Supplementary material

Rangewide adaptive plasticity in trees provides resilience to climate change

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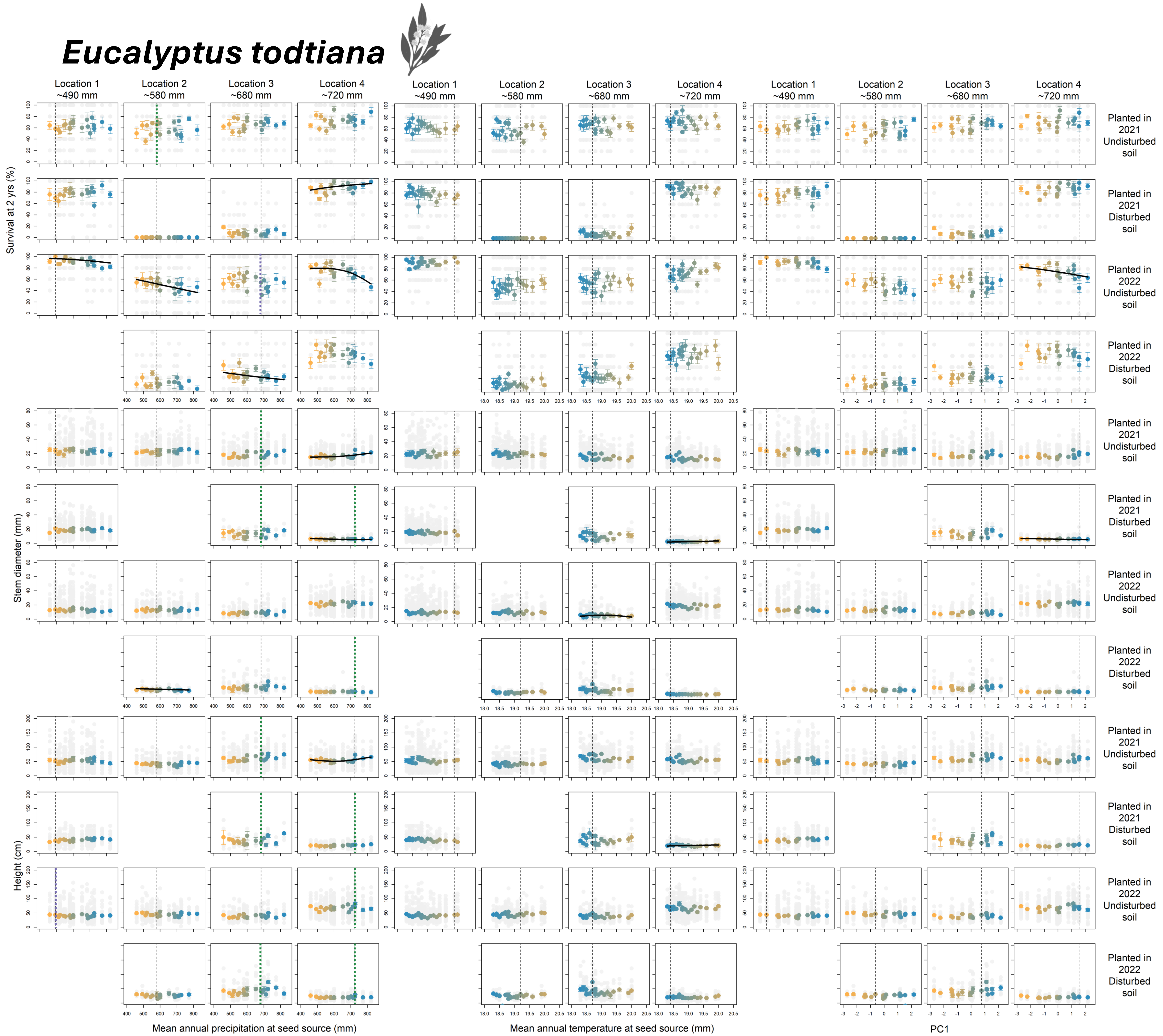
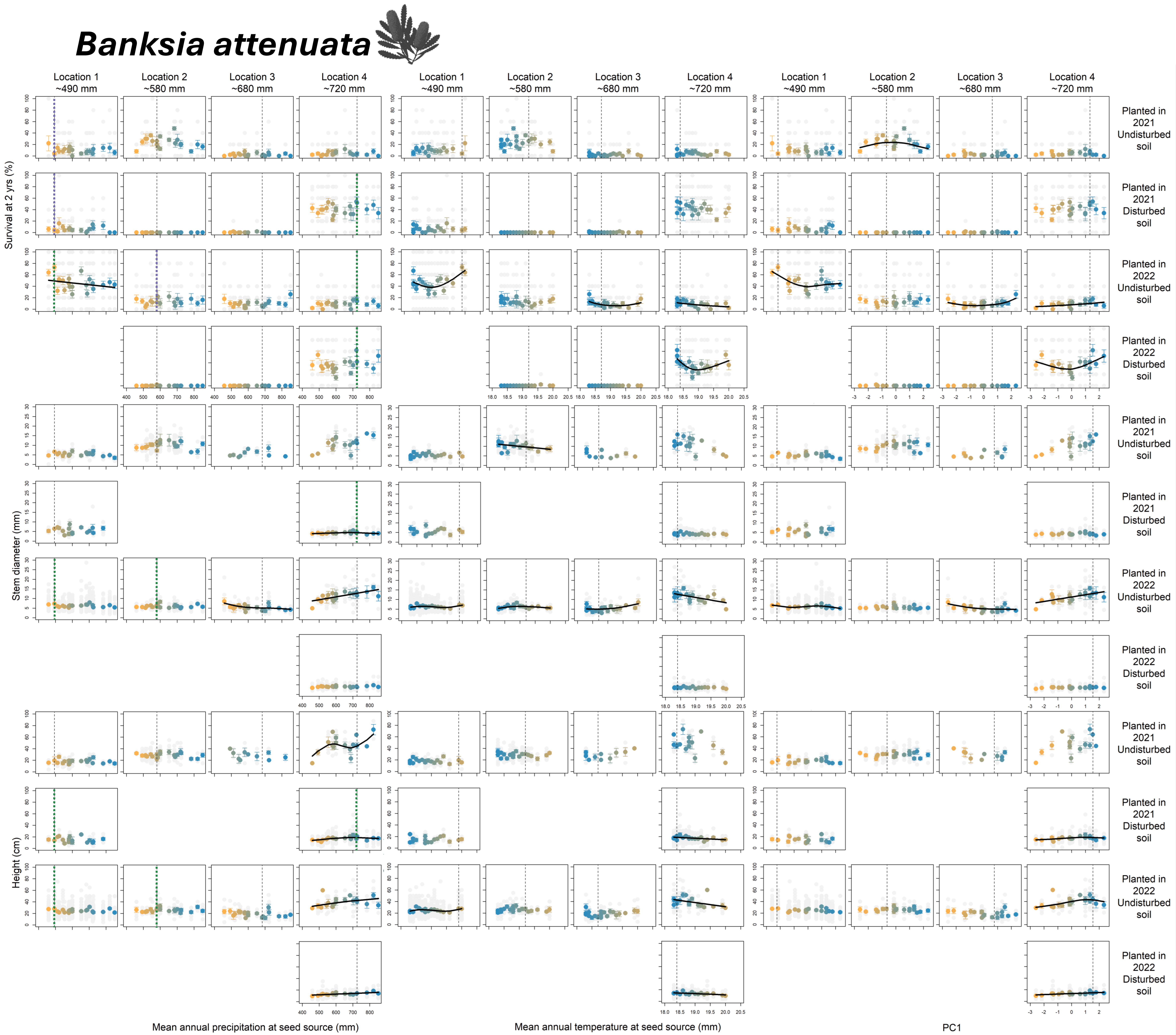


