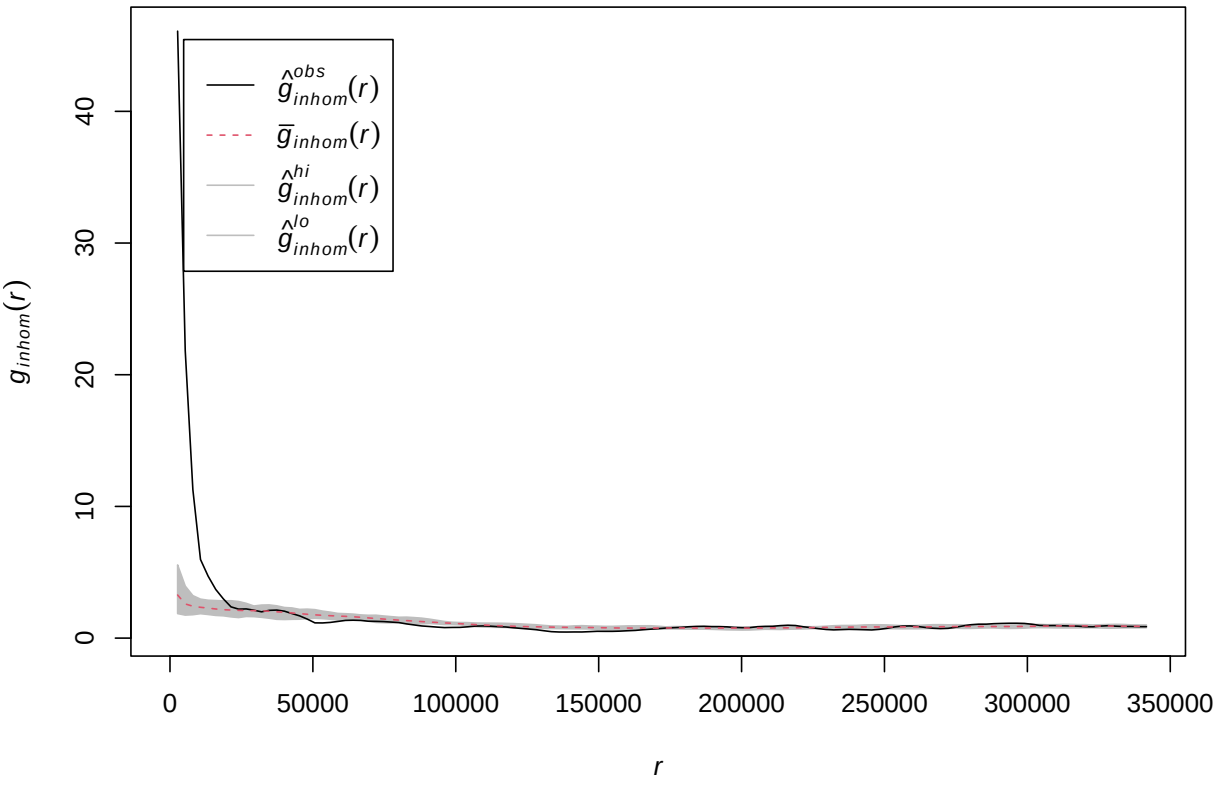
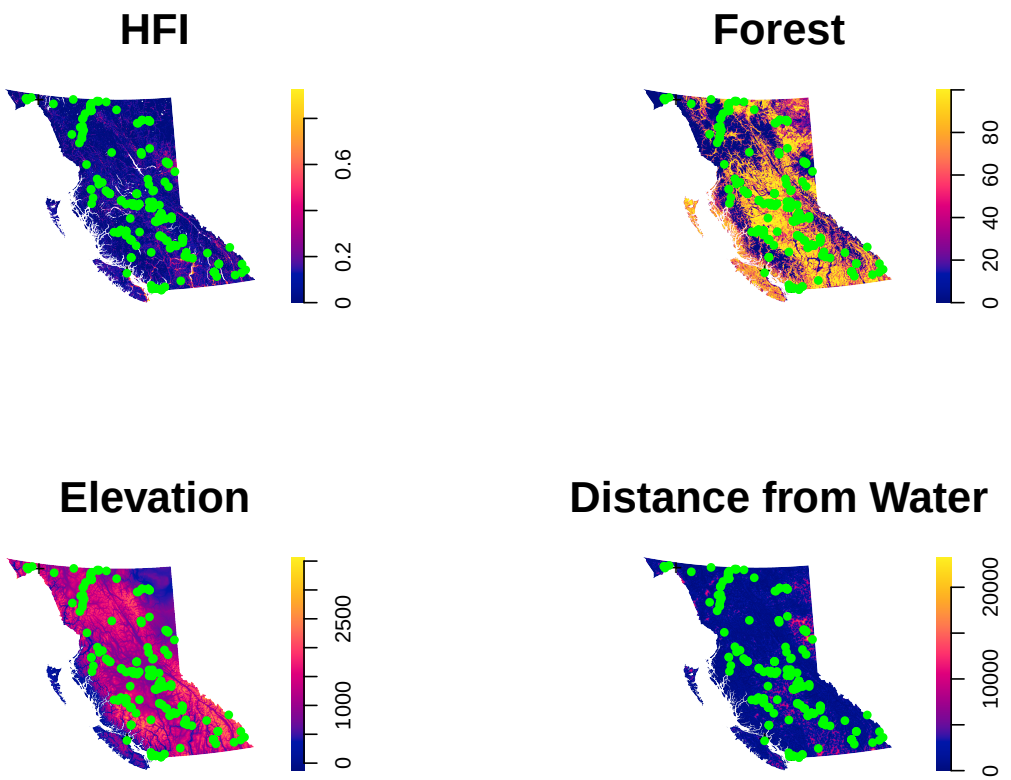


