RSPPlme4 simulated example

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March 07, 2022

Load Preliminaries

First we need to load the packages for simulating datasets, running models, organizing and plotting outputs.

```
# devtools::install_github("Bagchilab-Uconn/RSPPlme4")
library(RSPPlme4)
library(spatstat)
library(ggplot2)
library(tidyverse)
```

Data simulation

Creation of the simulated data is performed in this chunk. We generate a response variable (the distribution of points within `ppp` objects) and a random effect (`ranef`) from two fixed effects (`f` and `x`).

```
# set seed
set.seed(1234)

# set number of points
n <-  100

# create random covariate x
x <- runif(n = n, min = 0, max = 10)

# randomly assign group a or b (covariate f)
f <- sample(c("a", "b"), size = n, replace = TRUE)

# assign replicate
gr <- rep(1:10, each = n/10)

# create hyperframe
dat <- hyperframe(x = x, f = f, gr = gr)

# create basis for response variable
lin_pred1 <-  model.matrix(~ f + x, data = as.data.frame(dat, warn = FALSE)) %*%
  c(0.05, 0.05, 0.01)

# create response variable and add to hyperframe
dat$ppx1 <- lapply(lin_pred1, function(sigma)
```

```
                    rThomas(kappa =runif(n = 1, min = 3, max = 10),
                            mu = 5, sigma = sigma))

# create basis for random effect
ranef <- exp(rnorm(n = 10, mean = 0, sd = 0.2) )

# create random effect
lin_pred2  <- lin_pred1 * ranef[dat$gr]

# add random effect to hyperframe
dat$ppx2 <- lapply(lin_pred2, function(sigma)
  rThomas(kappa =runif(n = 1, min = 3, max = 10),
          mu = 10, sigma = sigma))
```

Models

Here, we run three models: the intercept-only model, the fixed effect only model, and the mixed effects model. Further, the results of these three models are plotted below.

