Temporal dynamics of seed-dispersal networks: Disentangling the role of direct and indirect biotic and climatic processes

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Appendix S1. Journal: Ecology

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S1 Introduction

This document holds data wrangling operations for formatting interaction and climate data from **Ramírez-Mejía et al. (2023) 'Temporal dynamics of seed-dispersal networks: Disentangling the role of direct and indirect biotic and climatic processes'**. It also shows the Bayesian model used to estimate temperature and rainfall at each specific site and month.

S2 Data generative model

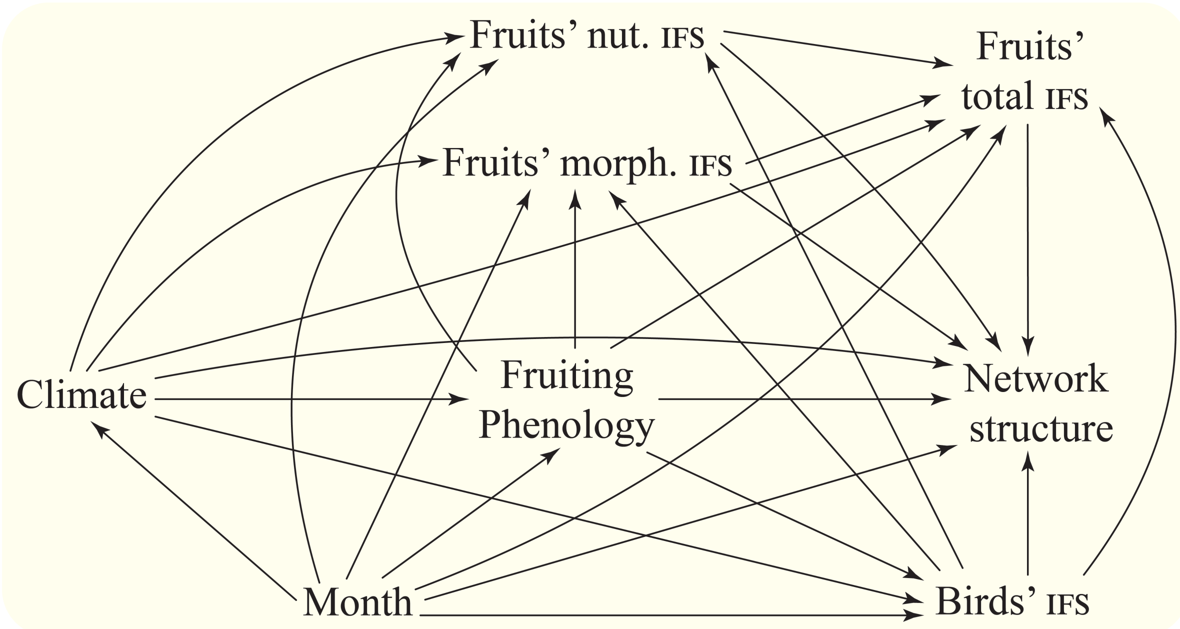

Figure S1: Data generative model showing how climate-driven bottom-up and direct biotic processes drive intra-annual temporal dynamics in seed dispersal networks on O ahu. Arrows indicate causal pathways, with direct effects shown as single paths (e.g., climate → fruiting phenology) and indirect (i.e., bottom-up) effects as mediated paths (e.g., climate → fruiting phenology → network structure). Climate = monthly cumulative rainfall and average temperature; Fruiting phenology = denotes the richness of fruit-producing plants and total fruit production. morph. = morphological; nutr. = nutritional. IFS = interaction functional space. Month = temporal variable accounting for seasonal autocorrelation not captured by other factors.

The composition and structure of ecological communities varies due to intra-annual life-cycle processes that affect the strength and occurrence of plant-animal interactions (Wolfe et al. 2017), so we expect the structure of the networks to vary throughout the year accordingly. Such biological regularities are driven by seasonal cues (Ramos-Robles et al. 2016), hence we expected monthly rainfall and temperature to affect the overall pool of traits of interacting species, and, consequently, the IFS of the networks. More precisely, we expect climate predictors to affect fruit IFS through two paths: (1) directly, because high temperature and precipitation can promote fruit development and ripening (Pau et al. 2020), which can promote a higher variety of morphological and nutritional traits to be chosen by frugivorous birds; (2) indirectly, since birds can track warmer and wetter conditions that promote molting and breeding activity (Wolfe et al. 2017), which are energetically costly and may result in a higher variety of fruit resources (i.e., larger fruit IFS) used by the birds (Murphy and King 1992). Lastly, since a large IFS may imply a broader set of traits and alternatives for species to engage in frugivory interactions (Bello et al. 2023), we predict it will have a positive effect on the emergence of more modular and specialized networks with reduced nestedness. The above causal assumptions are summarized in Figure 1.

S3 Study system

Sampling of interactions – We used passerine birds as a model system because they represent the primary group responsible for seed dispersal on O ahu (Vizentin-Bugoni et al., 2019). We selected seven sites encompassing environmental variation across the island (Appendix S1: Section 2.2) and documented frugivory events by capturing birds and collecting fecal samples from November 2014 to December 2017. At each site, during favorable weather conditions, we deployed ten 12 m $\times$ 2 m mist nets, keeping them open for seven hours from dawn to ensure 14 sampling hours per two-day netting session. Captured birds were placed in paper bags for up to 20 minutes to collect fecal samples, which were later processed in the laboratory to identify intact seeds. From 3,559 fecal samples across 21 bird species, we identified seed species by comparing them with a reference collection of seeds gathered directly from field sites or nearby areas. In total, we detected seeds from 47 plant species.