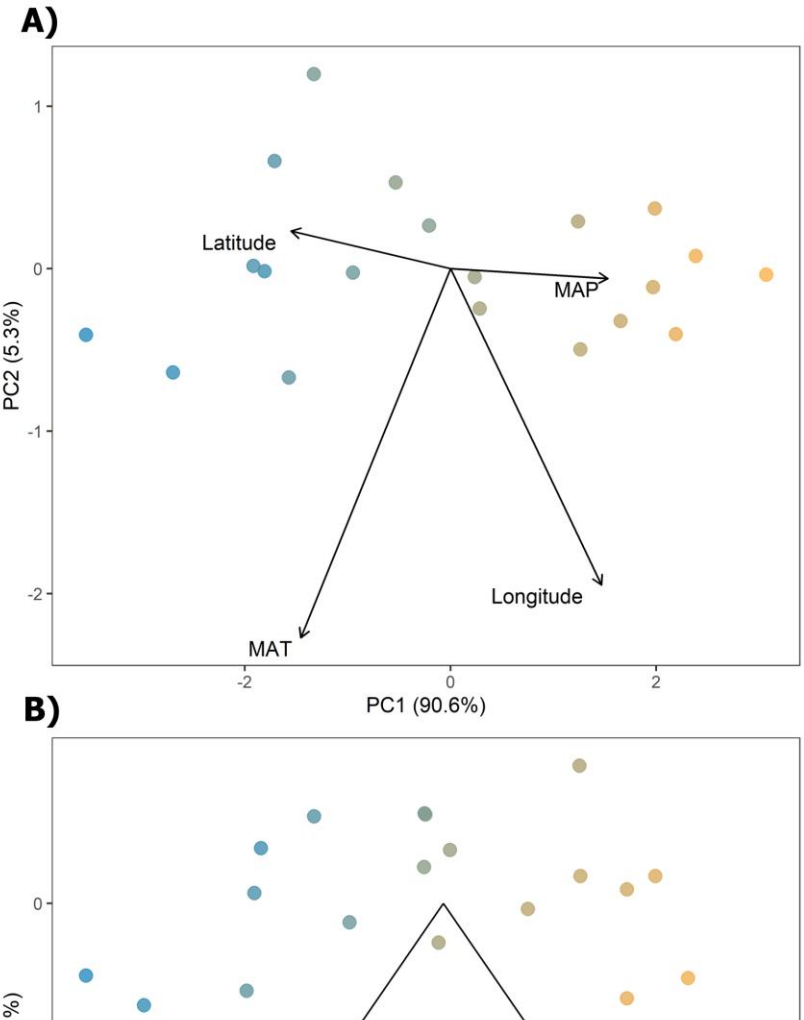
Eucalyptus todtiana
Location 1 ~490 mm
Location 2 ~580 mm
Location 3 ~680 mm
Location 4 ~720 mm
Planted in 2021 Undisturbed soil
Planted in 2021 Disturbed soil
Planted in 2022 Undisturbed soil
Planted in 2022 Disturbed soil
Survival at 2 yrs (%)
Stem diameter (mm)
Height (cm)
Mean annual precipitation at seed source (mm)
Mean annual temperature at seed source (mm)
PC1

