

Appendix S2: Growing degree methods and temporal autocorrelation

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Defining biological thresholds

```
# set seed for reproducibility
set.seed(20260117)

# biological thresholds
tb <- 5      # Base Temperature
topt <- 28   # Optimum Temperature
tu <- 40     # Upper Threshold
```

Daily growing degree day methods (based on daily maximum and minimum temperatures)

Method 1 (Traditional Linear, McMaster and Wilhelm, 1997): Calculates the average of the daily max/min temperatures first, then applies thresholds

```
# Method 1: Traditional Linear
# Source: McMaster and Wilhelm (1997)
calc_m1 <- function(temps) {
  d <- get_daily(temps)
  tavg <- (d$max + d$min) / 2
  # Linear with cutoffs
  dtt <- ifelse(tavg < tb, 0,
               ifelse(tavg > tu, tu - tb,
                     tavg - tb))
  sum(dtt)
}
```

Method 2 (Modified Linear, McMaster and Wilhelm, 1997): Applies thresholds to the max/min before averaging. First, get daily max/min from hourly data:

```
get_daily <- function(temps) {
  m <- matrix(temps, nrow = 24)
  list(max = apply(m, 2, max), min = apply(m, 2, min))
}

calc_m2 <- function(temps) {
  d <- get_daily(temps)
  # Adjusts daily extremes before averaging
  tm <- pmin(d$max, tu)
  tn <- pmax(d$min, tb)
  tavg <- (tm + tn) / 2
  dtt <- ifelse(tavg < tb, 0, tavg - tb)
  sum(dtt)
}
```

Hourly growing degree day: Calculate growth accumulation for every hour

Method 3 (Hourly Linear, Ritchie and NeSmith, 1991): Uses linear increase to optimum, linear decrease to upper threshold

```
calc_m3 <- function(th) {
  htt <- numeric(length(th))

  # Linear increase phase
  mk1 <- th >= tb & th <= topt
  htt[mk1] <- th[mk1] - tb

  # Linear decrease phase
  mk2 <- th > topt & th <= tu
  htt[mk2] <- (topt - tb) * ((tu - th[mk2]) / (tu - topt))

  sum(htt) / 24
}
```

Method 4 (Beta Function, Zhou and Wang, 2018): Uses a bell curve

```
calc_m4 <- function(th) {
  htt <- numeric(length(th))
  mk <- th > tb & th < tu

  exp_f <- (tu - topt) / (topt - tb)
  t1 <- (th[mk] - tb) / (topt - tb)
  t2 <- (tu - th[mk]) / (tu - topt)

  htt[mk] <- (topt - tb) * t1 * (t2 ^ exp_f)
  sum(htt) / 24
}
```

Simulation: We simulated three average temperature scenarios (Cold, Ambient, Hot) with three different temporal autocorrelation strengths (no autocorrelation, cold → hot, hot → cold) to test if the growing degree day methods could capture the order of temperatures (for full description, go to Section 2.2 of Methods)

```
means <- c(10, 20, 30)
scen_names <- c("cold", "ambient", "hot")
n_sims <- 100
res_mat <- NULL

for (s in 1:3) {
  m_temp <- means[s]
  l_lim <- m_temp - 10
  u_lim <- m_temp + 10

  for (i in 1:n_sims) {
    # 1. Generate random sequence (no autocorrelation) - 240 HOURS (10 DAYS)
    x_rand <- rnorm(240, m_temp, 2.5)
    x_rand[x_rand > u_lim] <- u_lim
    x_rand[x_rand < l_lim] <- l_lim
    x_rand <- ((x_rand - mean(x_rand)) / sd(x_rand)) * 2.5 + m_temp

    # 2. Generate cold -> hot sequence
    alpha <- 0.95
    gs <- numeric(240); gs[1] <- rnorm(1)
    for (k in 2:240) gs[k] <- alpha * gs[k-1] + rnorm(1) * sqrt(1 - alpha^2)
```

```

x_fwd <- x_rand[order(order(gs))]

# 3. Generate hot -> cold sequence
x_rev <- rev(x_fwd)

# Calculate growing degree day for 3 sequences
g_rand <- c(calc_m1(x_rand), calc_m2(x_rand), calc_m3(x_rand), calc_m4(x_rand))
g_fwd  <- c(calc_m1(x_fwd),  calc_m2(x_fwd),  calc_m3(x_fwd),  calc_m4(x_fwd))
g_rev  <- c(calc_m1(x_rev),  calc_m2(x_rev),  calc_m3(x_rev),  calc_m4(x_rev))

# Calculate differences in growing degree day units
d_fwd_rand <- g_fwd - g_rand # ColdHot - Random
d_rev_rand <- g_rev - g_rand # HotCold - Random
d_rev_fwd  <- g_rev - g_fwd  # HotCold - ColdHot

# Calculate error % for all pairwise comparisons
# 1. ColdHot vs Rand
pct_err_fr_1 <- abs(d_fwd_rand[1]) / max(g_rand[1], 0.1) * 100
pct_err_fr_2 <- abs(d_fwd_rand[2]) / max(g_rand[2], 0.1) * 100
pct_err_fr_3 <- abs(d_fwd_rand[3]) / max(g_rand[3], 0.1) * 100
pct_err_fr_4 <- abs(d_fwd_rand[4]) / max(g_rand[4], 0.1) * 100

# 2. HotCold vs Rand
pct_err_rr_1 <- abs(d_rev_rand[1]) / max(g_rand[1], 0.1) * 100
pct_err_rr_2 <- abs(d_rev_rand[2]) / max(g_rand[2], 0.1) * 100
pct_err_rr_3 <- abs(d_rev_rand[3]) / max(g_rand[3], 0.1) * 100
pct_err_rr_4 <- abs(d_rev_rand[4]) / max(g_rand[4], 0.1) * 100

# 3. HotCold vs ColdHot
pct_err_rf_1 <- abs(d_rev_fwd[1]) / max(g_fwd[1], 0.1) * 100
pct_err_rf_2 <- abs(d_rev_fwd[2]) / max(g_fwd[2], 0.1) * 100
pct_err_rf_3 <- abs(d_rev_fwd[3]) / max(g_fwd[3], 0.1) * 100
pct_err_rf_4 <- abs(d_rev_fwd[4]) / max(g_fwd[4], 0.1) * 100

# Store differences and % errors
res_mat <- rbind(res_mat, c(s,
                             # Raw Diffs
                             d_fwd_rand[1], d_fwd_rand[2], d_fwd_rand[3], d_fwd_rand[4], # Fwd-Rand
                             d_rev_rand[1], d_rev_rand[2], d_rev_rand[3], d_rev_rand[4], # Rev-Rand
                             d_rev_fwd[1], d_rev_fwd[2], d_rev_fwd[3], d_rev_fwd[4], # Rev-Fwd
                             # % Errors
                             pct_err_fr_1, pct_err_fr_2, pct_err_fr_3, pct_err_fr_4,
                             pct_err_rr_1, pct_err_rr_2, pct_err_rr_3, pct_err_rr_4,
                             pct_err_rf_1, pct_err_rf_2, pct_err_rf_3, pct_err_rf_4))
}
}

# Convert matrix to dataframe
res_df <- data.frame(res_mat)
colnames(res_df) <- c("scenario",
                     # Raw diffs
                     "diff_fr_eq1", "diff_fr_eq2", "diff_fr_eq3", "diff_fr_eq4",
                     "diff_rr_eq1", "diff_rr_eq2", "diff_rr_eq3", "diff_rr_eq4",