Figure 5: Pair correlation function assuming inhomogeneity

Relationship with Covariates

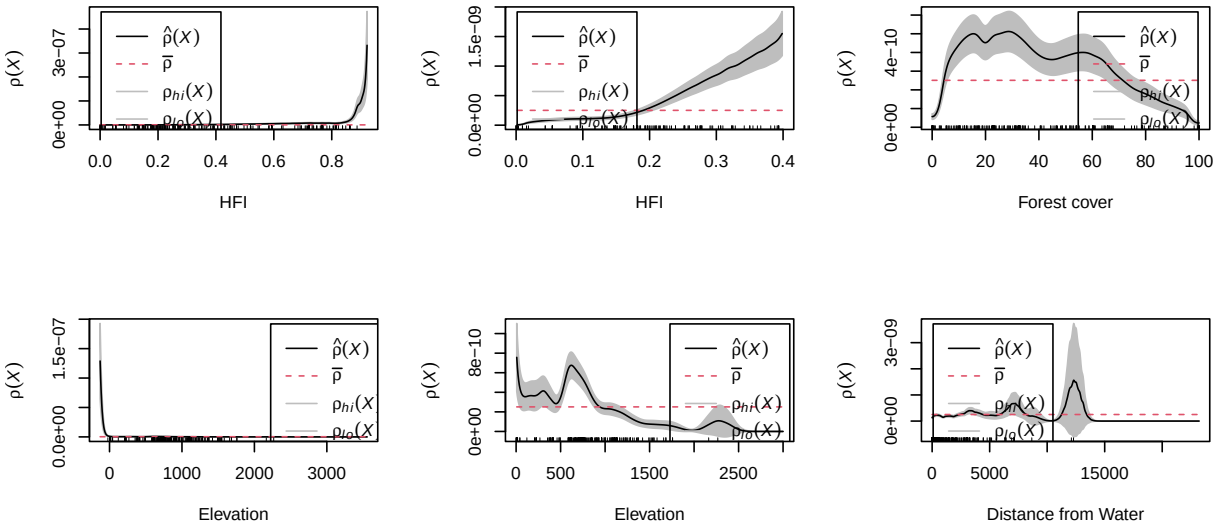
Our data includes 4 covariates which we are exploring: the elevation, the forest cover, the human footprint inventory (HFI), and the distance to water. Given our research questions, we will start with investigating the HFI and the forest cover.

Plotting Red Fox wrt HFI, Forest, Elevation, Distance to Water



Here we see the red fox is seen more in the averagely densed population area and near highly densed forest area. In case of elevation, red foxes are seen in moverately elevated area and where the distance to water is low to medium.

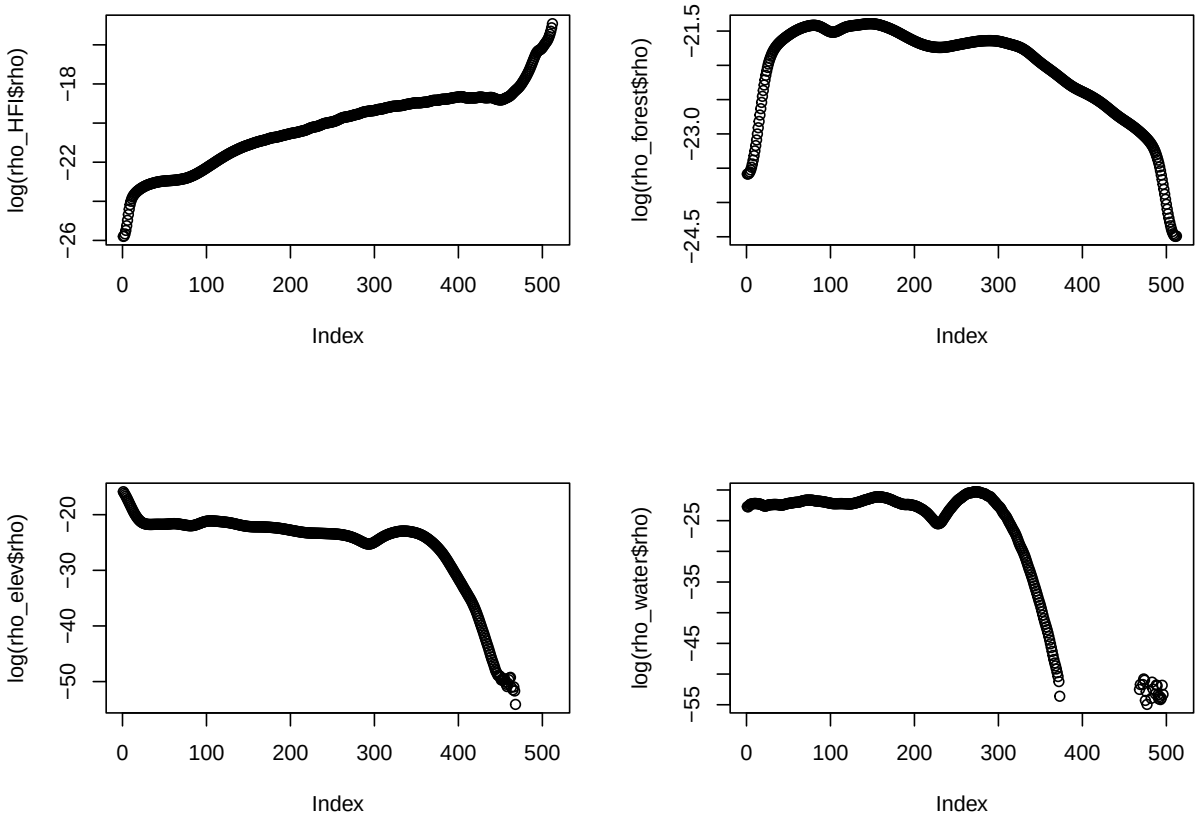
Smoothing Estimate of the 4 Covariates Transformation