Supplementary Fig. 1 | Associations between plant survival, growth, and climate across 20 provenances of *Eucalyptus todtiana*. Coloured points with standard error bars show the mean percentage survival (top row), stem diameter (middle row) or height (bottom row) observed for each provenance plotted against its climatic characteristics: MAP (column 1), MAT (column 2), and PC1 (column 3), with blue indicating source populations from wetter and cooler regions and yellow indicating those from drier and warmer regions. Solid black horizontal lines show significant non-linear relationships (GAMM $p < 0.05$). Grey dashed vertical lines show the local MAP at each trial location across the climate gradient (also indicated in top axis labels). Coloured dashed vertical lines indicate a significant local effect across analyses: green when the local provenance performed better than other provenances, purple when it performed worse.



Banksia attenuata
Location 1 ~490 mm
Location 2 ~580 mm
Location 3 ~680 mm
Location 4 ~720 mm
Planted in 2021 Undisturbed soil
Planted in 2021 Disturbed soil
Planted in 2022 Undisturbed soil
Planted in 2022 Disturbed soil
Survival at 2 yrs (%)
Stem diameter (mm)
Height (cm)
Mean annual precipitation at seed source (mm)
Mean annual temperature at seed source (mm)
PC1

Supplementary Fig. 2 | Associations between plant survival, growth, and climate across 20 provenances of *Banksia attenuata*. Coloured points with standard error bars show the mean percentage survival (top row), stem diameter (middle row) or height (bottom row) observed for each provenance plotted against its climatic characteristics: MAP (column 1), MAT (column 2), and PC1 (column 3), with blue indicating source populations from wetter and cooler regions and yellow indicating those from drier and warmer regions. Solid black horizontal lines show significant non-linear relationships (GAMM $p < 0.05$). Grey dashed vertical lines show the local MAP at each trial location across the climate gradient (also indicated in top axis labels). Coloured dashed vertical lines indicate a significant local effect across analyses: green when the local provenance performed better than other provenances, purple when it performed worse.