S4 Data wrangling

S4.1 Birds interactions

The following code harmonizes names, dates and codes among interaction and fruit morphology data sets.

```
# Andrés F. Ramírez-Mejía, Corey E. Tarwater, J. Patrick Kelley, Jinelle Sperry, Jeff Foster
```

```
pks <-
  c('dplyr', 'magrittr', 'lubridate', 'lubridate',
    'readxl', 'tibble', 'tidyr', 'ggplot2',
    'ggfortify', 'terra', 'raster', 'sf', 'patchwork',
    'cmdstanr', 'rethinking', 'animation')

sapply(pks, FUN = function(x) library(x, character.only = T))

extrafont::loadfonts(device = 'win')
```

```r
path_bird_fecal <-
  '/Users/andres/Documents/github_repos/hawaii_projects/data/FecalSongbirds_v1.xls'

path_bird_morpho <-
  '/Users/andres/Documents/github_repos/hawaii_projects/bird_morphology/BirdMorphol_JMG-Master_2019May17.xlsx'

bird_morpho <- read_xlsx(path_bird_morpho,
                         sheet = 1, col_names = T)

date_birds <- bird_morpho$date

bird_morpho <-
  lapply(seq_along(bird_morpho), FUN =
           function(i) {

             x <- bird_morpho[[i]]

             n <- sum(grep('^([0-9])', x))

             if (n > 0) {
               df <- tibble(v = as.numeric(x))
               colnames(df) <- colnames(bird_morpho)[i]
               df
             } else {
               bird_morpho[, i]
             }

           })

bird_morpho <- as_tibble(do.call('cbind', bird_morpho))

bird_morpho$date <- date_birds

bird_morpho <-
  bird_morpho[, c("site", "date", 'net', 'species',
                  "band_number", 'age', 'sex', 'tail',
                  'tarsus', 'wing', "total_culmen",
                  "nares_to_tip", "width", "depth", "gape",
                  "mass")]

bird_morpho <- split(bird_morpho, bird_morpho$species)

bird_morpho <- bird_morpho[unlist(lapply(bird_morpho, FUN = function(x) nrow(x) > 0))]

bird_morpho <- do.call('rbind', bird_morpho)

bird_seed <- read_xls(path_bird_fecal, sheet = 1)

bird_seed <- bird_seed[!is.na(bird_seed$Month), ]

bird_seed$Month <-
  sapply(bird_seed$Month,
         function(x) {
           if (x < 10) paste('0', x, sep = '')
           else as.character(x)
         })


bird_seed$Day <-
  sapply(bird_seed$Day,
         function(x) {
           if (nchar(x) == 1) paste0('0', x)
           else x
         })

bird_seed$Sample_Date <-
  bird_seed %$% paste(Year, Month, Day, sep = '-')
```

```
bird_seed$Sample_Date <- as.Date(bird_seed$Sample_Date)

codes_birds <- read_xls(path_bird_fecal, sheet = 2)

codes_plants <- read_xls(path_bird_fecal, sheet = 3)

coordinates_sites <- read_xls(path_bird_fecal, sheet = 4)

bird_morpho$date <- as.Date(bird_morpho$date)

dates_morpho <- unique(bird_morpho[, c('site', 'date')])

date_seeds <- unique(bird_seed[, c("Site", "Sample_Date")])

colnames(date_seeds) <- c('site', 'date')

date_seeds$dat_seed <- 1

dates_1 <- unique(bird_morpho[, c('site', 'date')])

dates_1$dat_trait <- 1

dates_1$site[grep('^PAL$', dates_1$site)] <- 'PAH'

dates_1 <- dates_1[dates_1$site != 'HOUSE', ]

date_join <- left_join(date_seeds, dates_1, by = c('site', 'date'))

# using band number to asses compatibility of dates

bird_morpho$band_number <-
  sapply(bird_morpho$band_number, FUN =
           function(x) {
             if (is.na(x)) {
               NA
             } else {
               x <- as.character(x)
               gsub('^(....)(.*)', '\\1-\\2', x)
             }
           })

code_traits <- unique(bird_morpho[, c('site', "date", "band_number")])
code_seeds <- unique(bird_seed[, c("Site", "Sample_Date", "Band_Num")])
colnames(code_seeds) <- colnames(code_traits)

compare_bands <-
  function(date1, site1, date2, site2) {
    seed <- code_seeds[code_seeds$date == date1 , ]
    trait <- code_traits[code_traits$date == date2, ]

    list(bands =
           list(trait = sort(trait$band_number), site_trait = unique(trait$site),
                seeds = sort(seed$band_number)), site_seed = unique(seed$site),
         prop_same = mean(seed$band_number %in% trait$band_number),
         prop_total = mean(seed$band_number %in% code_traits$band_number))

  }


date_join$correction <- date_join$date

t <- date_join
t$day <- day(t$date)
t$filter <-
  sapply(seq_along(t$day), FUN =
```

```r
           function(x) {
             i <- t$day[x] <= 12
             j <- is.na(t$dat_trait[x])
             (i+j) == 2
           })

t$year <- year(t$date)

t1 <- t[(t$filter), ] %$% aggregate(date ~ site + year, FUN = length)

t1 <- t1[order(t1$site), ]

t1$perc <- (t1$date/sum(t1$date))*100

t <- t[!(t$filter), ]

t$cod <- t %$% paste(site, date, sep = '_')

bird_seed$cod <- bird_seed %$% paste(Site, Sample_Date, sep = '_')

bird_seed1 <- split(bird_seed, bird_seed$cod)

indx <- names(bird_seed1) %in% t$cod

bird_seed1 <- do.call('rbind', bird_seed1[indx])

# data for constructing interaction networks
#saveRDS(bird_seed1, 'FecalSongbirds_CORRECTED.rds')
```

S4.2 Climatic data

The following code use raster data from the HCDP (Hawai'i climate data portal) and the coordinates of our sampling sites, to extract monthly temperature and cumulative rainfall from 2014 to 2018 in O'ahu island.

```r
path_environmental <-
  '/Users/andres/Documents/github_repos/hawaii_projects'

coords <-
  tribble(~lon,            ~lat,
          -158.08451944444, 21.443305555556,
          -158.19316666667, 21.536819444444,
          -157.87335833333, 21.376041666667,
          -158.1447694444, 21.506827777778,
          -158.1799,       21.536472222222,
          -157.81091388889, 21.338386111111,
          -158.04074722222, 21.632116666667)

coords$sites <- coordinates_sites$Acronym[-8]

folderRain <-
  paste0(path_environmental,
         '/rainfall_temperature/HCDP_data/rainfall/data_map/',
         '2015')

mapsRain <- dir(folderRain)

path_rain <- paste0(folderRain, '/', mapsRain[1])

rainfall <- rast(path_rain)
```

```
folderTEMP <-
  paste0(path_environmental,
         '/rainfall_temperature/HCDP_data/temperature/data_map/',
         '2015')

mapsTEMP <- dir(folderTEMP)

path_TEMP <- paste0(folderTEMP, '/', mapsTEMP[1])

temperature <- rast(path_TEMP)
```

```
par(mfrow = c(1, 2), mar = c(1, 1, 4, 1))
plot(rainfall, xlim = c(-158.3, -157.6), ylim = c(21.2, 21.75),
     main = 'Rainfall (January 2014)')
coords %$%
  points(lon, lat, col = 'red', pch = 16, cex = 0.5)
plot(temperature, xlim = c(-158.3, -157.6), ylim = c(21.2, 21.75),
     main = 'Temperature (January 2014)')
coords %$%
  points(lon, lat, col = 'red', pch = 16, cex = 0.5)
```