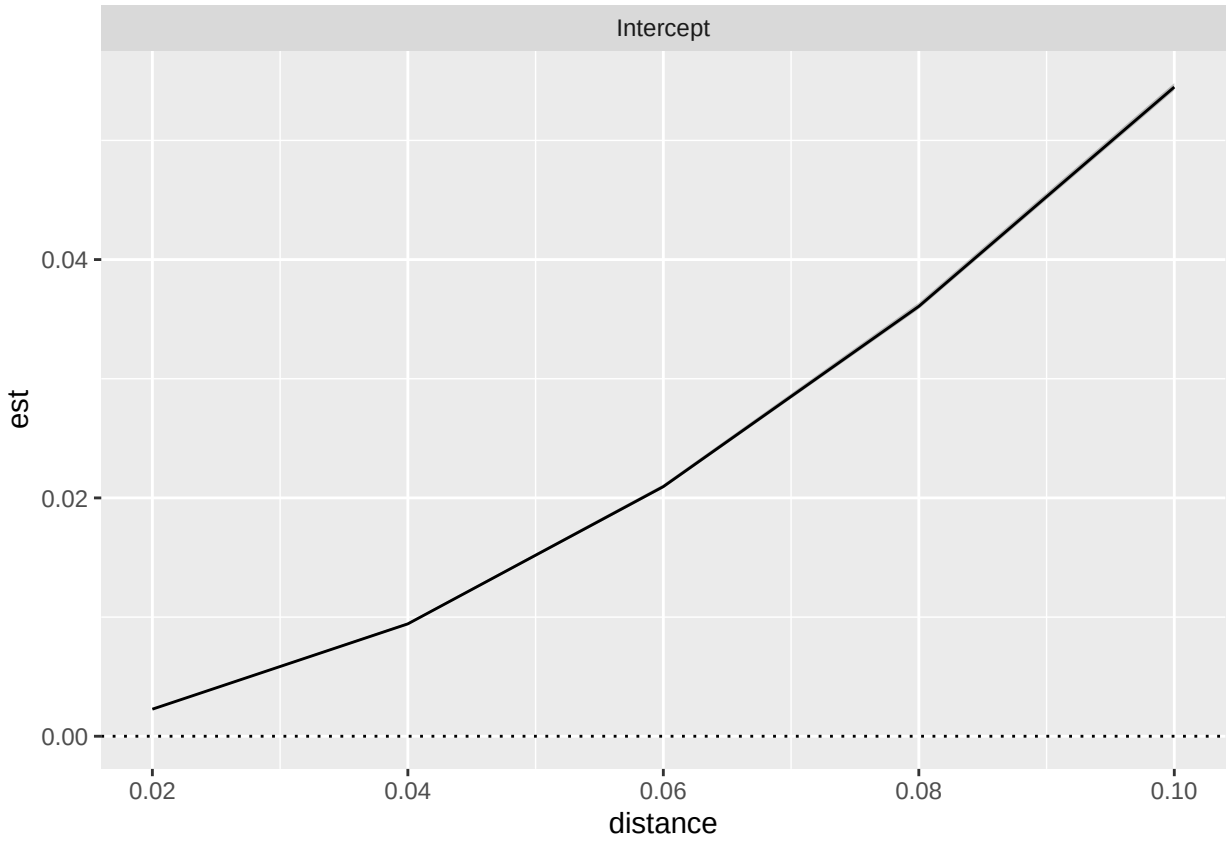
Intercept-only model

We use the 'klm' function with a model formula that only specifies an intercept. The code then computes and plots confidence intervals around the mean-K-function estimated by the model.

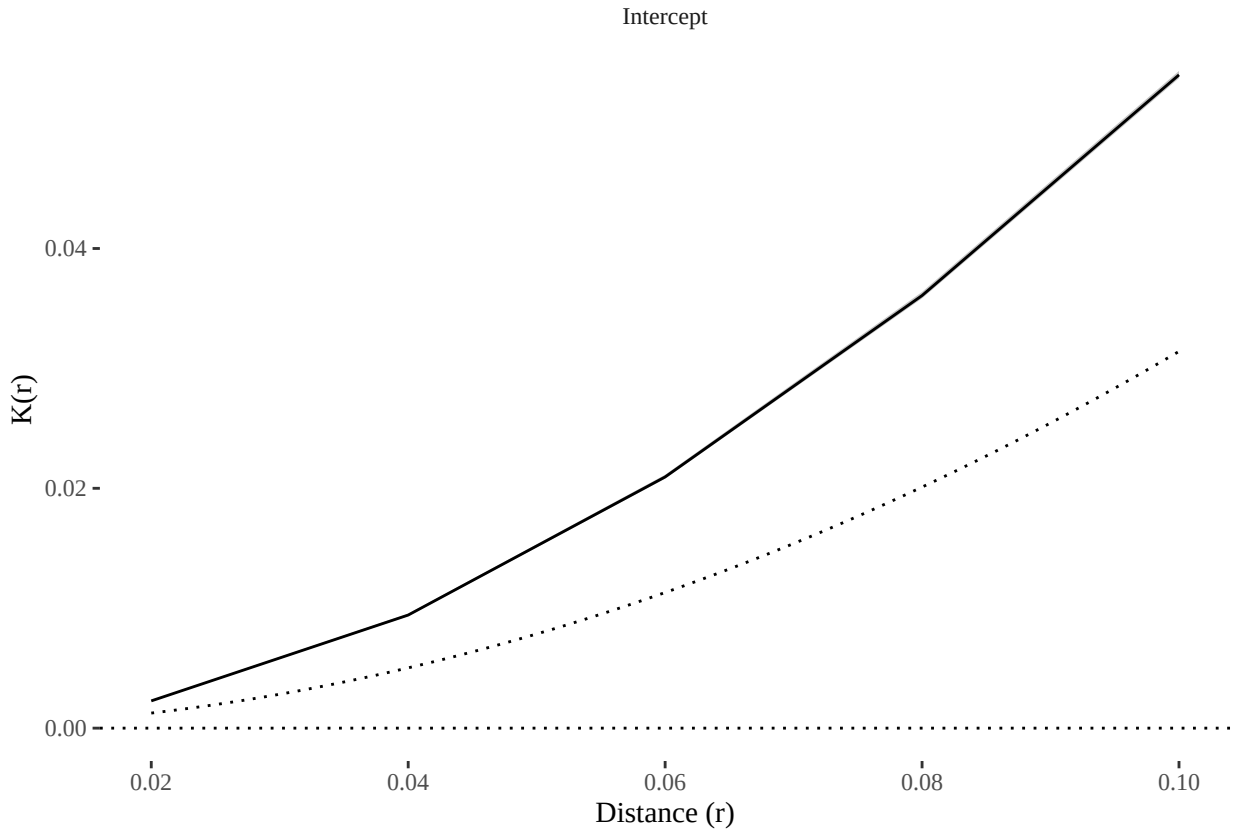
```
# model 1.1: intercept only
mod1.1 <- klm(ppx1 ~ 1, hyper = dat, r = seq(0, 0.1, 0.02),
            correction = "border", weights_type = "nx_A")

# generate confidence intervals for model 1.1
mod1.1_ci <- confint(mod1.1, nboot=500, level = 0.95, iseed = 4321)

# show model 1.1 confidence intervals
print(mod1.1_ci)
```

```
## , , (Intercept)
##
##                  0.02        0.04       0.06       0.08        0.1
## est      0.002272795 0.009430132 0.02094915 0.03607708 0.05447752
## lwr2.5%  0.002229759 0.009343741 0.02080297 0.03584231 0.05420163
## upr97.5% 0.002335217 0.009540220 0.02112979 0.03637523 0.05480533
```

```
# plot of model 1.1 fixed effects
pl <- plot(mod1.1_ci)
```