In the first figure for HFI, we could be fooled into thinking that there is no relationship up to around HFI = 0.4, until which it seems like an exponential relationship. However, zooming in from HFI 0 to 0.4, we see that the confidence bands don't intersect at all with the red line, which is the expected value given no relationship. This relationship appears non-linear and possibly exponential, where the greatest intensity of observed red foxes occurs at high HFIs. This relationship was expected, as our dataset is not exhaustive but rather is crowdsourced, and naturally foxes are more likely to be noticed by humans in spaces with higher HFIs.

Regarding forest cover we can observe that there seems to be non-linear relationship between forest cover and number of red foxs observed. The observance increase with increase in forest cover at intermediate coverage and then it decreases. Next is to observe if there is any correlation between the covariates (collinearity in the covariates dataset). This is necessary to avoid any identifiability issues in modeling the data.

Regarding the elevation, we see that there seems to be no relationship but after taking a closer look we see that there is non-linear relationship between elevation and the occurance of red foxes. The relationship appears to be non-linear as the graph is showing different results for different elevation and we cannot see any type of specific pattern from the same. In case of Distance to Water, we can observe from the above figure with red fox occurance with Distance to Water that there is non liner relationship between the two.



If we plot the log of the rho, we get a line that could be reasonably interpreted as linear for HFI however the plots for other covariets deosnt seem linear.

Fit models for the covariets

```
## Nonstationary Poisson process
## Fitted to point pattern dataset 'parks_ppp'
##
## Log intensity:  ~HFI
##
## Fitted trend coefficients:
## (Intercept)         HFI
##   -23.31421     5.98177
##
##               Estimate      S.E.    CI95.lo    CI95.hi Ztest       Zval
## (Intercept) -23.31421 0.1058336 -23.521645 -23.106785   *** -220.29132
## HFI           5.98177 0.2148471   5.560677   6.402862   ***   27.84199
## Problem:
##  Values of the covariate 'HFI' were NA or undefined at 0.56% (12 out of 2137)
## of the quadrature points

## Nonstationary Poisson process
## Fitted to point pattern dataset 'parks_ppp'
```

```
##
## Log intensity:  ~HFI + exp(HFI)
##
## Fitted trend coefficients:
## (Intercept)         HFI    exp(HFI)
##   -13.71641    22.17067   -10.35893
##
##              Estimate     S.E.   CI95.lo    CI95.hi Ztest      Zval
## (Intercept) -13.71641 1.404309 -16.46881 -10.964015   *** -9.767372
## HFI          22.17067 2.382441  17.50117  26.840165   ***  9.305861
## exp(HFI)    -10.35893 1.522442 -13.34286  -7.374997   *** -6.804153
## Problem:
##  Values of the covariate 'HFI' were NA or undefined at 0.56% (12 out of 2137)
## of the quadrature points

## Nonstationary Poisson process
## Fitted to point pattern dataset 'parks_ppp'
##
## Log intensity:  ~Forest + I(Forest^2)
##
## Fitted trend coefficients:
##   (Intercept)        Forest   I(Forest^2)
## -2.225373e+01  3.996522e-02 -5.280288e-04
##
##                  Estimate         S.E.       CI95.lo       CI95.hi Ztest
## (Intercept) -2.225373e+01 1.330469e-01 -2.251450e+01 -2.199297e+01   ***
## Forest       3.996522e-02 7.091557e-03  2.606603e-02  5.386442e-02   ***
## I(Forest^2) -5.280288e-04 7.699618e-05 -6.789385e-04 -3.771191e-04   ***
##                    Zval
## (Intercept) -167.262353
## Forest         5.635606
## I(Forest^2)   -6.857857

## Nonstationary Poisson process
## Fitted to point pattern dataset 'parks_ppp'
##
## Log intensity:  ~Elevation
##
## Fitted trend coefficients:
##   (Intercept)     Elevation
## -20.775522387  -0.001401046
##
##                  Estimate         S.E.       CI95.lo       CI95.hi Ztest
## (Intercept) -20.775522387 0.1298745141 -21.030071757 -20.520973016   ***
## Elevation    -0.001401046 0.0001421902  -0.001679734  -0.001122358   ***
##                    Zval
## (Intercept) -159.966122
## Elevation     -9.853321

## Nonstationary Poisson process
## Fitted to point pattern dataset 'parks_ppp'
##
## Log intensity:  ~Dist_Water
```

```
##
## Fitted trend coefficients:
##   (Intercept)    Dist_Water
## -2.211986e+01  1.071969e-05
##
##                  Estimate         S.E.       CI95.lo       CI95.hi Ztest
## (Intercept) -2.211986e+01 8.745074e-02 -2.229126e+01 -2.194846e+01   ***
## Dist_Water   1.071969e-05 3.419673e-05 -5.630466e-05  7.774404e-05
##                     Zval
## (Intercept) -252.9408319
## Dist_Water     0.3134712
```