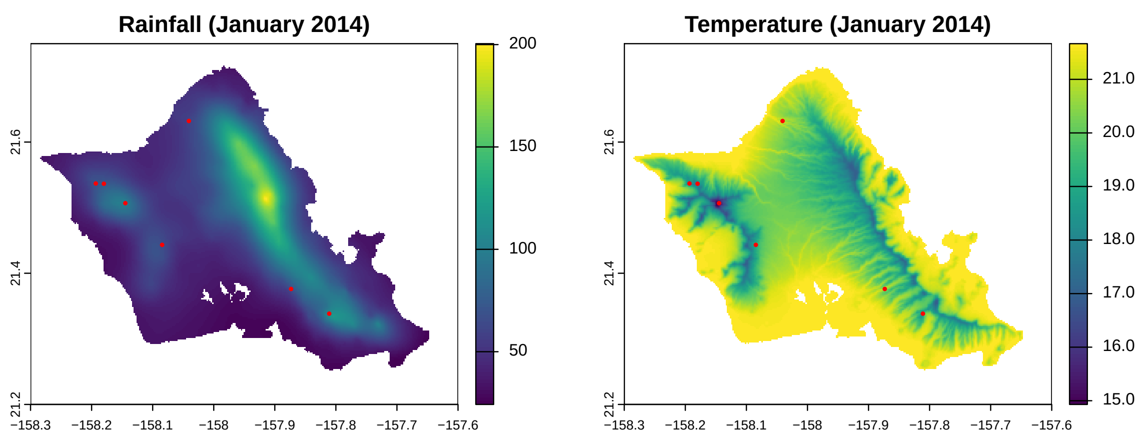

Figure S2: Patterns of temperature and cumulative ranfall in Oahu island. Red dotes shows indicates the location of our sampling sites.

```r
par(mfrow = c(1, 1))
```

```r
rainfall_data <-
  lapply(2014:2017, FUN =
           function(x) {

             folder <-
               paste0(path_environmental,
                      '/rainfall_temperature/HCDP_data/rainfall/data_map/',
                      x)

             maps <- dir(folder)

             path <- paste0(folder, '/', maps)

             dat <- lapply(path, FUN =
                             function(i) {
                               rainfall <- rast(i)
                               d <- extract(rainfall, coords[, -3])
                               month <- gsub('^(.*)(..)(.tif)$', '\\2', i)
                               date <- as.Date(paste0(x, '-', month, '-', '01'))
                               d$date <- date
                               d$month <- as.numeric(month)
                               d$year <- x
                               colnames(d)[2] <- 'rainfall_mm'
                               d$sites <- coordinates_sites$Acronym[-8]
                               d[, -1]
                             })

             dat <- do.call('rbind', dat)
             dat
           })

rainfall_data <- as_tibble(do.call('rbind', rainfall_data))

rainfall_data$z_rainfall <- as.vector(scale(rainfall_data$rainfall_mm))

rainfall_data <- split(rainfall_data, rainfall_data$sites)

rainfall_data <-
  do.call('rbind',
          lapply(rainfall_data, FUN =
                   function(i) {
                     i <- i[i$year != 2014, ]
                     i$month_id <- 1:nrow(i)
                     i
                   }))

temp_data <-
  lapply(2014:2017, FUN =
           function(x) {

             folder <-
               paste0(path_environmental,
                      '/rainfall_temperature/HCDP_data/temperature/data_map/',
                      x)

             maps <- dir(folder)

             path <- paste0(folder, '/', maps)

             dat <- lapply(path, FUN =
                             function(i) {
                               temp <- rast(i)
                               d <- extract(temp, coords[, -3])
                               month <- gsub('^(.*)(..)(.tif)$', '\\2', i)
```

```r
                              date <- as.Date(paste0(x, '-', month, '-', '01'))
                              d$date <- date
                              d$month <- as.numeric(month)
                              d$year <- x
                              colnames(d)[2] <- 'temperature'
                              d$sites <- coordinates_sites$Acronym[-8]
                              d[, -1]
                            })

             dat <- do.call('rbind', dat)
             dat
           })

temp_data <- as_tibble(do.call('rbind', temp_data))

temp_data$z_temperature <- as.vector(scale(temp_data$temperature))

temp_data <- split(temp_data, temp_data$sites)

temp_data <-
  do.call('rbind',
          lapply(temp_data, FUN =
                   function(i) {
                     i <- i[i$year != 2014, ]
                     i$month_id <- 1:nrow(i)
                     i
                   }))

# Data for climatic models

# saveRDS(list(temperature = temp_data,
#              rainfall = rainfall_data), 'rainfall_temperature.rds')
```

S5 Pipeline 1: Climate models

S5.1 Data collection

Climatic predictors — We used the HCDP (Hawai'i climate data portal) for monthly average temperature and rainfall data from 2014 to 2017 on O ahu, and filtered the data for the coordinates of our sampling sites (Kodama et al., 2024; McLean et al., 2020). Then we used hierarchical Gaussian process time series models to estimate monthly rainfall and temperature at each site. We included year as a grouping factor, used partial pooling to estimate it, employed a log-normal distribution as the likelihood function, and utilized quadratic and periodic kernels to account for temporal and spatial correlations. We also defined prior probabilities that encompass plausible values of rainfall and temperature. The models were fitted using three chains, 10000 sampling and 1000 warmup iterations, and a thinning rate of 10 to run the algorithm. Then, we conducted sampling diagnostics to guarantee ess > 100 per Markov Chain, R-hat < 1.05 for chain convergence, and verified model fit through posterior predictive simulations. The models were fitted using the Hamiltonian Monte Carlo (HMC) algorithm implemented in Stan 2.36 language (Stan Development Team 2024) and its R interface with the CmStanR 0.81 package (Gabry & Češnovar 2022).

```
temp_data <- readRDS('rainfall_temperature.rds')[[1]]

rainfall_data <- readRDS('rainfall_temperature.rds')[[2]]

dat_rainfall <-
  list(
    N = nrow(rainfall_data),
    M = 12,
    N_year = 3,
    L = max(as.numeric(as.factor(rainfall_data$sites))),
    t = rainfall_data$month_id,
    year_id = as.numeric(as.factor(rainfall_data$year)),
    month = rainfall_data$month,
    level = as.numeric(as.factor(rainfall_data$sites)),
    rainfall = rainfall_data$rainfall_mm,
    period = 12
  )
```

We used a times series Gaussian processes hierarchical model to estimate average rainfall and temperature per site and month, from 2014 to 2018.