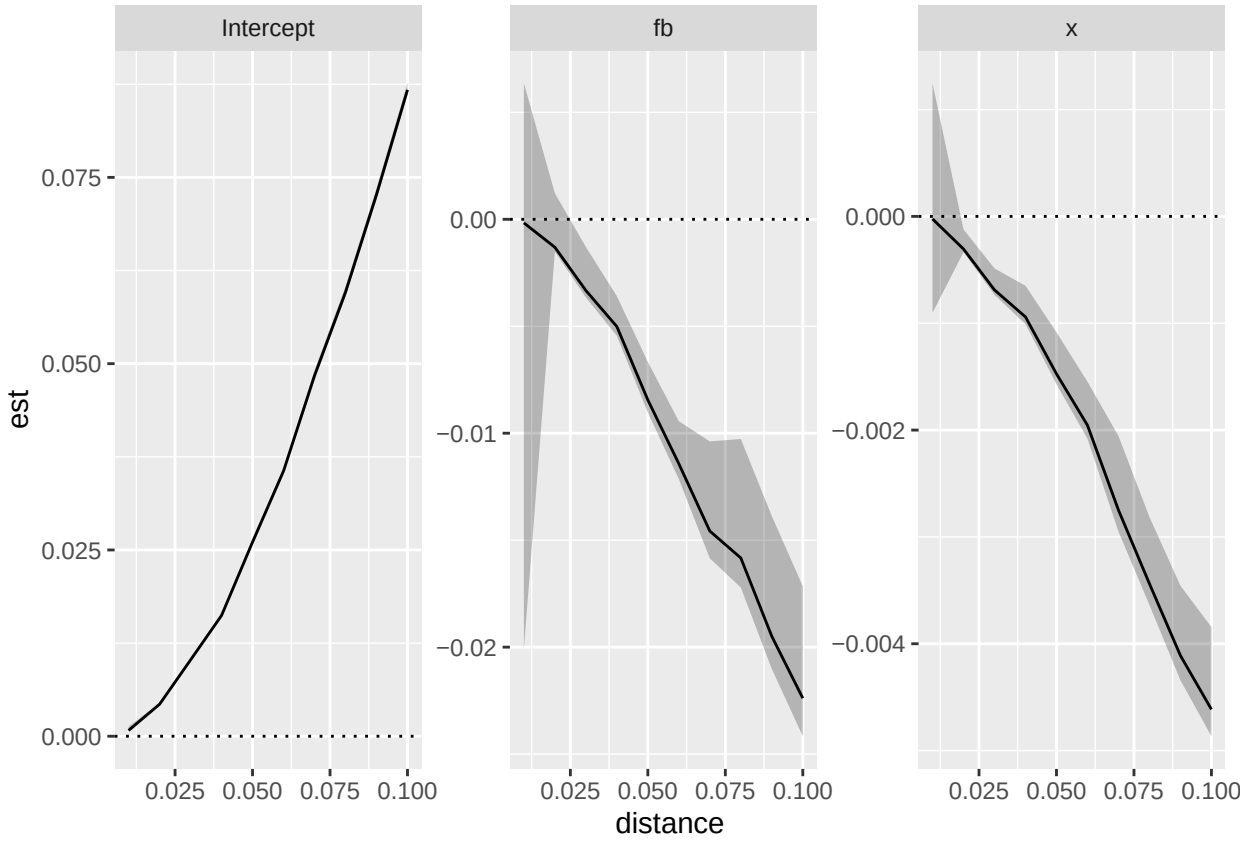

```
pl +  geom_function(fun = function(x) pi * x^2, linetype = "dotted") +
  labs(x = "Distance (r)", y = "K(r)") + ggthemes::theme_tufte()
```