Supplementary Fig. 3 | Climatic and geographic characteristics of provenances. A) Principal component analysis (PCA) of long term mean annual temperature (MAT, 1970–2000), long term mean annual precipitation (MAP, 1970–2000), longitude, and latitude for each provenance. B) PCA of MAT and MAP only, with PC1 which explains 92.2% of variation in data used in subsequent analyses. Provenance climate data were obtained from WorldClim[11] V2.1

Supplementary Note 1 | Species information

Banksia attenuata R.Br. (Proteaceae) and *Eucalyptus todtiana* F.Muell (Myrtaceae) are dominant and common tree species in Banksia woodlands of the Swan Coastal Plain, a Federally listed Threatened Ecological Community[1] of the South West Australian Floristic Region (SWAFR), a globally recognized biodiversity hotspot[2]. The region experiences a Mediterranean climate, with hot, dry summers and cool, wet winters[2], and is among the most fire-prone on earth. Consequently, the biodiverse vegetation has evolved traits in response to drought associated with its Mediterranean climate, nutrient-deficient soils and fire.

The distribution of *E. todtiana* is largely continuous along the Swan Coastal Plain and Eneabba sandplain, extending ca. 400km north from Perth (Extended data Fig. 5). *Banksia attenuata* overlaps this distribution but is also the most widespread Banksia in Western Australia, extending further north, south and east, and is found across much of SWWA. Both species are priorities for the ecological restoration of disturbed lands across their distribution[3].

Eucalyptus todtiana is a small, broad tree with a mallee growth form, typically reaching 9–15 m in height. It is long-lived, resprouts after fire from a lignotuber, flowers profusely, and attracts nectar-feeding birds and insects as pollinators. *E. todtiana* produces many small, lightweight seeds that lack aerodynamic traits. These seeds are released and fall close to the parent tree, with dispersal influenced by factors such as tree height, canopy width, seed weight, and wind strength. While long-distance dispersal events are rare, they can occur via strong wind events, especially common after fire, or through dispersal by large birds such as cockatoos who may disperse fruit-bearing seed while feeding on the seeds[4].

Banksia attenuata is a long-lived tree species that grows up to 10 m tall in open forests of the more mesic south but is typically a multi-stemmed shrub to 1.5m high in the northern heathlands[5]. The shrub form resprouts after fire from a lignotuber. As with most banksias, seeds are stored in persistent infructescences (cones) in the plant canopy, potentially for several years (serotiny), and the release of seed is typically cued to fire[6]. The seeds, although winged, are primarily dispersed by gravity and then blown by wind across the soil surface, generally remaining close to the parent plant[7]. However, long-distance dispersal of up to 2.6km has been detected[5]. The species has a long evolutionary history of ca. 19 million years[8], implying a strong capacity for resilience to variable environmental conditions.

Supplementary Note 2 | Seed preparation

For each species, fruit containing mature seed was sourced from five arbitrarily chosen maternal plants of broadly equivalent size, age, fecundity, and health from each of 20 wild provenances from across a latitudinal climate gradient (Fig. 1). As much as possible, all source population properties (size, state) were standardised by targeting large populations in healthy plant communities within nature reserves.

For *E. todtiana*, fruit (capsules) were harvested between December 2020 and February 2021 for use in the 2021 and 2022 planting years. For *B. attenuata*, cones bearing fruit were collected during the same period for use in the 2021 planting year, and again between December 2021 and January 2022 for the 2022 planting year.

For *B. attenuata,* seeds were processed by burning cones to open woody follicles from which seed were extracted and viability assessed by x-ray using a Faxitron Specimen Radiography System (MX-20). Seeds were considered filled and viable if the x-rays showed a full, intact embryo with a thick, evenly white seed coat, free of cracks or hollows. Seeds deemed viable were then sorted into envelopes and stored at 20˚C prior to hand-sowing directly into the trial sites in June and July of 2021 and July of 2022.