S5.2 Rainfall

S5.2.1 Mathematic notation of the model

The following model assess variation of cumulative rainfall across sites and months, including as random effect the year. The model uses a *periodic kernel* ($\sigma_f^2 \cdot exp(-\frac{2 \cdot \sin^2(\frac{\pi |t_i - t_j|}{period})}{\zeta^2})$) to estimate the covariance matrix of the Gaussian processes term to account temporal correlation and circularity among months.

$$
\begin{aligned}
&Temperature_i \sim \text{log-normal}(\mu_i, \sigma) \\
&log(\mu_i) = \alpha + f_{[site\ i,\ month\ i]} + \theta_{year\ i} \\
&K_{[site,month]}[i,j] = \sigma^2_{[site,month]} \cdot exp(-\frac{2 \cdot \sin^2(\pi|t_i - t_j|/period)}{\zeta^2_{[site,month]}}) \\
&K_{[site,month]} = L_{K_{[site,month]}} \cdot L^T_{K_{[site,month]}} \\
&f_{[site\ i,\ month\ i]} = L_{K_{[site,month]}} \cdot \eta_{[site,month]} \\
&\zeta_{[site,month]} \sim \text{inv-Gamma}(5,5) \\
&\sigma_{[site,month]} \sim cauchy(0,1) \\
&\eta_{[site,month]} \sim \mathcal{N}(0,1) \\
&\alpha \sim \mathcal{N}(5,1) \\
&\theta_{year} = \mu_\theta + Z_\theta \cdot \sigma_\theta \\
&Z_\theta \sim \mathcal{N}(0,1) \\
&\mu_\theta \sim \mathcal{N}(0,0.25) \\
&\sigma_\theta \sim Exp(1)
\end{aligned}
$$

Stan code

```
cat(file = 'climate_model.stan',
    '
    data {
      int N;                // Total observations (252)
      int M;                // N months (12)
      int L;                // levels of factor (sites) (7)
      int N_year;           // N year
      array[N] int year_id;  // years
      array[N] int t;       // number of time points (1, ..., 36)
      array[N] int month;   // month indices (1, ..., 12)
      array[N] int level;   // factor (grouping variable) (1, ..., 7)
      vector[N] rainfall;   // rainfall data
      int period;           // period of circular time (12)
    }

    parameters {
      real alpha;
      real<lower = 0> sigma;                // noise for the likelihood
      vector<lower = 0>[L] length_scale;    // length scale (smooth term)
      vector<lower = 0>[L] sigma_f;         // noise for GP
      array[L] vector[M] eta;    // latent variables for each month
      vector[N_year] z_year;
      real mu_year;
      real<lower = 0> sigma_year;
    }

    transformed parameters {
      array[L] vector[M] f;
      for (l in 1:L) {
        matrix[M, M] K;
        matrix[M, M] L_K;

        for (i in 1:(M-1)) {
          for (j in (i+1):M) {
```

```
          real distance = abs(i - j);
          real periodic_distance = fmin(distance, period - distance);
          // periodic kernel
          K[i, j] = sigma_f[l]^2 * exp(-2 * square(sin(pi()*periodic_distance / period))/square(length_scale[l
          K[j, i] = K[i, j];
        }
        K[i, i] = sigma_f[l]^2 + 1e-9;
      }
      K[M, M] = sigma_f[l]^2 + 1e-9;

      // cholesky decomposition
      L_K = cholesky_decompose(K);

      // transforme the latent variable eta to the GP
      f[l] = L_K * eta[l];
    }

    vector[N_year] year;
    year = mu_year + z_year * sigma_year;

  }

  model {
    sigma ~ cauchy(0, 1);
    length_scale ~ inv_gamma(5, 5);
    sigma_f ~ cauchy(0, 1);
    for (l in 1:L) {
      eta[l] ~ normal(0, 1);
    }

    alpha ~ normal(5, 1);

    z_year ~ normal(0, 1);
    mu_year ~ normal(0, 0.25);
    sigma_year ~ exponential(1);

    for (n in 1:N) {
      rainfall[n] ~ lognormal(alpha + f[level[n]][month[n]] +
                              year[year_id[n]], sigma);
    }
  }

  generated quantities {
    vector[N] y_pred;

    for (i in 1:N) {
      y_pred[i] = lognormal_rng(alpha + f[level[i]][month[i]] +
                                year[year_id[i]], sigma);
    }
  }
  ')
```

S5.2.2 Fitting the model

```
file <- paste0(getwd(), '/climate_model.stan')

fit_climate <- cmdstan_model(file, compile = T)

mod_temperature <-
  fit_climate$sample(
    data = dat_temperature,
```

```
    chains = 3,
    parallel_chains = 3,
    iter_sampling = 1e4,
    iter_warmup = 1e3,
    thin = 10,
    seed = 123
  )
```

S5.2.3 Sampling diagnostics

```
summary_rain <- mod_rainfall$summary()

summary_rain %$% plot(rhat ~ ess_bulk)
summary_rain %$% points(rhat ~ ess_tail, col = 'red')
```

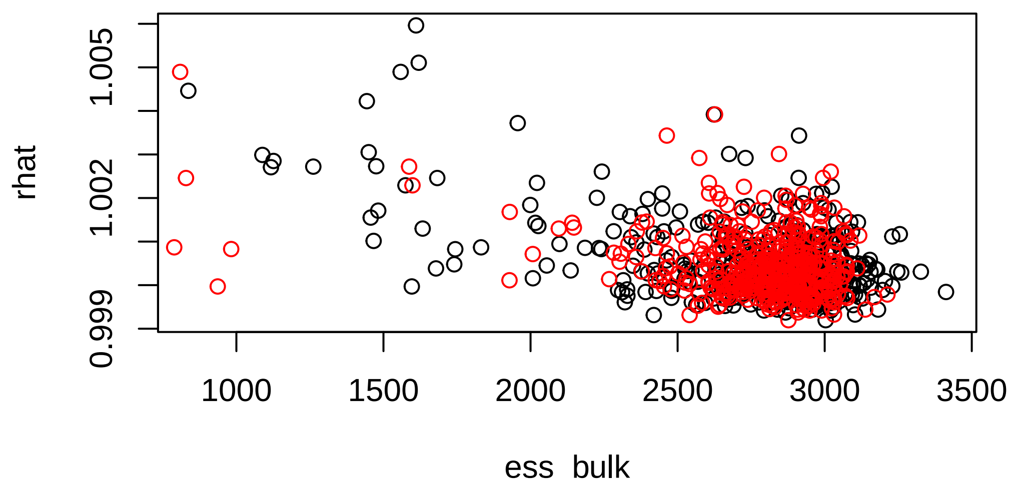

Figure S3: Rhat values vs effective sampling size (ess). Rhat < 1.05 indicates that the Markov Chains converged to the same stationary distribution. ess must be at least 100 per chain in order to be reliable

```
ppcheck_rainfall <- mod_rainfall$draws('y_pred', format = 'matrix')

plot(density(dat_rainfall$rainfall), main = '',
     ylim = c(0, 0.008), xlim = c(-40, 900), xlab = 'Cumulative rainfall')
for (i in 1:100) lines(density(ppcheck_rainfall[i, ]), lwd = 0.1)
lines(density(dat_rainfall$rainfall), col = 'red', lwd = 2)
```