We have fitted 6 models and we came to observe that HFI, exp(HFI), Forest, I(Forest^2) and elevation seems to be highly significant however Distance to Water seems to be in-significant for the occurrence of red foxes in the BC area.

```
## [1] 10468.83
```

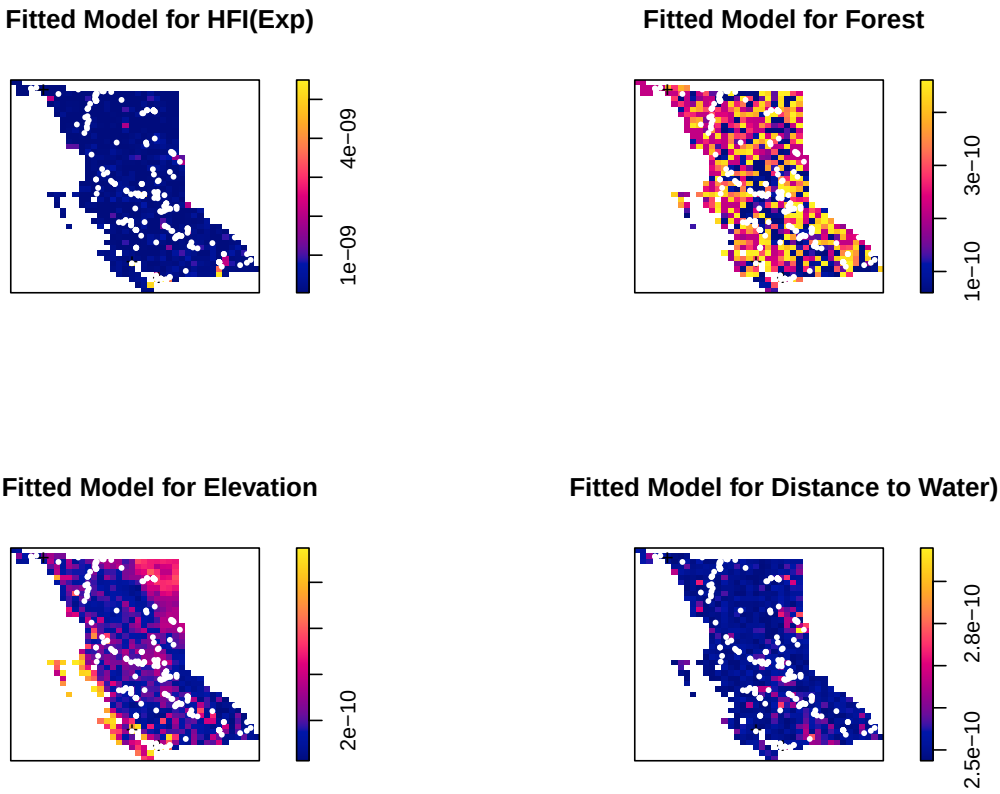
```
## [1] 10420.78
```

```
## [1] 10931.26
```

```
## [1] 10896.99
```

```
## [1] 11000.3
```

Plot the fitted models



Does not look like a good fit for all points in forest and also not easy to interpret. Here Elevation is significant but Dist to Water is not significant.

2. Checking collinearity

```
##             ..1         ..2         ..3         ..4
## ..1  1.00000000  0.06616335 -0.26217406  0.04822162
## ..2  0.06616335  1.00000000 -0.26625709  0.13249159
## ..3 -0.26217406 -0.26625709  1.00000000 -0.03497584
## ..4  0.04822162  0.13249159 -0.03497584  1.00000000
```

We see that no covariate is strongly collinear with another, and so we can move on without taking so into account and treating the covariates as independent.

3. Finalize and summarize about other two variables - elevation and water.

Elevation is significant so that is included in the model.

##End of EDA and covariates analysis

Model Fitting

From our assessment on individual covariates, we see that there is non-linear relationship between the covariates and the red fox point data. Based on this knowledge, we move forward to fit the first base model with covariates that are showing strong trend with red fox data and also of research interest. For this purpose, the selected covariates are 1. Elevation 2. HFI and 3. Forest Cover.

`ppm` function from `spatstat` package is used for building the model using the `ppp` object and linear and quadratic terms of *Elevation*, HFI and *Forest*. We call this model as *model*1.

```
## Nonstationary Poisson process
## Fitted to point pattern dataset 'parks_ppp'
##
## Log intensity:  ~Forest + I(Forest^2) + HFI + I(HFI^2) + Elevation +
## I(Elevation^2)
##
## Fitted trend coefficients:
##    (Intercept)         Forest    I(Forest^2)            HFI       I(HFI^2)
##  -2.413811e+01   6.206401e-03  -1.160232e-04   1.185642e+01  -7.371997e+00
##      Elevation I(Elevation^2)
##   1.364005e-03  -9.678328e-07
##
##                      Estimate         S.E.       CI95.lo       CI95.hi Ztest
## (Intercept)    -2.413811e+01 3.220178e-01 -2.476925e+01 -2.350696e+01   ***
## Forest          6.206401e-03 7.444014e-03 -8.383599e-03  2.079640e-02
## I(Forest^2)    -1.160232e-04 7.767304e-05 -2.682596e-04  3.621315e-05
## HFI             1.185642e+01 1.088713e+00  9.722583e+00  1.399026e+01   ***
## I(HFI^2)       -7.371997e+00 1.232831e+00 -9.788301e+00 -4.955694e+00   ***
## Elevation       1.364005e-03 5.226588e-04  3.396126e-04  2.388397e-03    **
## I(Elevation^2) -9.678328e-07 2.819525e-07 -1.520449e-06 -4.152160e-07   ***
##                       Zval
## (Intercept)    -74.9589241
## Forest           0.8337439
## I(Forest^2)     -1.4937385
## HFI             10.8903097
## I(HFI^2)        -5.9797320
## Elevation        2.6097427
## I(Elevation^2)  -3.4326094
## Problem:
##  Values of the covariate 'HFI' were NA or undefined at 0.56% (12 out of 2137)
## of the quadrature points
```