For *E. todtiana,* fruit was dried in a 50˚C degree oven to open and release seed and chaff. Seeds were then separated from chaff and germinated in forestry tubes containing native soil mix at 20˚C. In 2021, low germination required some seeds to be re-sown, resulting in seedling age differences of up to 11 weeks among the different sow batches. For the 2022 planting, three seeds were sown per forestry tube to ensure one seedling per pot, eliminating the need for re-sowing and reducing seedling age differences to two weeks among the different sow batches. Once germinated, 2-week-old seedlings were transferred to a glasshouse for 2 weeks, and then to an open courtyard, initially under shade cloth, and under reticulation. At approximately 5 months from germination, seedlings were planted at the field trial sites in July 2021 and 2022, with height of each seedling recorded prior to planting.

Supplementary Note 3 | Trial site preparation

Provenance trials were conducted at four mine-site locations: Eneabba, Cooljarloo, Gingin and Gnangara, Western Australia (Fig. 1). At these sites, shallow strip mining of sand for mineral or construction sands is followed by staged restoration of disturbed areas post-mining. At Cooljarloo, Tronox has been mining and restoring since 1998, at Eneabba, Iluka Resources since 1976, and at Gingin and Gnangara, Heidelberg since 1988. After mining, pit in-filling with tailings, often clay-rich and/or overburden is followed by landform contouring, topsoil replacement and ripping[9]. At Cooljarloo, native seed are broadcast with stabilisation provided by a nurse crop of oats and mulch. At Eneabba, native seed are broadcast, followed by land imprinting with stabilisation provided by a dilute bitumen emulsion crust, and supplementary planting to boost species diversity occurs later in the season[10]. At Gnangara and Gingin, native seed are broadcast with subsequent planting of seedlings[3]. Fertiliser is applied at all post-mining sites.

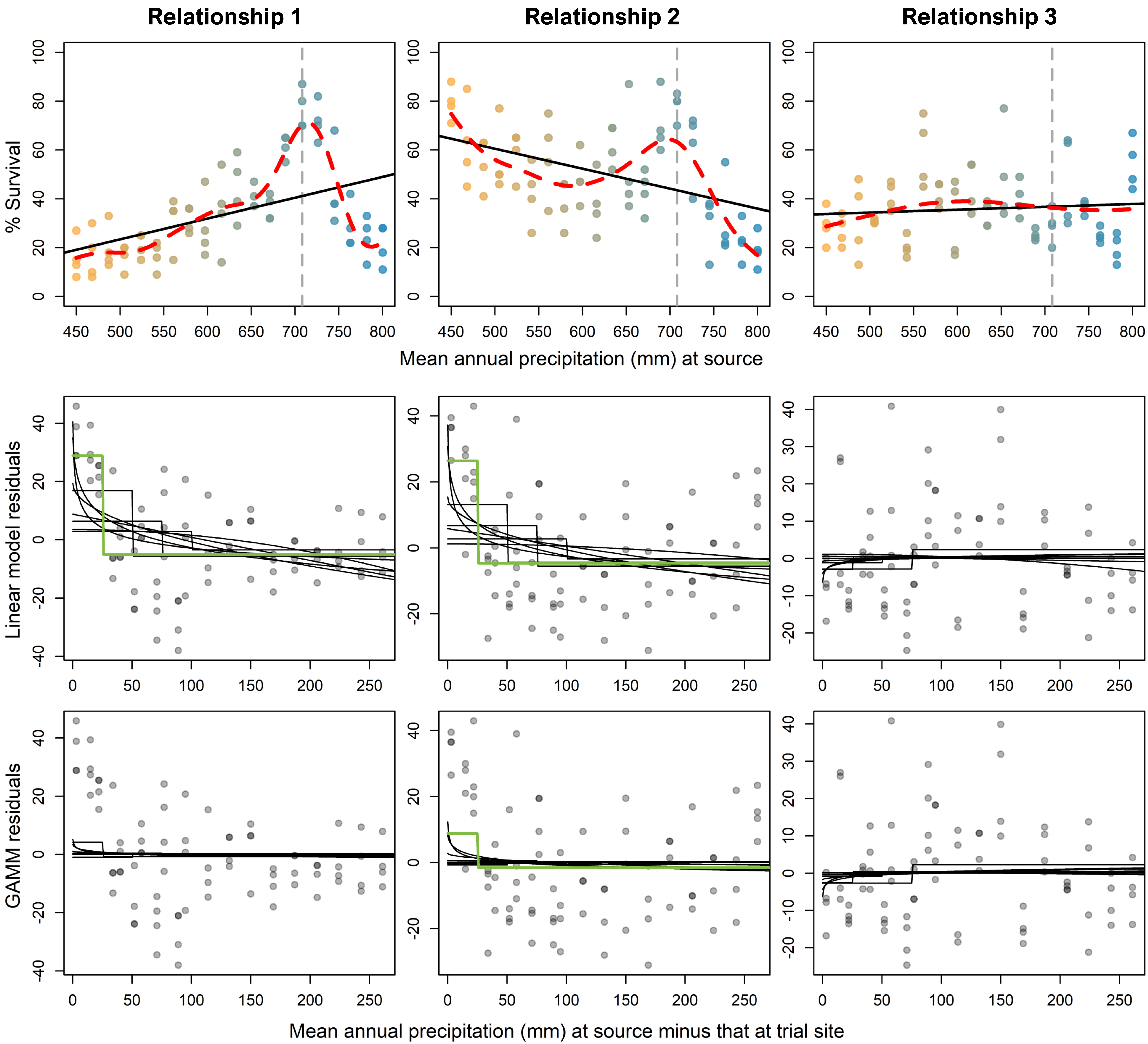
All locations included a paired adjacent unmined site where vegetation had been previously cleared, but the underlying substrate remained largely intact. At Eneabba and Cooljarloo, these sites were used to stockpile topsoil. Following removal of the stored topsoil, these sites were then prepared as for the post-mining sites, but without additional seed sowing. At Gnangara and Gingin, sites were planted with radiata pine (*Pinus radiata*) in ca. 1980 and harvested for forestry in ca. 2005, then left fallow for ca. 15 years prior to the start of our trials. At this time, sites were cleared of vegetation and soils ripped to a depth of ca. 10cm. At Gingin, no suitable unmined site occurred adjacent to the mine site, so a suitable site at the same latitude was established at Wilbinga, ca. 30km to the west of the Gingin site (Fig 1).