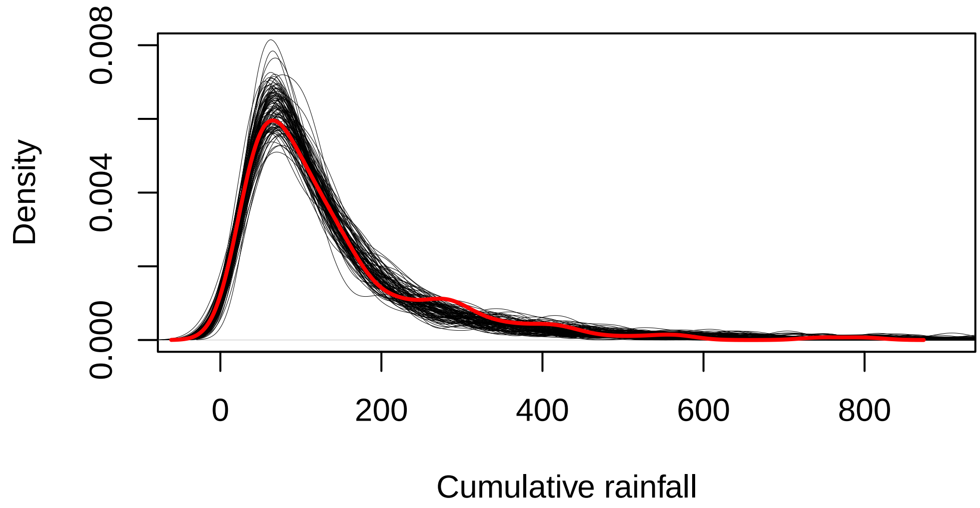

Figure S4: Posterior predictive checks of the model describing monthly cumulative rainfalla across seven sites in the Oahu island.

S5.2.4 Extracting posterior draws

```
post_rainfall <- mod_rainfall$draws(c('alpha', 'f', 'year', 'sigma'), format = 'df')

post_rainfall <-
  list(year = post_rainfall[, grep('^year', colnames(post_rainfall))],
       alpha = post_rainfall$alpha,
       f = post_rainfall[, grep('^f', colnames(post_rainfall))],
       sigma = post_rainfall$sigma)

dat_rainfall <- as_tibble(do.call('cbind', dat_rainfall[6:9]))

site_month <- unique(dat_rainfall[, c('level', "month")])

est_rainfall2 <-
  lapply(1:12, FUN =
           function(x) {

             cc <- paste0('^(.*)(,', x, '\\])$')

             mu <- mean(dat_rainfall$rainfall)
             sigma <- sd(dat_rainfall$rainfall)

             indx <- grep(cc, colnames(post_rainfall$f))

             post <- apply(post_rainfall$f[, indx, drop = T], 1, mean)
             a <- post_rainfall$alpha
             year <- apply(post_rainfall$year, 1, mean)
```

```
            sigma <- post_rainfall$sigma

            mu_est <- a + post + year

            mu_est <- exp(mu_est)

            tibble(mu = mean(mu_est) ,
                   li_mu = quantile(mu_est, 0.025),
                   ls_mu = quantile(mu_est, 0.975),
                   month = x)

          })

est_rainfall2 <- do.call('rbind', est_rainfall2)

for (i in 2:3) {
  est_rainfall2[[i]] <-
    (est_rainfall2[[i]] - mean(est_rainfall2$mu)) /
    sd(est_rainfall2$mu)
}

est_rainfall2$mu <- as.vector(scale(est_rainfall2$mu))

est_rainfall <-
  lapply(1:nrow(site_month), FUN =
           function(x) {
             site <- site_month$level[x]
             month <- site_month$month[x]

             f_GP <-
               paste0('f[', site, ',', month, ']')

             post <- post_rainfall$f[, f_GP, drop = T]
             a <- post_rainfall$alpha
             year <- apply(post_rainfall$year, 1, mean)
             sigma <- post_rainfall$sigma

             mu_est <- a + post + year
             mu_est <- mu_est

             set.seed(555)
             post_pred <- rlnorm(length(post), mu_est, sigma)

             tibble(mu = mean(exp(mu_est)),
                    li_mu = quantile(exp(mu_est), 0.025),
                    ls_mu = quantile(exp(mu_est), 0.975),
                    li_pred = quantile(post_pred, 0.025),
                    ls_pred = quantile(post_pred, 0.975),
                    sites = site,
                    month = month)

           })

est_rainfall <- do.call('rbind', est_rainfall)

est_rainfall$sites <- as.factor(est_rainfall$sites)
est_rainfall$sites <- factor(est_rainfall$sites,
                             labels = levels(as.factor(rainfall_data$sites)))

dat_rainfall$level <- as.factor(dat_rainfall$level)
dat_rainfall$sites <- factor(dat_rainfall$level,
                             labels = levels(as.factor(rainfall_data$sites)))
```

S5.2.5 Plotting posterior distribution

```
ggplot() +
  # geom_ribbon(data = est_rainfall,
  #             aes(month, ymin = li_pred, ymax = ls_pred, fill = sites),
  #             alpha = 0.2) +
  geom_ribbon(data = est_rainfall,
              aes(month, ymin = li_mu, ymax = ls_mu, fill = sites),
              alpha = 0.2) +
  geom_line(data = est_rainfall,
            aes(month, mu, color = sites)) +
  geom_point(data = dat_rainfall,
             aes(month, rainfall, color = sites), size = 0.8) +
  facet_wrap(~sites, scales = 'free_y') +
  scale_x_continuous(breaks = 1:12) +
  labs(y = 'Rainfall (mm)', x = 'Years') +
  theme_bw() +
  theme(panel.grid = element_blank(),
        text = element_text(size = 14),
        legend.position = 'none')
```