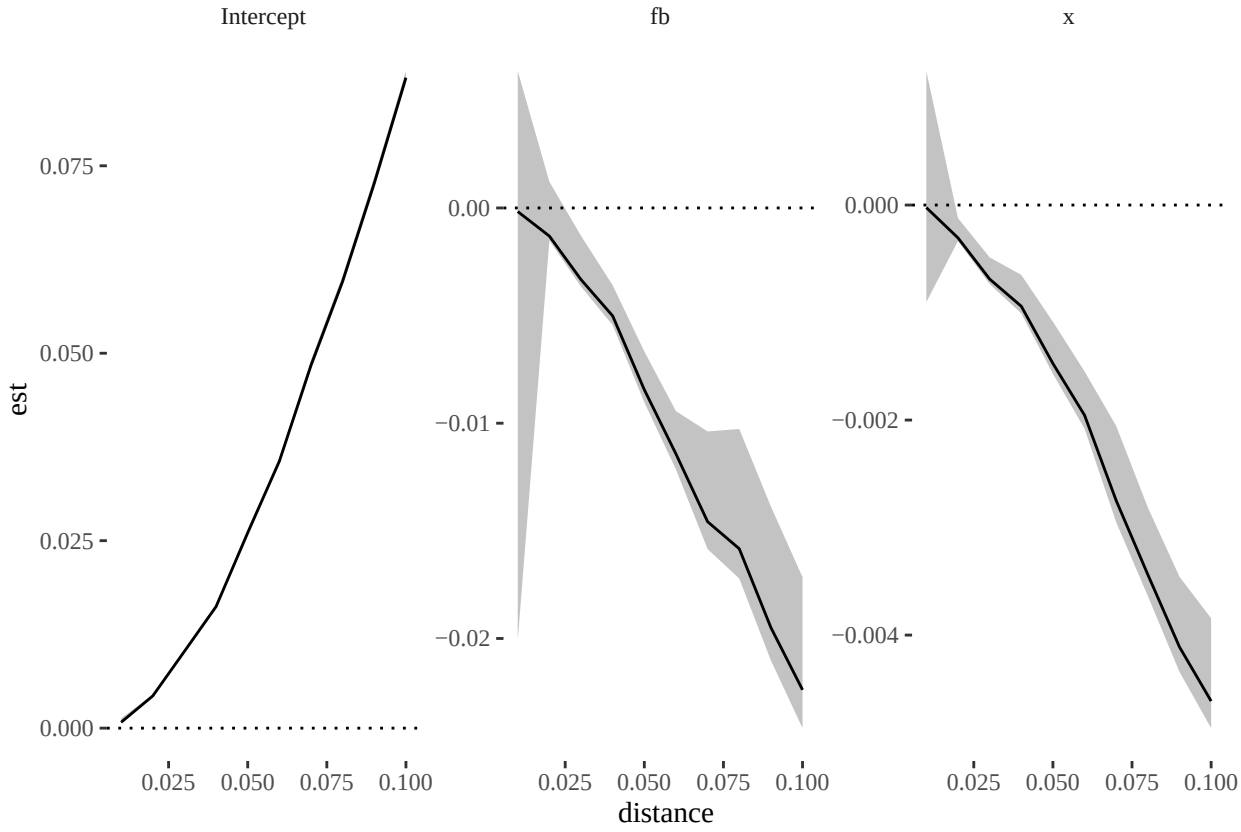


Fixed-effects-only model

In the next model, we modify the formula to include effects of `f` and `x` on the K-function. Once again, we fit the model and compute confidence intervals, then plot the parameter estimates.

```
# model 1.2: add in covariates f and x
mod1.2 <- klm(ppx1 ~ f + x, hyper = dat, r = seq(0, 0.1, 0.01),
              correction = "border", weights_type = "nx_A")

# generate confidence intervals for model 1.2
mod1.2_ci <- confint(mod1.2, nboot = 500, level = 0.99, iseed = 9876)


# plot of model 1.2 fixed effects
plot(mod1.2_ci) + ggthemes::theme_tufte()
```