Supplementary Note 4 | Testing for local provenance effects.

The R code below outlines our approach to testing the "narrow local effect," where the local and some near-local provenances perform better than the other provenances.

For this analysis we explored patterns in the residuals from the outputs of both linear mixed-effect models and Generalized Additive Models (GAMMs) in relation to the difference in a climatic variable (MAP) between the local population and that of the provenances. By analysing residuals, we controlled for general trends between provenance performance and MAP, allowing us to detect when local and near-local provenances outperformed the trend. We created nine functions to represent a narrow local effect. Four functions were slopes showing gradual to sharp decreases in performance with increasing rainfall differences from the local population. Another four functions were step functions representing sharp drops in performance at rainfall differences of 10% 20% 30% 40% of the rainfall range from that of the local population. The final function was a linear relationship, representing a consistent decline in performance as the mean annual precipitation (MAP) increasingly differs from that of the local population. The function that best fitted the data was identified using the Akaike Information Criterion (AIC). A local effect was considered significant if the p-value of the function with the best fit was below $\alpha = 0.05$.

This code runs in R[12] using example datasets and generates plots that illustrate the functions. The following packages are required: gamm4 function from the gamm4 package[13].



Relationship 1
Relationship 2
Relationship 3
% Survival
Mean annual precipitation (mm) at source
Linear model residuals
GAMM residuals
Mean annual precipitation (mm) at source minus that at trial site

