Kericho

greyhypotheses

Problem 4

Considering the time series model

$$\begin{aligned} Y(t) = \beta_0 + \beta_1 t + \beta_2 I(pmax(t-50,0)) + \beta_3 I(t>225) \\ + \beta_4 minT(t-k) + \beta_5 maxT(t-k) + \beta_6 Rain(t-k) \\ + \mathcal{W}(t) + Z(t) \end{aligned} \tag{1}$$

for the Kericho malaria cases data, wherein

variable	description
t	time (months)
$minT$	mininum temperature
$maxT$	maximum temperature
$Rain$	rainfall (millimetres)
k	lag; $k = 2$ months
$\mathcal{W}(t)$	A Matern processwhereby $\kappa = 2.5$
$Z(t)$	Gaussian noise

Data Set-up

The original data set, with appended time dependent variables, is

```
'data.frame': 310 obs. of  11 variables:
 $ Year   : int  1979 1979 1979 1979 1979 1979 1979 1979 1979 1979 ...
 $ Month  : Ord.factor w/ 12 levels "Jan"<"Feb"<"Mar"<..: 1 2 3 4 5 6 7 8 9 10 ...
 $ Cases  : int  25 25 20 30 18 18 15 15 10 20 ...
 $ Rain   : num  3.7 3.2 5.6 8.3 8.1 5.4 5.5 6.1 5.7 5.6 ...
 $ minT   : num  11.8 11.3 10.9 12 10.9 11.4 10.2 10.1 10.2 11.1 ...
 $ maxT   : num  24 23.5 25.1 23.6 22.9 22.1 22.1 23 23.9 25.2 ...
 $ VCAP   : num  78.5 56.6 131.9 467.6 277 ...
 $ CasesLN: num  3.22 3.22 3 3.4 2.89 ...
 $ datestr: chr  "1979-01" "1979-02" "1979-03" "1979-04" ...
 $ date   : Date, format: "1979-01-01" "1979-02-01" ...
 $ time   : num  0 1 2 3 4 5 6 7 8 9 ...
```

The function *TimeDependentLag()* creates lagged fields. Hence, the lagged minimum temperature, maximum temperature, and rain fields:

```
LaggedSeries <- function (variable) {
  temporary <- TimeDependentLag(frame = instances,
                                frame.date = 'date',
```

```
                                frame.date.granularity = 'month',
                                frame.focus = variable,
                                lags = seq(from = 2, to = 2) )
  series <- temporary$frame[temporary$lagfields]

  return(series)
}
lagged.variables <- lapply(X = c('minT', 'maxT', 'Rain'), FUN = LaggedSeries)
lagged.variables <- dplyr::bind_cols(lagged.variables)
instances <- cbind(instances, lagged.variables)
```

Exercise 1: Model Fitting

Prior to fitting *Eq. 1*, records that have `NaN` values . . .

```
condition <- !is.na(instances$rain_lag_2) | !is.na(instances$mint_lag_2) |
  !is.na(instances$maxt_lag_2)
excerpt <- instances[condition, ]
```

Hence, via the `fit.matern()` function

```
fit2.5 <- fit.matern(
  form = as.formula(log(Cases) ~ time + I(pmax(time - 50, 0)) + I(time > 225)
    + mint_lag_2 + maxt_lag_2 + rain_lag_2),
  time = 'time',
  start.cov.pars = c(1,5),
  kappa = 2.5,
  data = excerpt,
  method = 'nlminb')
```