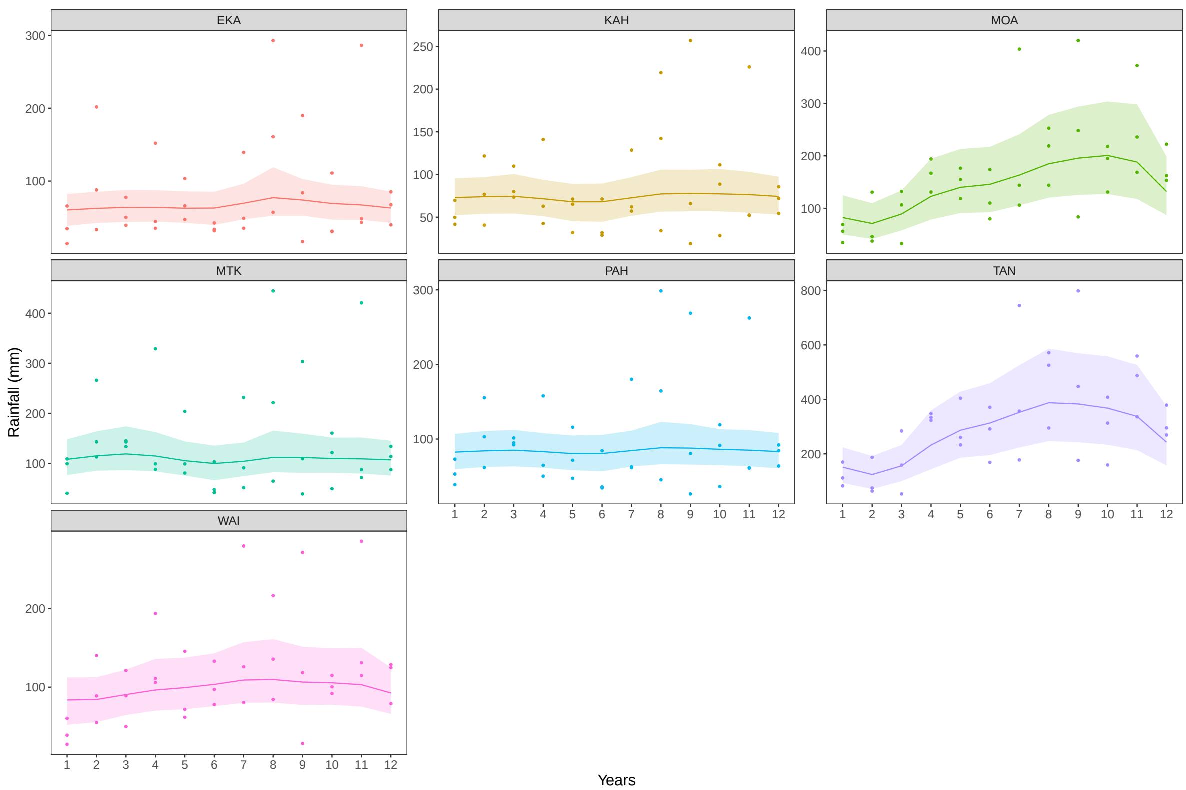

Figure S5: Monthly cumulative rainfall at seven studied localities in the Oahu island

S5.3 Temperature

S5.3.1 Mathematic notation of the model

The following model assess variation of average temperature across sites and months, including as random effect the year. The model uses a *periodic kernel* ($\sigma_f^2 \cdot exp(-\frac{2 \cdot \sin^2(\frac{\pi|t_i - t_j|}{period})}{\zeta^2})$) to estimate the covariance matrix of the Gaussian processes term to account temporal correlation and circularity among months.

$$
\begin{aligned}
&Temperature_i \sim \text{Student-T}(\nu = 7, \mu_i, \sigma) \\
&\mu_i = \alpha + f_{[site\ i,\ month\ i]} + \theta_{year\ i} \\
&K_{[site,month]}[i,j] = \sigma^2_{[site,month]} \cdot exp(-\frac{2 \cdot \sin^2(\pi|t_i - t_j|/period)}{\zeta^2_{[site,month]}}) \\
&K_{[site,month]} = L_{K_{[site,month]}} \cdot L^T_{K_{[site,month]}} \\
&f_{[site\ i,\ month\ i]} = L_{K_{[site,month]}} \cdot \eta_{[site,month]} \\
&\zeta_{[site,month]} \sim \text{inv-Gamma}(5,5) \\
&\sigma_{[site,month]} \sim cauchy(0,1) \\
&\eta_{[site,month]} \sim \mathcal{N}(0,1) \\
&\alpha \sim \mathcal{N}(20,5) \\
&\theta_{year} = \mu_\theta + Z_\theta \cdot \sigma_\theta \\
&Z_\theta \sim \mathcal{N}(0,1) \\
&\mu_\theta \sim \mathcal{N}(0,0.25) \\
&\sigma_\theta \sim Exp(1)
\end{aligned}
$$

S5.3.2 Stan code

```
dat_temperature <-
  list(
    N = nrow(temp_data),
    M = 12,
    N_year = 3,
    L = max(as.numeric(as.factor(temp_data$sites))),
    t = temp_data$month,
    year_id = as.numeric(as.factor(temp_data$year)),
    month = temp_data$month,
    level = as.numeric(as.factor(temp_data$sites)),
    temperature = temp_data$temperature,
    period = 12
  )


cat(file = 'climate_model.stan',
```

```
'
data {
  int N;                // Total observations (252)
  int M;                // N months (12)
  int L;                // levels of factor (sites) (7)
  int N_year;           // N year
  array[N] int year_id;  // years
  array[N] int t;       // number of time points (1, ..., 36)
  array[N] int month;   // month indices (1, ..., 12)
  array[N] int level;   // factor (grouping variable) (1, ..., 7)
  vector[N] temperature;   // rainfall data
  int period;           // period of circular time (12)
}

parameters {
  real alpha;
  real<lower = 0> sigma;                // noise for the likelihood
  vector<lower = 0>[L] length_scale;    // length scale (smooth term)
  vector<lower = 0>[L] sigma_f;         // noise for GP
  array[L] vector[M] eta;    // latent variables for each month
  vector[N_year] z_year;
  real mu_year;
  real<lower = 0> sigma_year;
}

transformed parameters {
  array[L] vector[M] f;
  for (l in 1:L) {
    matrix[M, M] K;
    matrix[M, M] L_K;

    for (i in 1:(M-1)) {
      for (j in (i+1):M) {
        real distance = abs(i - j);
        real periodic_distance = fmin(distance, period - distance);
        // periodic kernel
        K[i, j] = sigma_f[l]^2 * exp(-2 * square(sin(pi()*periodic_distance / period))/square(length_scale[l]
        K[j, i] = K[i, j];
      }
      K[i, i] = sigma_f[l]^2 + 1e-9;
    }
    K[M, M] = sigma_f[l]^2 + 1e-9;

    // cholesky decomposition
    L_K = cholesky_decompose(K);

    // transforme the latent variable eta to the GP
    f[l] = L_K * eta[l];
  }

  vector[N_year] year;
  year = mu_year + z_year * sigma_year;

}

model {
  sigma ~ cauchy(0, 1);
  length_scale ~ inv_gamma(5, 5);
  sigma_f ~ cauchy(0, 1);
  for (l in 1:L) {
    eta[l] ~ normal(0, 1);
  }

  alpha ~ normal(20, 5);

  z_year ~ normal(0, 1);
  mu_year ~ normal(0, 0.25);
```

```
      sigma_year ~ exponential(1);

      for (n in 1:N) {
        temperature[n] ~ student_t(7, alpha + f[level[n]][month[n]] +
                                   year[year_id[n]], sigma);
      }
    }

    generated quantities {
      vector[N] y_pred;

      for (i in 1:N) {
        y_pred[i] = student_t_rng(7, alpha + f[level[i]][month[i]] +
                                 year[year_id[i]], sigma);
      }
    }
    ')
```

S5.3.3 Fitting the model

```
file <- paste0(getwd(), '/climate_model.stan')

fit_climate <- cmdstan_model(file, compile = T)

mod_temperature <-
  fit_climate$sample(
    data = dat_temperature,
    chains = 3,
    parallel_chains = 3,
    iter_sampling = 1e4,
    iter_warmup = 1e3,
    thin = 10,
    seed = 123
  )
```