Supplementary Fig. 4 | Detecting local effects. The top row shows potential relationships between plant height and the long-term mean annual precipitation (MAP) of the provenances, which may or may not indicate a local effect. Hypothetical data are shown as points coloured by MAP, with fitted models overlaid: linear (black solid line), GAMM (red dashed line), and local rainfall (grey dashed vertical line). The middle and bottom rows display residuals from the corresponding models above, plotted against the absolute difference in MAP between the provenance and the trial site. Residuals from the linear model are shown in the middle row, and those from the GAMM in the bottom row. The nine functions used to test for a local effect are shown as black lines. The green line marks the best-fitting function, identified by the lowest AIC value, if that best-fitting function is significant at $p < 0.05$. No green line is shown in the right column, as none of the nine functions were significant.

```
##############################################
##############################################
## PACKAGES
##############################################
##############################################
#install.packages("gamm4")
library(gamm4)

##############################################
##############################################
## CREATING EXAMPLE DATA
##############################################
##############################################

######################
## Location 1
df1 <- data.frame(
  Rainfall = round(seq(450, 800, length.out = 20)),
  Height = c(
c(15,30,18,20,25,20,35,36,17,54,39,37,32,65,70,63,38,22,13,28),c(27,10,15,9,19,22,39,28,22,38,51,4
1,39,61,87,72,31,28,28,11)),
  Plot = 1,
  trial_site_combination = "Location 1")
df2 <- data.frame(
  Rainfall = round(seq(450, 800, length.out = 20)),
  Height = c(
c(8,8,13,20,15,16,35,26,27,34,59,47,32,65,80,70,38,22,23,18),c(13,20,33,17,25,9,15,36,47,14,29,37,4
2,55,70,82,68,42,33,28)),
  Plot = 2,
  trial_site_combination = "Location 1")

######################
## Location 2
df3 <- data.frame(
  Rainfall = round(seq(450, 800, length.out = 20)),
  Height = c(
c(80,64,41,77,60,40,35,46,62,54,69,37,32,65,70,63,38,22,13,28),c(78,45,63,46,45,56,65,26,47,38,52,
42,47,60,83,72,37,21,22,19)),
  Plot = 1,
  trial_site_combination = "Location 2")
df4 <- data.frame(
  Rainfall = round(seq(450, 800, length.out = 20)),
  Height = c(
c(88,55,63,50,65,26,55,36,37,34,59,47,42,68,80,70,33,25,23,18),c(71,85,53,50,65,46,75,46,47,24,69,
87,52,88,80,40,13,55,33,11)),
    Plot = 2,
  trial_site_combination = "Location 2")

######################
## Location 3
df5 <- data.frame(
  Rainfall = round(seq(450, 800, length.out = 20)),
  Height = c(
c(20,34,41,30,35,20,75,46,47,54,39,37,32,25,30,63,38,22,13,48),c(30,24,48,32,38,26,67,46,43,54,37,
34,37,24,37,64,37,24,17,44)),
```

```
  Plot = 1,
  trial_site_combination = "Location 3")
df6 <- data.frame(
  Rainfall = round(seq(450, 800, length.out = 20)),
  Height                                    =                                    c(
c(28,30,23,30,45,16,45,36,17,34,29,77,42,28,20,30,33,25,23,58),c(38,20,13,31,47,19,49,39,19,39,29,
49,49,23,29,33,39,29,26,67)),
  Plot = 2,
  trial_site_combination = "Location 3")

df_combine=rbind(df1,df2,df3,df4,df5,df6)

############################################
############################################
## LOCAL EFFECT FUNCTIONS
############################################
############################################

ff = function(rfdiff,res2) {

# model 1
fmr1 = lm(res2~rfdiff)
preds = predict(fmr1, data.frame(rfdiff = 0:300))
lines(0:300,preds,col='black')

# model 2
fmr2 = lm(res2~I(rfdiff ^2))
preds = predict(fmr2, data.frame(rfdiff = 0:300))
lines(0:300,preds,col='black')

# model 3
fmr3 = lm(res2~log(rfdiff+1))
preds = predict(fmr3, data.frame(rfdiff = 0:300))
lines(0:300,preds,col='black')

# model 4
fmr4 = lm(res2~sqrt(rfdiff))
preds = predict(fmr4, data.frame(rfdiff = 0:300))
lines(0:300,preds,col='black')

# model 5
fmr5 = lm(res2~log(log(rfdiff+1)+1))
preds = predict(fmr5, data.frame(rfdiff = 0:300))