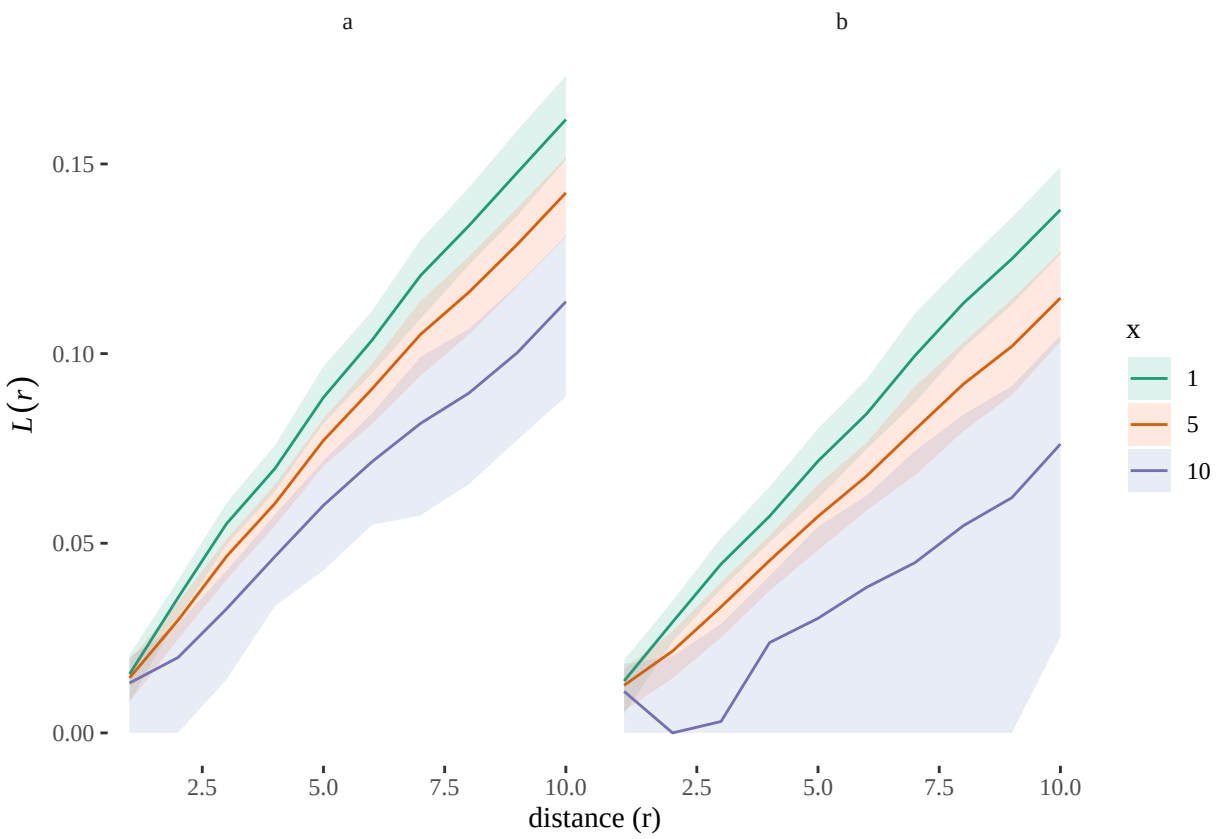

Intercept
fb
x
est
distance
0.075
0.050
0.025
0.000
0.00
−0.01
−0.02
0.000
−0.002
−0.004
0.025
0.050
0.075
0.100



It is also possible to generate predictions of the K-functions under specific combinations of covariates. We demonstrate that below. Note we plot predictions as L-functions to aid interpretability.

```
# alternate creation of model 1.2 confidence intervals
nd1 <- expand.grid(x = c(1, 5, 10),  f = c("a", "b"))
mod1.2_ci <- confint(mod1.2, nboot = 500, level = 0.99, iseed = 9876,
                     newdata=nd1)


# make model 1.2 predictions able to be plotted
preds1.2  <- as.data.frame.table(mod1.2_ci$predictions)
preds1.2[, c("x", "f")] <- nd1[as.numeric(preds1.2$Var1), c("x", "f")]
preds1.2 <- pivot_wider(preds1.2, names_from = Var3, values_from = Freq) %>%
  rename("distance" = "Var2") %>%
  select(-Var1) %>% mutate(distance = as.numeric(distance))

K2L <- function(K) sqrt(K/pi)

# plot model 1.2 predictions
ggplot(preds1.2, aes(x = distance, y = K2L(est), ymin = K2L(lwr), ymax =K2L(upr),
                     group = as.factor(x))) +
  geom_ribbon(alpha = 0.2, aes(fill = as.factor(x))) +
  geom_path(aes(color = as.factor(x))) +
  facet_wrap(~f) +
  scale_color_brewer(palette="Dark2") + scale_fill_brewer(palette="Set2") +
  ggthemes::theme_tufte() +
```

```
  labs(x = "distance (r)", y = expression(italic(L(r))), color = "x", fill = "x")
```



Mixed-effects models

Often, replicates are not independent of each other - and that dependence needs to be accounted for to reduce spurious inferences (e.g., as a result of pseudoreplication or Simpson's paradox). The `klmer` function uses syntax from the `lme4` package for mixed effects models.

```
# model 2: adding random effects
mod2 <- klmer(ppx2 ~ 1 + f + x +  (1| gr), hyper = dat, r = seq(0, 0.1, 0.01),
              correction = "border", weights_type = "nx_A")

# generate confidence intervals for model 2
mod2_ci <- confint(mod2, nboot = 500, ncore = 16)
```