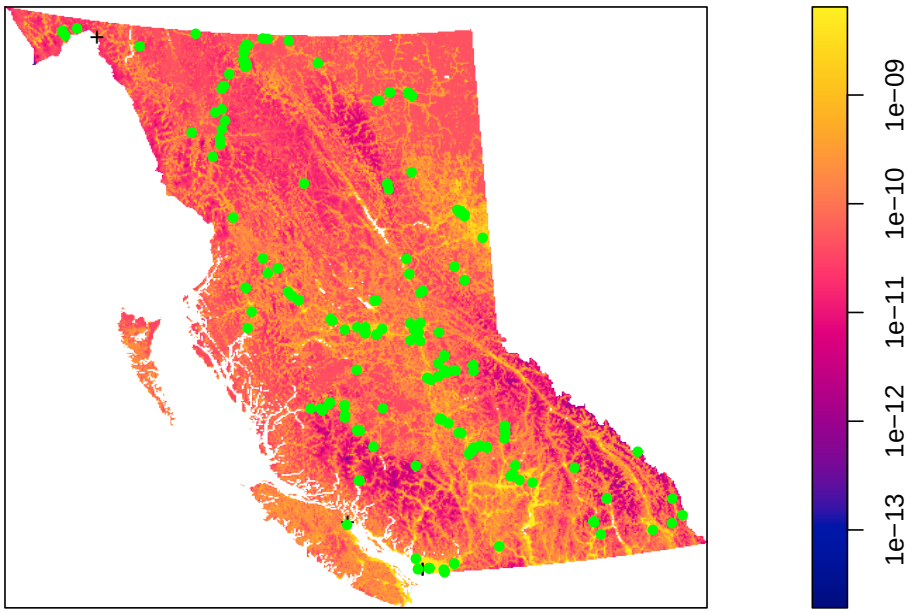
The results indicate that covariates HFI and *Elevation* show strong significance and explain occurrence of red fox data in either linear or quadratic terms. Though forest cover showed non-linear relationship in second moment analysis, in this combined model with other covariates, its not significant.

As our next step, we drop the covariate *Forest* from the model and build the next model with HFI and *Elevation* with linear and quadratic terms using `ppm` function. We call this as $Model2$.

```
## Nonstationary Poisson process
## Fitted to point pattern dataset 'parks_ppp'
##
## Log intensity:  ~HFI + I(HFI^2) + Elevation + I(Elevation^2)
##
```

```
## Fitted trend coefficients:
##    (Intercept)            HFI       I(HFI^2)      Elevation I(Elevation^2)
##  -2.426748e+01   1.242099e+01  -7.734861e+00   1.255468e-03  -9.320293e-07
##
##                      Estimate         S.E.       CI95.lo       CI95.hi Ztest
## (Intercept)    -2.426748e+01 2.983606e-01 -2.485226e+01 -2.368270e+01   ***
## HFI             1.242099e+01 1.073719e+00  1.031654e+01  1.452544e+01   ***
## I(HFI^2)       -7.734861e+00 1.222941e+00 -1.013178e+01 -5.337941e+00   ***
## Elevation       1.255468e-03 5.201189e-04  2.360535e-04  2.274882e-03     *
## I(Elevation^2) -9.320293e-07 2.837978e-07 -1.488263e-06 -3.757958e-07    **
##                       Zval
## (Intercept)    -81.336078
## HFI             11.568195
## I(HFI^2)        -6.324804
## Elevation        2.413809
## I(Elevation^2)  -3.284131
## Problem:
##  Values of the covariate 'HFI' were NA or undefined at 0.56% (12 out of 2137)
## of the quadrature points
##
## *** Fitting algorithm for 'glm' did not converge ***
```

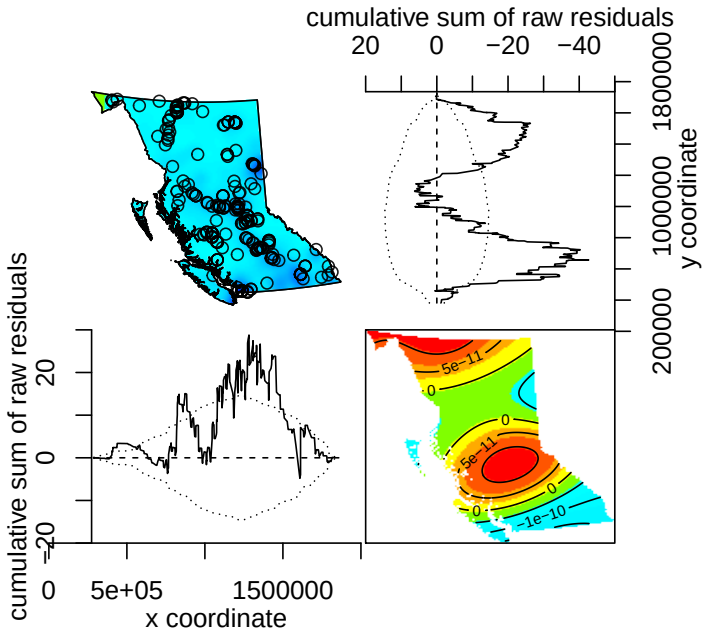
Based on the model results, both HFI and Elevation show strong significance and explain occurrence of red fox data in both linear or quadratic terms. For understanding the fit of the model, we plot the model and red fox locations together by overlaying location data on the model plot.