lines(0:300,preds,col='black')

# model 6
fmr6 = lm(res2~(rfdiff>25))
preds = predict(fmr6, data.frame(rfdiff = 0:300))
lines(0:300,preds,col='black')

# model 7
fmr7 = lm(res2~I(rfdiff>50))
preds = predict(fmr7, data.frame(rfdiff = 0:300))
lines(0:300,preds,col='black')
```

```
# model 8
fmr8 = lm(res2~ I(rfdiff>75))
preds = predict(fmr8, data.frame(rfdiff = 0:300))
lines(0:300,preds,col='black')

# model 9
fmr9 = lm(res2~(rfdiff>100))
preds = predict(fmr9, data.frame(rfdiff = 0:300))
lines(0:300,preds,col='black')

# return best model based on AIC
mdlist=list(fmr1,fmr2,fmr3,fmr4,fmr5,fmr6,fmr7,fmr8,fmr9)
bi=which.min(AIC(fmr1,fmr2,fmr3,fmr4,fmr5,fmr6,fmr7,fmr8,fmr9)[,2])
bm = mdlist[[bi]]
local_model_names=list("fmr1","fmr2","fmr3","fmr4","fmr5","fmr6","fmr7","fmr8","fmr9")
best_local_model_name=local_model_names[[bi]]
p_value=round(anova(bm)[1,5],5)

  # add line to plot if significant p-value
   if(p_value <0.051){
		preds = predict(bm, data.frame(rfdiff = 0:300))
		lines(0:300,preds,lwd=2,col='#7fbc41')
    }
}

#############################################
#############################################
## PLOTTING
#############################################
############################################

save_figure <- FALSE
#save_figure <- TRUE

if (save_figure) {
png(filename = "Local_effect_figure.png",
    res = 800, height = 8, width = 9, units = "in", bg = "white")
}

custom_colors <- rev(colorRampPalette(colors = c("#2b8cbe", "#feb24c"))(20))

set <- matrix(
  c(1, 4, 7, 10,
    1, 3, 3, 3,
    1, 5, 8, 11,
    1, 6, 9, 12,
    2, 2, 2, 2),
  nrow = 5, ncol = 4, byrow = TRUE)

nf <- layout(set, heights = c(4,0.5, 4, 4, 0.6), widths = c(0.5, 5.5, 5.5, 5.5))
layout.show(nf)

par(mar = c(0, 0, 0, 0))
plot(1:5, 1:5, type = "n", axes = FALSE, xlab = "", ylab = "", ann = FALSE)
text(4, 4.45, "Height (cm)", cex = 1.4, srt = 90, xpd = NA)
```

```
text(4, 2.9, "Linear model residuals", cex = 1.4, srt = 90, xpd = NA)
text(4, 1.6, "GAMM residuals", cex = 1.4, srt = 90, xpd = NA)

plot(1:5, 1:5, type = "n", axes = FALSE, xlab = "", ylab = "", ann = FALSE)
text(3, 3, "Absolute difference in MAP(mm) between the provenances and the trial site", cex = 1.4)

plot(1:5, 1:5, type = "n", axes = FALSE, xlab = "", ylab = "", ann = FALSE)
text(3, 3, "Mean annual precipitation (mm) at source ", cex = 1.4)


######################
## BEGIN LOOP
######################

for (i in unique(df_combine$trial_site_combination)) {

  df <- subset(df_combine, trial_site_combination == i)

  par(mar = c(2, 2.5, 1, 0.1))
  plot(df$Rainfall, df$Height,
       col = adjustcolor(custom_colors[as.factor(df$Rainfall)], alpha.f = 0.8),
       pch = 20, ylab = " ", xlab = "", cex = 1.8,
       ylim = c(0, 100), cex.lab = 1.4, cex.axis = 1.1)

  abline(v = 708, col = "dark grey", lty = 2, lwd = 2)

  linear_model <- lm(Height ~ Rainfall, data = df)
  abline(linear_model, col = "black", lwd = 2)
  df$residuals_lm <- residuals(linear_model)

  gamm_model <- gamm4(Height ~ s(Rainfall),
                      random = ~(1 | Plot),
                      data = df)

  xseq <- seq(min(df$Rainfall), max(df$Rainfall), length.out = 200)
  pred <- predict(gamm_model$gam,
                  newdata = data.frame(Rainfall = xseq),
                  type = "response")
  lines(xseq, pred, col = "red", lty = 2, lwd = 3)

  plot(abs(711 - df$Rainfall), df$residuals_lm,
       col = adjustcolor("black", alpha.f = 0.3),
       pch = 20, cex = 1.5, xlab = " ", ylab = " ", main = " ",
       bg = "white", cex.lab = 1.4, cex.axis = 1.1)

  res2 <- df$residuals_lm
  rfdiff <- abs(708 - df$Rainfall)
  ff(rfdiff, res2)

  plot(abs(711 - df$Rainfall), df$residuals_lm,
       col = adjustcolor("black", alpha.f = 0.3),
       pch = 20, cex = 1.5, xlab = " ", ylab = " ", main = " ",
       bg = "white", cex.lab = 1.4, cex.axis = 1.1)

  res2 <- residuals(gamm_model$gam, type = "deviance")
```

```
  rfdiff <- abs(708 - df$Rainfall)
  ff(rfdiff, res2)
}


if (save_figure) {
  dev.off()
}
```

References

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