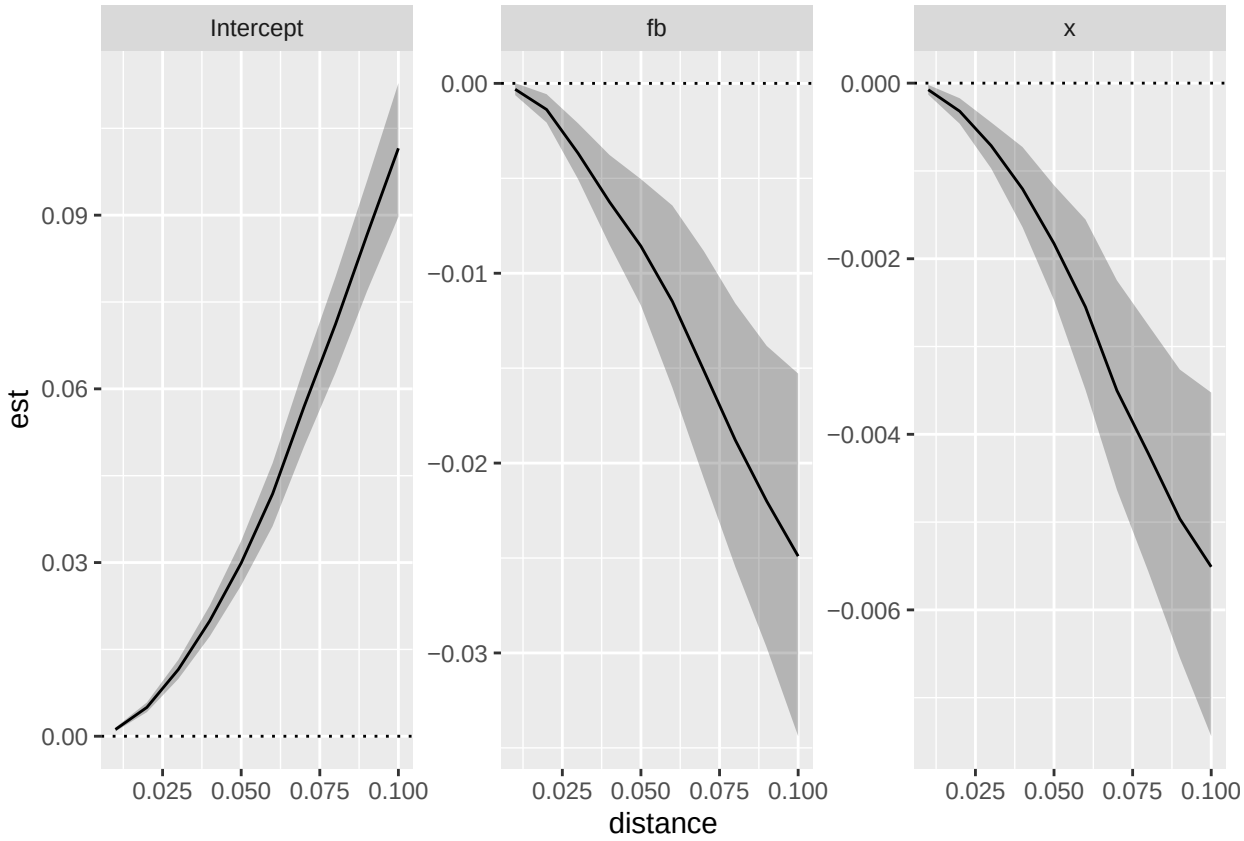
```
## clusters closed on exit
```

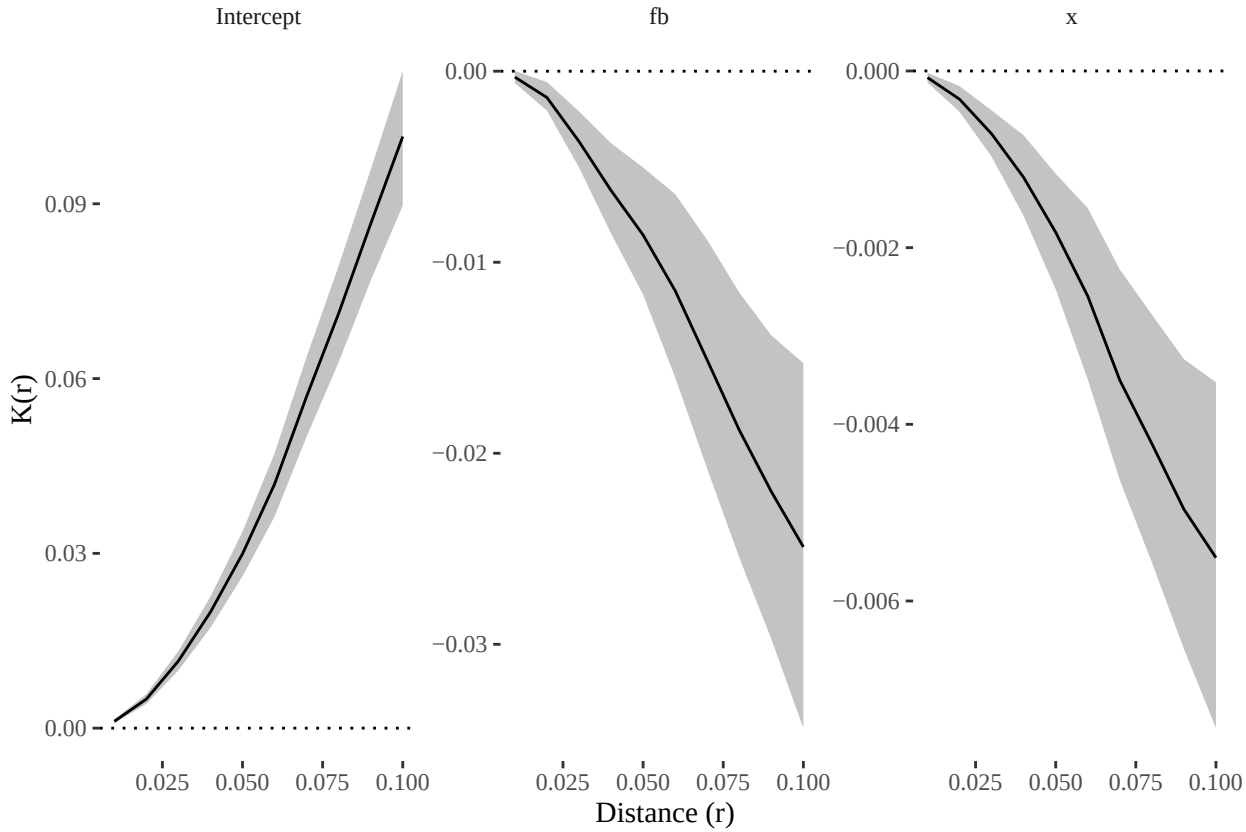
```
# show model 2 confidence intervals
print(mod2_ci)
```

```
## , , (Intercept)
##
```

```
##             0.01        0.02        0.03       0.04       0.05       0.06
## est 0.0011680260 0.004985416 0.011529417 0.01993112 0.02992305 0.04187721
## lwr 0.0008197916 0.004162228 0.009895813 0.01723944 0.02605749 0.03628505
## upr 0.0015046608 0.005832803 0.013211714 0.02257609 0.03373770 0.04718186
##           0.07       0.08       0.09        0.1
## est 0.05693056 0.07118157 0.08656927 0.10154402
## lwr 0.05001980 0.06278673 0.07681706 0.08969596
## upr 0.06372971 0.07933645 0.09585853 0.11279987
##
## , , fb
##
##              0.01          0.02         0.03         0.04         0.05
## est -3.102939e-04 -0.0013784401 -0.003676855 -0.006243774 -0.008574534
## lwr -6.173621e-04 -0.0020646042 -0.005042791 -0.008492862 -0.011700114
## upr  1.221315e-05 -0.0005688738 -0.002102004 -0.003768356 -0.005041947
##             0.06         0.07        