```

```

"diff_rf_eq1", "diff_rf_eq2", "diff_rf_eq3", "diff_rf_eq4",
# % Errors
"pct_fr_eq1", "pct_fr_eq2", "pct_fr_eq3", "pct_fr_eq4",
"pct_rr_eq1", "pct_rr_eq2", "pct_rr_eq3", "pct_rr_eq4",
"pct_rf_eq1", "pct_rf_eq2", "pct_rf_eq3", "pct_rf_eq4")

# Aggregate means by scenario
agg_mean <- aggregate(. ~ scenario, res_df, mean)

```

Mean difference in growing degree days: Here we show the difference in growing degree day units (a value of 0 means the method is not able to differentiate between the temperature regimes with different intensities of temporal autocorrelation)

Table 1: Difference: Cold->Hot Sequence vs Random

Scenario	Eq1	Eq2	Eq3	Eq4
cold	0.1900	0.1641	0	0
ambient	-0.1359	-0.1359	0	0
hot	0.1615	0.1615	0	0

Table 2: Difference: Hot->Cold Sequence vs Random

Scenario	Eq1	Eq2	Eq3	Eq4
cold	0.1900	0.1641	0	0
ambient	-0.1359	-0.1359	0	0
hot	0.1615	0.1615	0	0

Table 3: Difference: Hot->Cold Sequence vs Cold->Hot Sequence

Scenario	Eq1	Eq2	Eq3	Eq4
cold	0	0	0	0
ambient	0	0	0	0
hot	0	0	0	0

Mean relative error (%): Here the error is shown as a percentage of the total GDD accumulated.

Table 4: Relative Error (%): Cold->Hot vs Random

Scenario	Eq1	Eq2	Eq3	Eq4
cold	2.3719	2.0946	0	0
ambient	0.9949	0.9949	0	0
hot	0.4614	0.4614	0	0

Table 5: Relative Error (%): Hot->Cold vs Random

Scenario	Eq1	Eq2	Eq3	Eq4
cold	2.3719	2.0946	0	0
ambient	0.9949	0.9949	0	0
hot	0.4614	0.4614	0	0

Table 6: Relative Error (%): Hot->Cold vs Cold->Hot

Scenario	Eq1	Eq2	Eq3	Eq4
cold	0	0	0	0
ambient	0	0	0	0
hot	0	0	0	0

Conclusion: The growing degree day calculations distinguished between strong versus no autocorrelation thermal regimes only in the few instances where the hourly temperature sequence altered the daily maxima and minima.

References McMaster, G. S., & Wilhelm, W. W. (1997). Growing degree-days: one equation, two interpretations. *Agricultural and Forest Meteorology*, 87(4), 291-300.

Ritchie, J. T., & NeSmith, D. S. (1991). Temperature and crop development. In *Modeling plant and soil systems* (pp. 5-29). American Society of Agronomy.

Zhou, G., & Wang, Q. (2018). A new nonlinear method for calculating growing degree days. *Scientific Reports*, 8(1), 10149.