S5.3.4 Sampling diagnostics

```
summary_temp <- mod_temperature$summary()

summary_temp %$% plot(rhat ~ ess_bulk)
summary_temp %$% points(rhat ~ ess_tail, col = 'red')
```

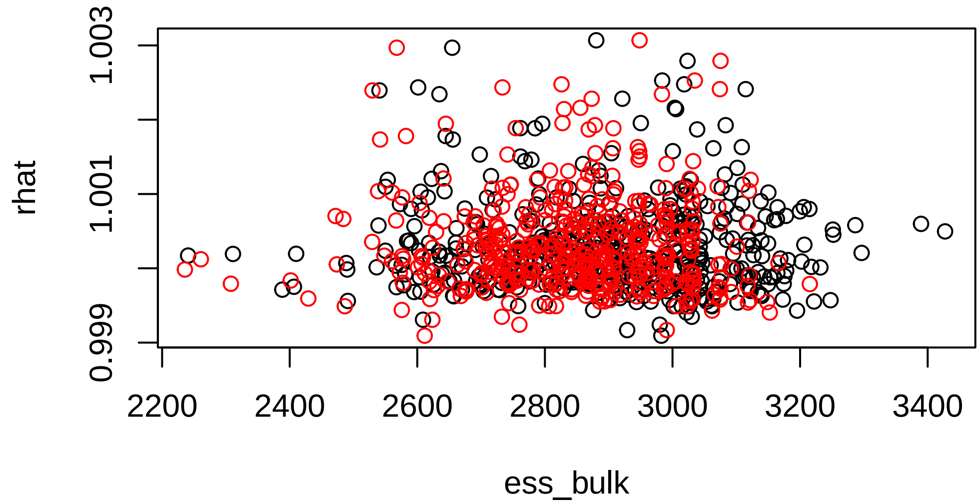

Figure S6: Rhat values vs effective sampling size (ess). Rhat < 1.05 indicates that the Markov Chains converged to the same stationary distribution. ess must be at least 100 per chain in order to be reliable

```
ppcheck_temp <- mod_temperature$draws('y_pred', format = 'matrix')

plot(density(dat_temperature$temperature), main = '', ylim = c(0, 0.2),
     xlab = 'Average monthly temperature')
for (i in 1:400) lines(density(ppcheck_temp[i, ]), lwd = 0.1)
lines(density(dat_temperature$temperature), col = 'red', lwd = 2)
```

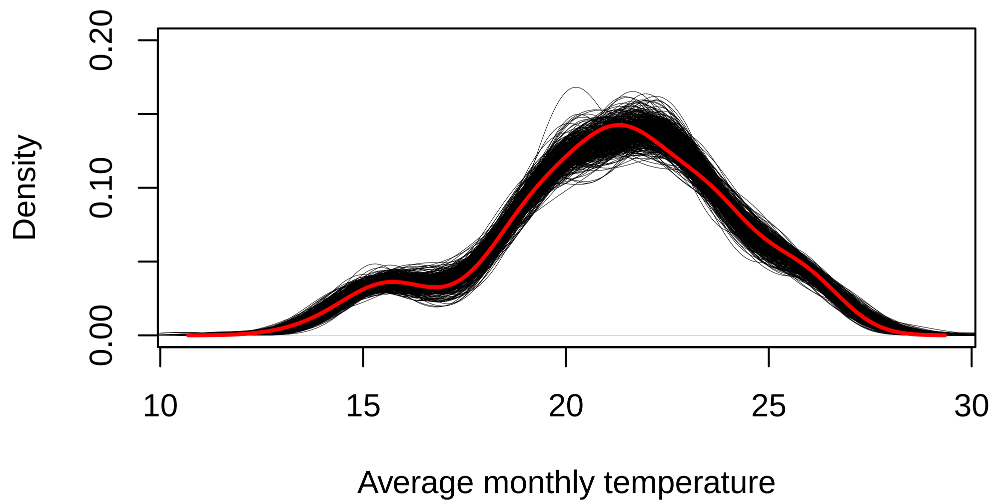

Figure S7: Posterior predictive checks of the model describing monthly average temperature across seven sites in the Oahu island.

S5.3.5 Extracting posterior draws

```
post_temp <- mod_temperature$draws(c('alpha', 'f', 'year', 'sigma'), format = 'df')

post_temp <-
  list(f = post_temp[, grep('^f', colnames(post_temp))],
       year = post_temp[, grep('^year', colnames(post_temp))],
       alpha = post_temp$alpha,
       sigma = post_temp$sigma)

dat_temperature <- as_tibble(do.call('cbind', dat_temperature[1:7]))

est_temp2 <-
  lapply(1:12, FUN =
           function(x) {

             cc <- paste0('^(.*)(,', x, '\\])$')

             indx <- grep(cc, colnames(post_rainfall$f))

             post <- apply(post_temp$f[, indx, drop = T], 1, mean)
             a <- post_temp$alpha
             year <- apply(post_temp$year, 1, mean)
             sigma <- post_temp$sigma

             mu_est <- a + post + year

             tibble(mu = mean(mu_est) ,
```

```
                    li_mu = quantile(mu_est, 0.025),
                    ls_mu = quantile(mu_est, 0.975),
                    month = x)

           })

est_temp2 <- do.call('rbind', est_temp2)

for (i in 2:3) {
  est_temp2[[i]] <-
    (est_temp2[[i]] - mean(est_temp2$mu)) /
    sd(est_temp2$mu)
}

est_temp2$mu <- as.vector(scale(est_temp2$mu))

est_rainfall2$class <- 'Rainfall'
est_temp2$class <- 'Temperature'

# saveRDS(rbind(est_rainfall2,
#                est_temp2), 'climate_for_plot.rds')

est_temp <-
  lapply(1:nrow(site_month), FUN =
           function(x) {
             site <- site_month$level[x]
             month <- site_month$month[x]

             f_GP <-
               paste0('f[', site, ',', month, ']')

             post <- post_temp$f[, f_GP, drop = T]
             sigma <- post_temp$sigma
             a <- post_temp$alpha
             year <- apply(post_temp$year, 1, mean)

             mu_est <- a + post + year

             set.seed(555)
             post_pred <- rstudent(7, length(post), mu_est, sigma)

             tibble(mu = mean(mu_est),
                    li_mu = quantile(mu_est, 0.025),
                    ls_mu = quantile(mu_est, 0.975),
                    li_pred = quantile(post_pred, 0.025),
                    ls_pred = quantile(post_pred, 0.975),
                    sites = site,
                    month = month)

           })

est_temp <- do.call('rbind', est_temp)

est_temp$sites <- as.factor(est_temp$sites)
est_temp$sites <- factor(est_temp$sites,
                         labels = levels(as.factor(temp_data$sites)))

# saveRDS(list(rainfall = est_rainfall,
#               temperature = est_temp), 'AVG_climate_data.rds')
```