It can be noted that the red fox locations are captured well with yellow color in the background which is an indicator of high intensity area as predicted by the model. As the model seem to capture the red fox locations reasonably well, we then proceed with other diagnostics to validate the model and compare with other models to select the best.

First we use the `diagnose.ppm` function to diagnose the given model based on residuals. The plot shows cumulative sum of raw residuals against x and y coordinates respectively. To the top right, we can see the residual plot of the cumulative sum of raw residuals against y coordinates. The residuals are showing a good fit in the intermediate y coordinates range and the negative high residuals for high and low coordinates indicates the model predictions are higher than actuals. The the bottom left is the residual plot of the cumulative sum of raw residuals against x coordinates. The model overall has a good fit as seen in the plot with residuals mostly within the dotted band and the prediction is low when compared to actual in the higher x coordinate zones.

Overall, the model is providing a good fit in the intermediate x and y coordinate areas and has tendency to deviate in the high and low coordinate areas of BC.




```
## Model diagnostics (raw residuals)
## Diagnostics available:
##  four-panel plot
##  mark plot
##  smoothed residual field
##  x cumulative residuals
##  y cumulative residuals
##  sum of all residuals
## sum of raw residuals in entire window = -5.478e-06
## area of entire window = 9.483e+11
## quadrature area = 9.39e+11
## range of smoothed field =  [-1.561e-10, 1.393e-10]

##
##  Chi-squared test of fitted Poisson model 'fit_red2' using quadrat
##  counts
##
## data:  data from fit_red2
## X2 = 152.84, df = 16, p-value < 2.2e-16
## alternative hypothesis: two.sided
##
## Quadrats: 21 tiles (irregular windows)
```

Additionally, we do a quadrat test on the model which uses a chi-squared test and we get a small p value that indicates the model has significant deviations.

We move on to assess this model deeply against a few other models and also investigate further to decide if this is the best choice among the models evaluated.

Model Selection and Validation

With a model that fits the data identified, we proceed to do a thorough validation of this model and also compare with a few other models to select the best one for our data.

First, we start with a simple test evaluating the AIC score of both the models above which are model 1 and 2. The AIC scores are 10401.62 and 10403.57 respectively. We conclude that there is not a huge difference in terms of this score between the models. A likehood ratio tests also suggest, we cannot reject that one model is better than the other.

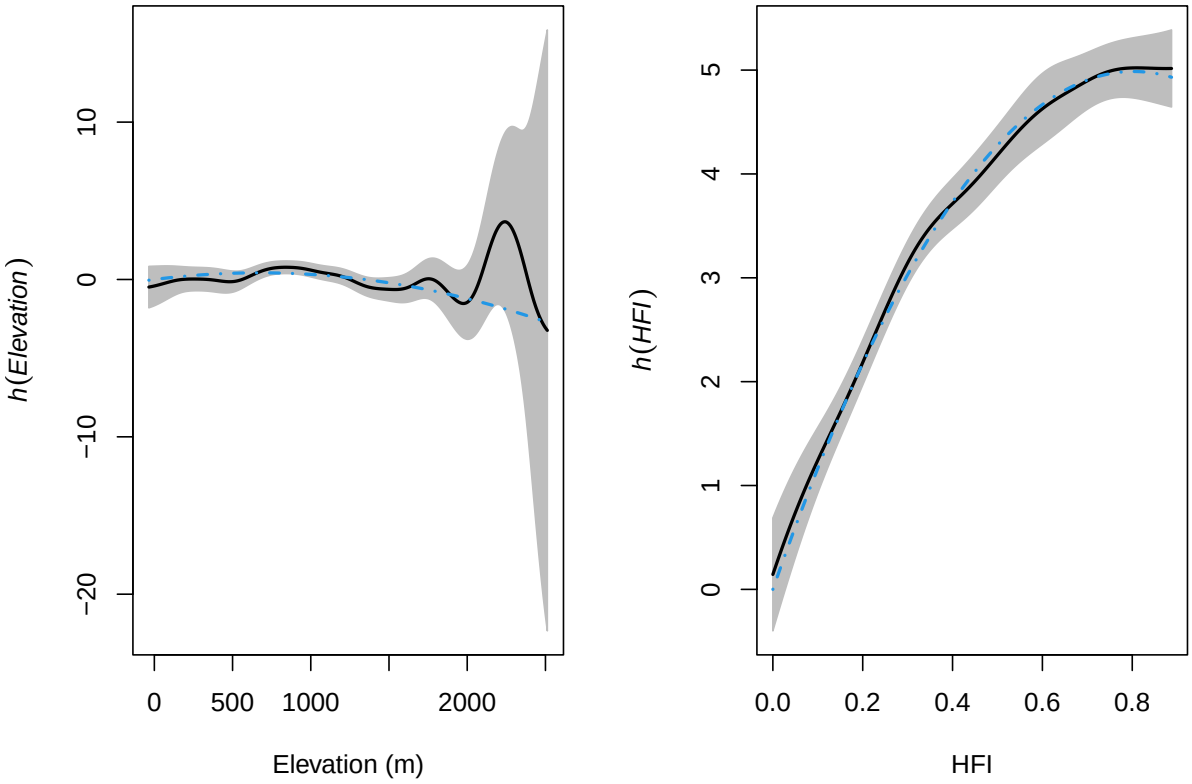
As we are interested in a parsimonious model, between the two models the selected one is $Model2$ which has only two covariates elevation and HFI.

```
## [1] 10401.62
```

```
## [1] 10403.57
```