The summary of the model fitted for *Eq. 1* is . . .

```
Geostatistical linear model
Call:
linear.model.MLE(formula = log(Cases) ~ time + I(pmax(time -
    50, 0)) + I(time > 225) + mint_lag_2 + maxt_lag_2 + rain_lag_2,
    coords = as.formula(paste("~", time, "+ t_aux")), data = data,
    kappa = 2.5, start.cov.pars = ..1, method = "nlminb")

                        Estimate     StdErr z.value   p.value
(Intercept)            1.5546882  0.5374136  2.8929 0.0038169 **
time                   0.0266066  0.0053688  4.9558 7.205e-07 ***
I(pmax(time - 50, 0)) -0.0258646  0.0059857 -4.3211 1.553e-05 ***
I(time > 225)TRUE      0.6931965  0.1792059  3.8682 0.0001097 ***
mint_lag_2             0.1449852  0.0418763  3.4622 0.0005357 ***
maxt_lag_2            -0.0140655  0.0078728 -1.7866 0.0740030 .
rain_lag_2             0.0185512  0.0101402  1.8295 0.0673303 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Log-likelihood: 98.64848

Covariance parameters Matern function (kappa=2.5)
             Estimate StdErr
log(sigma^2) -1.61326 0.1580
log(phi)     -0.49494 0.1617
log(tau^2)   -2.72287 0.5096

Legend:
```

```
sigma^2 = variance of the Gaussian process
phi = scale of the spatial correlation
tau^2 = variance of the nugget effect
```

The natural logarithm scale values of σ^2, ϕ^2, and τ^2, and their confidence intervals:

```
parameters <- data.frame(estimates$cov.pars)
parameters$interval <- qnorm(p = 0.975, lower.tail = TRUE) * parameters$StdErr
parameters[, c('ln_lower_ci', 'ln_upper_ci')] <- parameters$Estimate +
  matrix(data = parameters$interval) %*%  matrix(data = c(-1, 1), nrow = 1, ncol = 2)
```

Consequently, their normal scale values are

```
parameters[, c('lower_ci', 'upper_ci')] <- as.matrix(exp(parameters[, c('ln_lower_ci', 'ln_upper_ci')]))
```

Hence

```
                Estimate    StdErr ln_lower_ci ln_upper_ci   lower_ci  upper_ci
log(sigma^2) -1.6132574 0.1580131  -1.9229573  -1.3035574 0.14617404 0.2715640
log(phi)     -0.4949422 0.1616900  -0.8118489  -0.1780356 0.44403635 0.8369126
log(tau^2)   -2.7228684 0.5095813  -3.7216294  -1.7241074 0.02419451 0.1783322
```

Exercise 2: Predictions

The foci herein are the $ln(cases)$ point predictions, and their 95% prediction intervals, w.r.t. the months of the Kericho data set. Using the *time.predict*() function of *auxiliary_function.R*:

```
  predictor <- time.predict(
    fitted.model = fit2.5,
    predictors = excerpt[, c('time', 'mint_lag_2', 'maxt_lag_2', 'rain_lag_2')],
    time.pred = excerpt$time,
    scale.pred = 'exponential')
```

```
log(Cases) ~ time + I(pmax(time - 50, 0)) + I(time > 225) + mint_lag_2 +
    maxt_lag_2 + rain_lag_2
```

creates the *time.predict*() object of predictions, including the confidence intervals. The resulting graph . . .

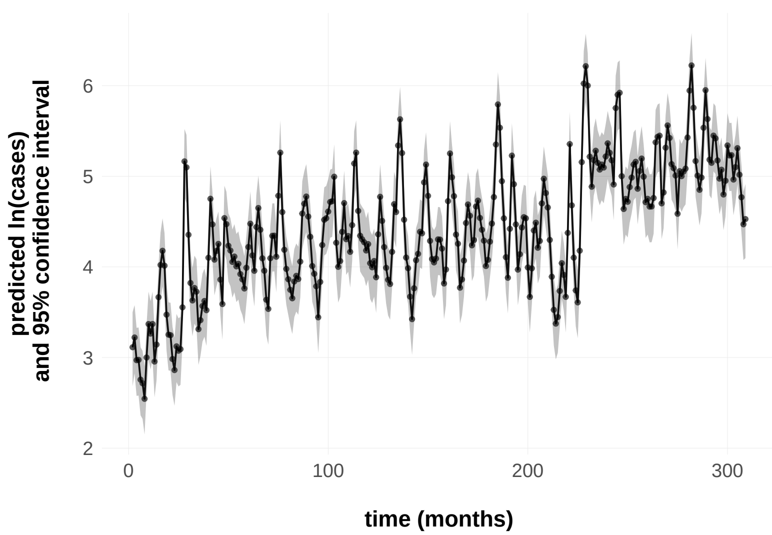

Figure 1: Predictions: ln(cases) and confidence interval