S5.3.6 Plotting posterior distribution

```
ggplot() +
  # geom_ribbon(data = est_temp,
  #             aes(month, ymin = li_pred, ymax = ls_pred, fill = sites),
  #             alpha = 0.2) +
  geom_ribbon(data = est_temp,
              aes(month, ymin = li_mu, ymax = ls_mu, fill = sites),
              alpha = 0.2) +
  geom_line(data = est_temp,
            aes(month, mu, color = sites)) +
  geom_point(data = temp_data,
             aes(month, temperature, color = sites), size = 0.8) +
  facet_wrap(~sites, scales = 'free') +
  labs(y = 'Temperature (°C)', x = 'Years') +
  scale_x_continuous(breaks = 1:12) +
  theme_bw() +
  theme(panel.grid = element_blank(),
        text = element_text(size = 14),
        legend.position = 'none')
```

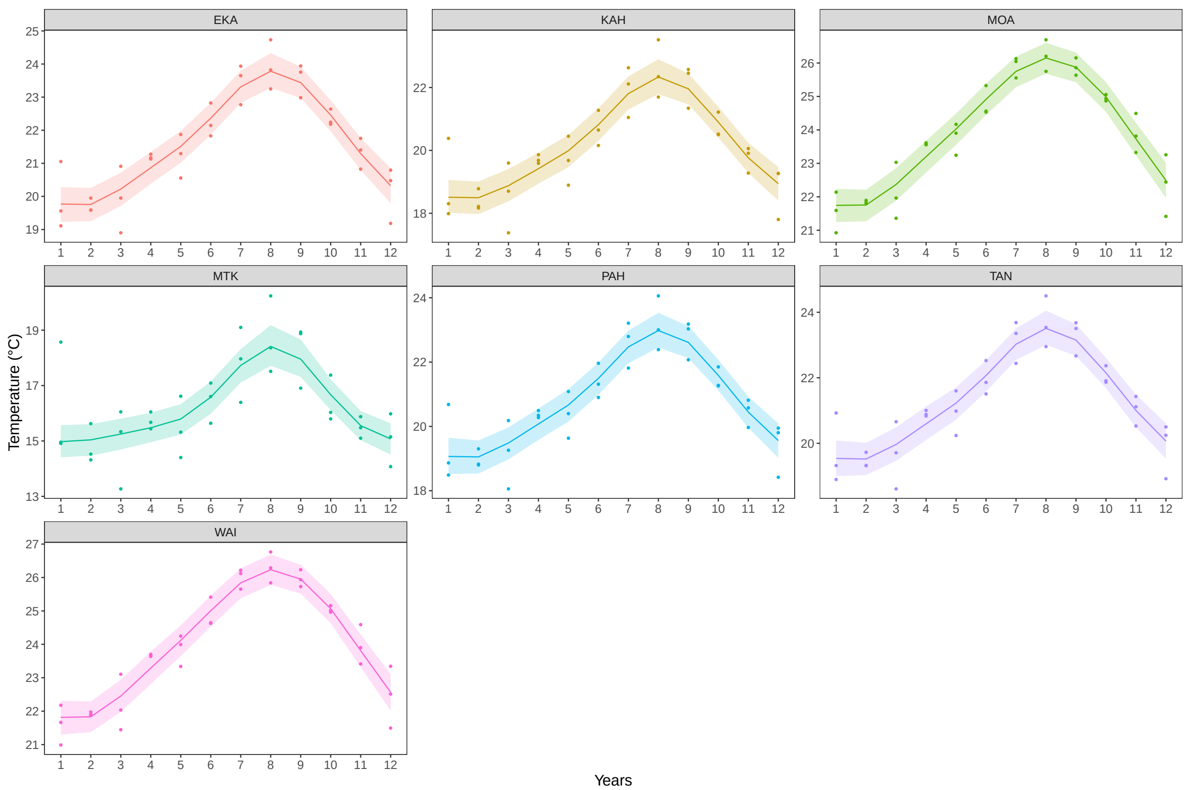

Figure S8: Monthly average monthly temperature at seven studied localities in the Oahu island

S6 Computational environment

```r
sessionInfo()
```

```
R version 4.5.1 (2025-06-13)
Platform: aarch64-apple-darwin20
Running under: macOS Sequoia 15.5

Matrix products: default
BLAS:   /Library/Frameworks/R.framework/Versions/4.5-arm64/Resources/lib/libRblas.0.dylib
LAPACK: /Library/Frameworks/R.framework/Versions/4.5-arm64/Resources/lib/libRlapack.dylib;

locale:
[1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8

time zone: America/Sao_Paulo
tzcode source: internal

attached base packages:
[1] parallel  stats     graphics  grDevices utils     datasets  methods
[8] base

other attached packages:
 [1] animation_2.7       rethinking_2.42     posterior_1.6.1
 [4] cmdstanr_0.9.0.9000 patchwork_1.3.1     sf_1.0-21
 [7] raster_3.6-32       sp_2.2-0            terra_1.8-54
[10] ggfortify_0.4.18    ggplot2_3.5.2       tidyr_1.3.1
[13] tibble_3.3.0        readxl_1.4.5        lubridate_1.9.4
[16] magrittr_2.0.3      dplyr_1.1.4

loaded via a namespace (and not attached):
 [1] shape_1.4.6.1        gtable_0.3.6         tensorA_0.36.2.1
 [4] xfun_0.52            processx_3.8.6       lattice_0.22-7
 [7] vctrs_0.6.5          tools_4.5.1          ps_1.9.1
[10] generics_0.1.4       proxy_0.4-27         pkgconfig_2.0.3
[13] KernSmooth_2.23-26   checkmate_2.3.2      RColorBrewer_1.1-3
[16] distributional_0.5.0 lifecycle_1.0.4      compiler_4.5.1
[19] farver_2.1.2         stringr_1.5.1        codetools_0.2-20
[22] htmltools_0.5.8.1    class_7.3-23         yaml_2.3.10
[25] Rttf2pt1_1.3.12      extrafontdb_1.0      pillar_1.11.0
[28] MASS_7.3-65          classInt_0.4-11      abind_1.4-8
```

```
[31] tidyselect_1.2.1     digest_0.6.37        mvtnorm_1.3-3
[34] stringi_1.8.7        purrr_1.0.4          labeling_0.4.3
[37] extrafont_0.19       fastmap_1.2.0        grid_4.5.1
[40] cli_3.6.5            loo_2.8.0            e1071_1.7-16
[43] withr_3.0.2          scales_1.4.0         backports_1.5.0
[46] timechange_0.3.0     rmarkdown_2.29       matrixStats_1.5.0
[49] gridExtra_2.3        cellranger_1.1.0     coda_0.19-4.1
[52] evaluate_1.0.4       knitr_1.50           rlang_1.1.6
[55] Rcpp_1.1.0           glue_1.8.0           DBI_1.2.3
[58] rstudioapi_0.17.1    jsonlite_2.0.0       R6_2.6.1
[61] units_0.8-7
```

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