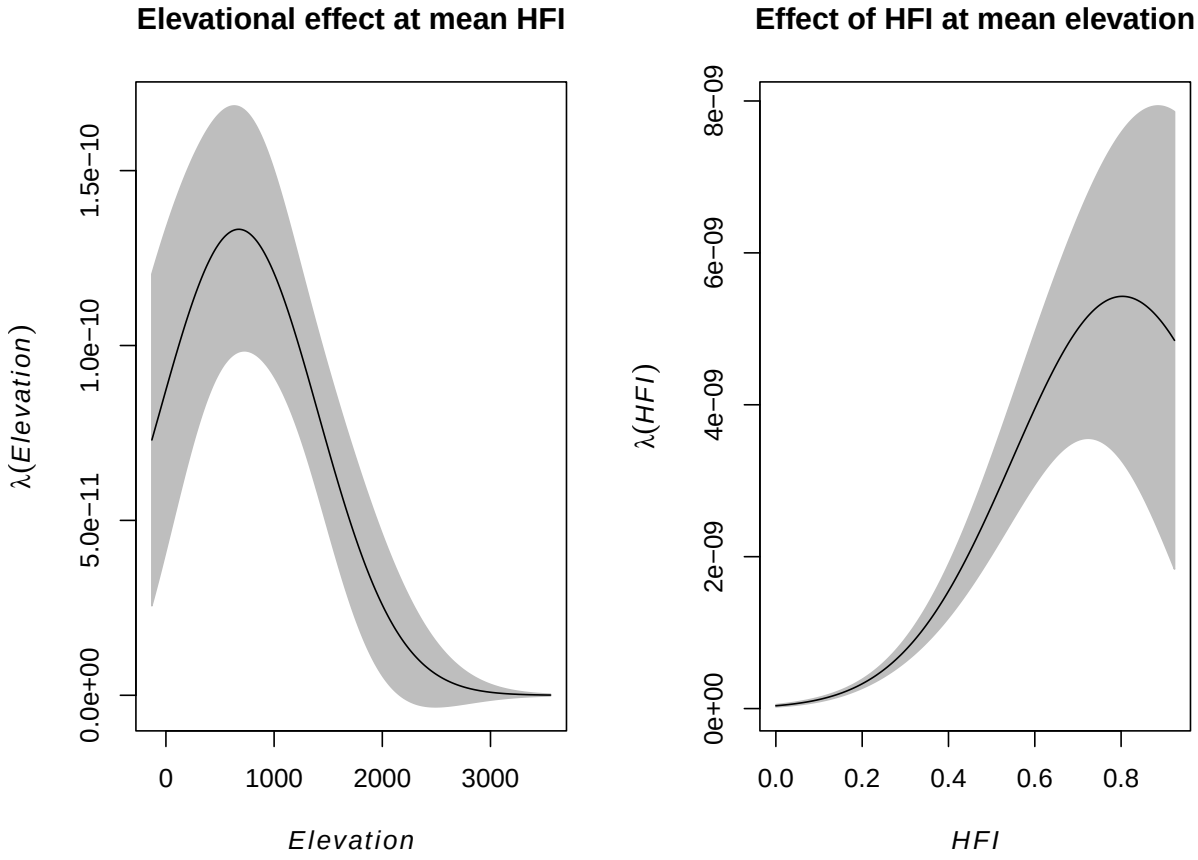
```
## Analysis of Deviance Table
##
## Model 1: ~HFI + I(HFI^2) + Elevation + I(Elevation^2)     Poisson
## Model 2: ~Forest + I(Forest^2) + HFI + I(HFI^2) + Elevation + I(Elevation^2)      Poisson
##   Npar Df Deviance Pr(>Chi)
## 1    5
## 2    7  2   5.9418  0.05126 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

For the selected model $Model2$, next we look at the partial residuals for each of the covariates using 'parres' function which show the fitted effect of a covariate alongside the observed effect.



Based on the plot for HFI, we see that the model is capturing the patterns in the data really well. Looking at the plot for Elevation, the model is capturing the patterns in the data very well except for higher elevation.

Using `effectfun()`, we also look at the influence of individual covariates. This computes the intensity of a fitted point process model as a function of one of its covariates.



Based on the plot, we can see that intensity of the model can be described well as a function of elevation and HFI.

Though the model evaluation so far is very promising to select this model, we see that the intensity or occurrence of red fox at higher elevation is still not captured well. We try to evaluate first by adding a higher order polynomial for elevation but it results in convergence error. So, we compare with a non parametric alternative using an additive modelling framework like GAMs as it allows more flexibility using both `ppm` and `bs` functions. We call this as our `Model 3`.

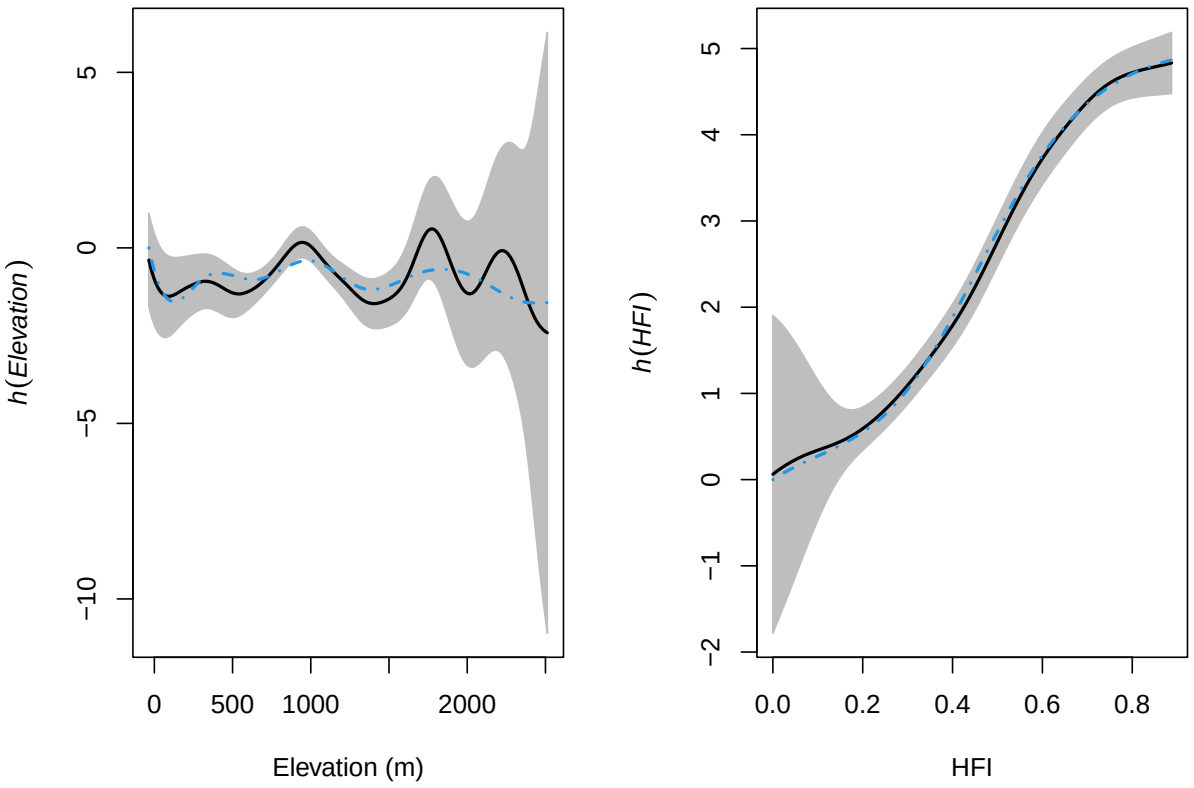
```
## Nonstationary Poisson process
## Fitted to point pattern dataset 'parks_ppp'
##
## Log intensity:  ~bs(Elevation, 12) + bs(HFI, 5)
##
## Fitted trend coefficients:
##         (Intercept)  bs(Elevation, 12)1  bs(Elevation, 12)2  bs(Elevation, 12)3
##        -23.06011643         -2.50238970         -0.03994102         -1.39988574
##  bs(Elevation, 12)4  bs(Elevation, 12)5  bs(Elevation, 12)6  bs(Elevation, 12)7
##           0.22518356         -1.66175832         -0.54356329         -0.57428415
##  bs(Elevation, 12)8  bs(Elevation, 12)9 bs(Elevation, 12)10 bs(Elevation, 12)11
##          -1.89370408         -1.12420362         -4.85151633          6.54909789
## bs(Elevation, 12)12         bs(HFI, 5)1         bs(HFI, 5)2         bs(HFI, 5)3
##        -29.55917527          0.33782061          0.39850473          4.19857566
##         bs(HFI, 5)4         bs(HFI, 5)5
##           4.73799410          4.86649751
```