0.08        0.09         0.1
## est -0.011487204 -0.015125508 -0.01878599 -0.02200701 -0.02490362
## lwr -0.016027769 -0.020813562 -0.02545901 -0.02972015 -0.03438776
## upr -0.006431394 -0.008834535 -0.01158551 -0.01382611 -0.01528585
##
## , , x
##
##              0.01          0.02          0.03          0.04         0.05
## est -7.486473e-05 -0.0003201355 -0.0007118293 -0.0012055738 -0.001827317
## lwr -1.307212e-04 -0.0004624090 -0.0009705949 -0.0016423075 -0.002472120
## upr -2.006626e-05 -0.0001716925 -0.0004465533 -0.0007280485 -0.001163610
##             0.06         0.07         0.08         0.09          0.1
## est -0.002549483 -0.003500892 -0.004218620 -0.004961898 -0.005509386
## lwr -0.003492092 -0.004631314 -0.005563354 -0.006542172 -0.007439245
## upr -0.001553059 -0.002247077 -0.002756479 -0.003262015 -0.003524346
```

```
# plot model 2 fixed effects
plot(mod2_ci) + ggthemes::theme_tufte() +
  labs(x = "Distance (r)", y = "K(r)")
```


Intercept
fb
x
est
distance
0.09
0.06
0.03
0.00
−0.01
−0.02
−0.03
0.000
−0.002
−0.004
−0.006
0.025
0.050
0.075
0.100