```
##
## For standard errors, type coef(summary(x))
## Problem:
##  Values of the covariate 'HFI' were NA or undefined at 0.56% (12 out of 2137)
## of the quadrature points
```

For a quick assessment, we compare the AIC score of both models and do a quadrat test to validate if one model is superior to the other. The resulting AIC score for the GAMs model is 10408.13 which is higher than the `Model 2`. Also the quadrat test indicates any one model is not superior to the other.

```
## [1] 10403.57
```

```
## [1] 10408.13
```



Additionally. the partial residuals as well show that the `Model 2` has captured the underlying data better and even in the higher elevation area, the output from `Model 3` is not convincing.

```
## Analysis of Deviance Table
##
## Model 1: ~HFI + I(HFI^2) + Elevation + I(Elevation^2)     Poisson
## Model 2: ~bs(Elevation, 12) + bs(HFI, 5)      Poisson
##   Npar Df Deviance Pr(>Chi)
## 1    5
```

```
## 2   18 13   21.436  0.06473 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Based on the results above, we conclude `Model 2` as the winner to describe the red fox intensity in British Columbia.

Discussion: Provide a brief summary of your findings. Length: ca. 1 page.

References: Include references to all necessary literature.

1. Data: GBIF.org (09 April 2023) GBIF Occurrence Download https://doi.org/10.15468/dl.p6tsaa
2. Research topics: https://cwf-fcf.org/en/resources/encyclopedias/fauna/mammals/red-fox.html