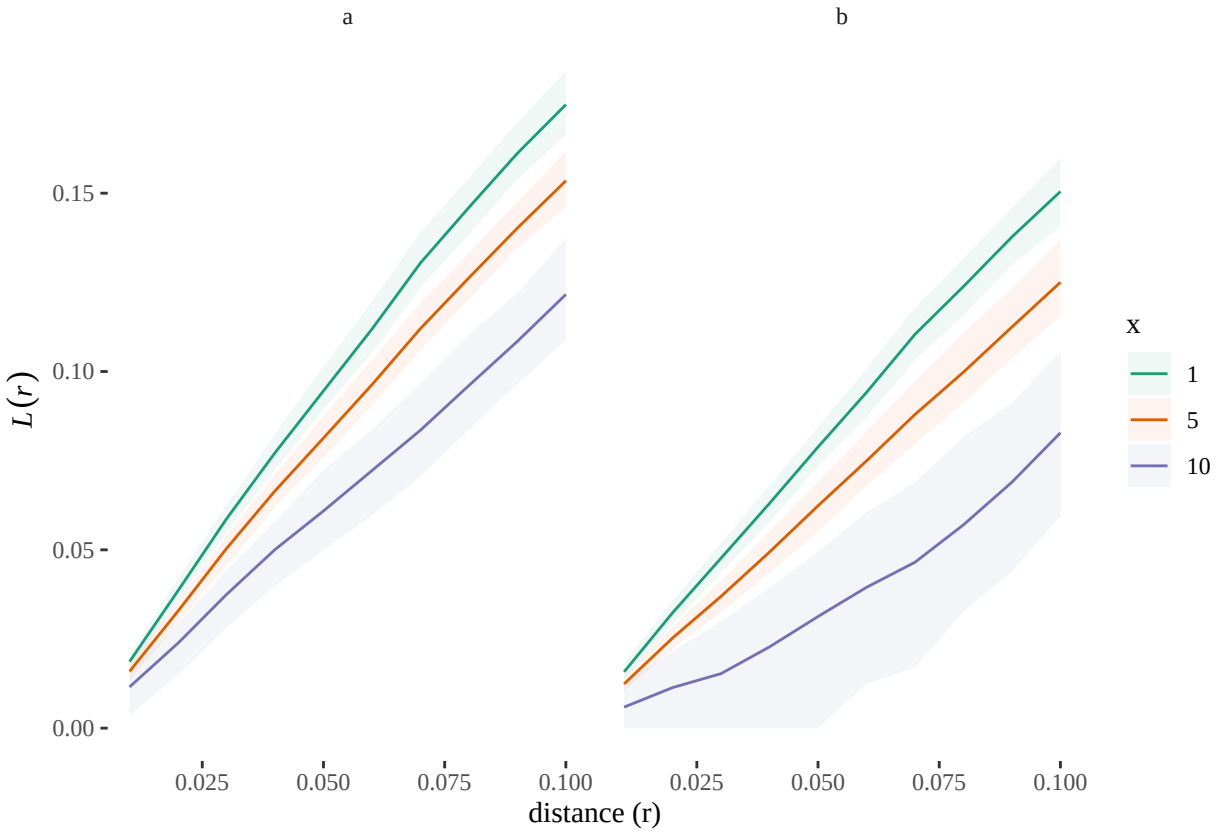


As in the case of the fixed-effects only models, it is possible to make predictions with associated confidence intervals for specific combinations of covariates. These are generated and plotted below.

```
# alternative creation of model 2 confidence intervals
mod2_ci <- confint(mod2, nboot = 99, ncore = 16,
                   newdata  = nd1)
```

```
## clusters closed on exit
```

```
# make model 2 predictions able to be plotted
preds2  <- as.data.frame.table(mod2_ci$predictions)
preds2[, c("x", "f")] <- nd1[as.numeric(preds2$Var2), c("x", "f")]
preds2 <- pivot_wider(preds2, names_from = Var3, values_from = Freq) %>%
  rename("distance" = "Var1") %>%
  mutate(distance = as.numeric(as.character(distance)))

# plot model 2 predictions
ggplot(preds2, aes(x = distance, y = K2L(est), ymin = K2L(lwr), ymax = K2L(upr),
                   colour = as.factor(x), fill = as.factor(x))) + facet_wrap(~f) +
  geom_ribbon(alpha = 0.1, color = NA, aes(group = as.factor(x))) +geom_path() +
  scale_color_brewer(palette="Dark2") + scale_fill_brewer(palette="Set2") +
  labs(x = "distance (r)", y = expression(italic(L(r))), color = "x", fill = "x") +
  ggthemes::theme_tufte()
```


a
b
0.15
0.10
0.05
0.00
L(r)
0.025
0.050
0.075
0.100
distance (r)
x
1
5
10