Appendix B

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R build: Geospatial 4.4.0

Analysis of combined data set from this study and the literature from 1940–2024

Full criteria, references, and dataset details are available in Supplemental Tables 1 and 2.

Import species/hybrid countsAll per site

```
countsAll <- read.csv("../data/Barr1957_plusLit_plusThisStudy.txt", sep = "\t")
countsAllSp <- SpatialPoints(coords = cbind(countsAll$long,countsAll$lat))
```

Genotypes in p/q notation: Cx. pipiens = pp Cx. quinquefasciatus = qq

Create a dataframe of countsAll

```
# start data frame and name fields
countsAllDf <- as.data.frame(countsAll[,c(2,1,4,5,6,9,10,7,8)])
names(countsAllDf) <- c("locality","site","pp","pq","qq","latitude","longitude","year","h_index")

# name rows
rownames(countsAllDf)<- countsAllDf$site
```

Pie charts on a map

Convert countsAll to proportions (frequency):

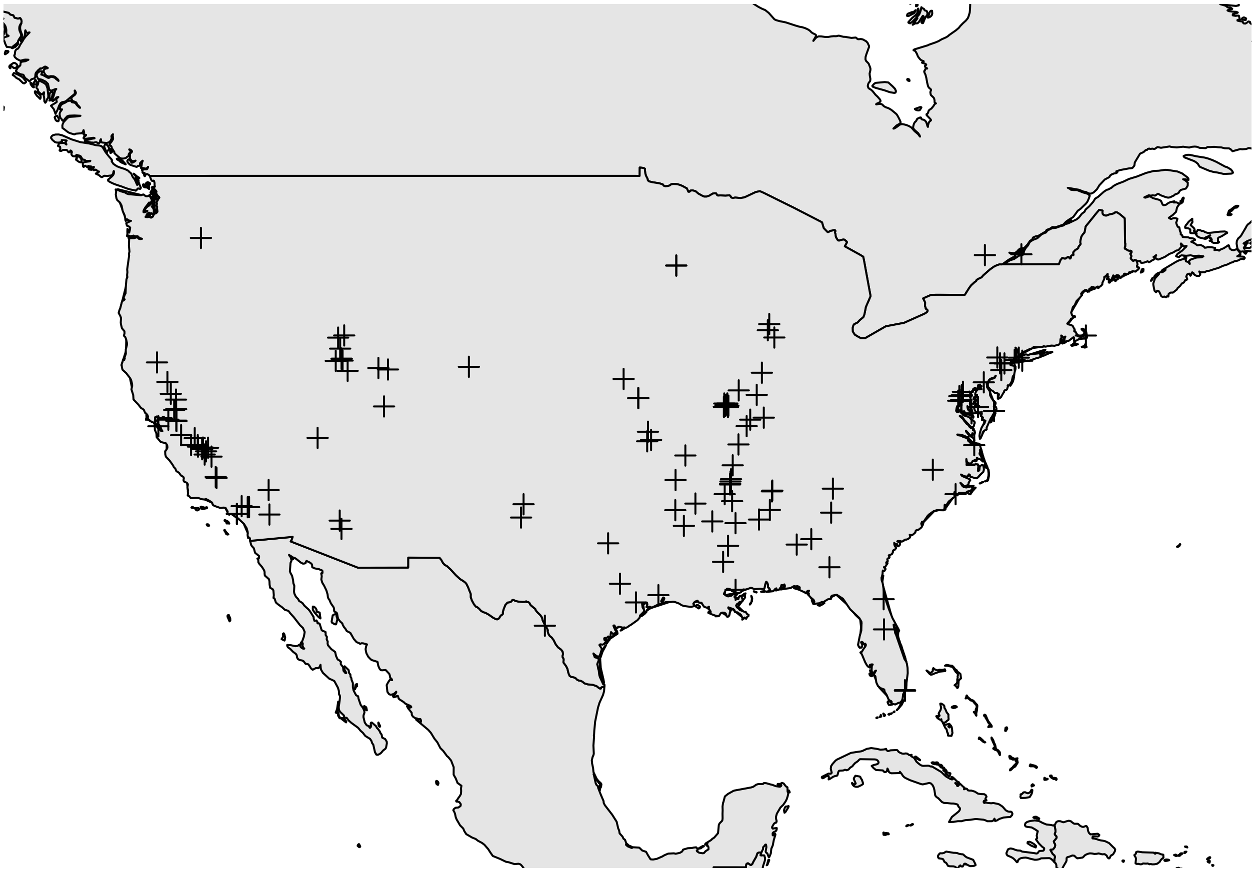
```
freqsDf <- as.data.frame(countsAllDf[,c("pp","pq","qq")])
freqsDf <- as.matrix.data.frame(t(apply(freqsDf, 1, function(row) row / sum(row))))
```

One pie chart at a time, to check code

Plot points on map to check data:

```
# Set xpd to NA to allow for plotting in the margins
par(xpd = NA)

#create and plot coord = long, lat
coord <- as.data.frame(countsAllDf[,c("longitude","latitude")])

#plot coordinates onto map
map("usa")
```

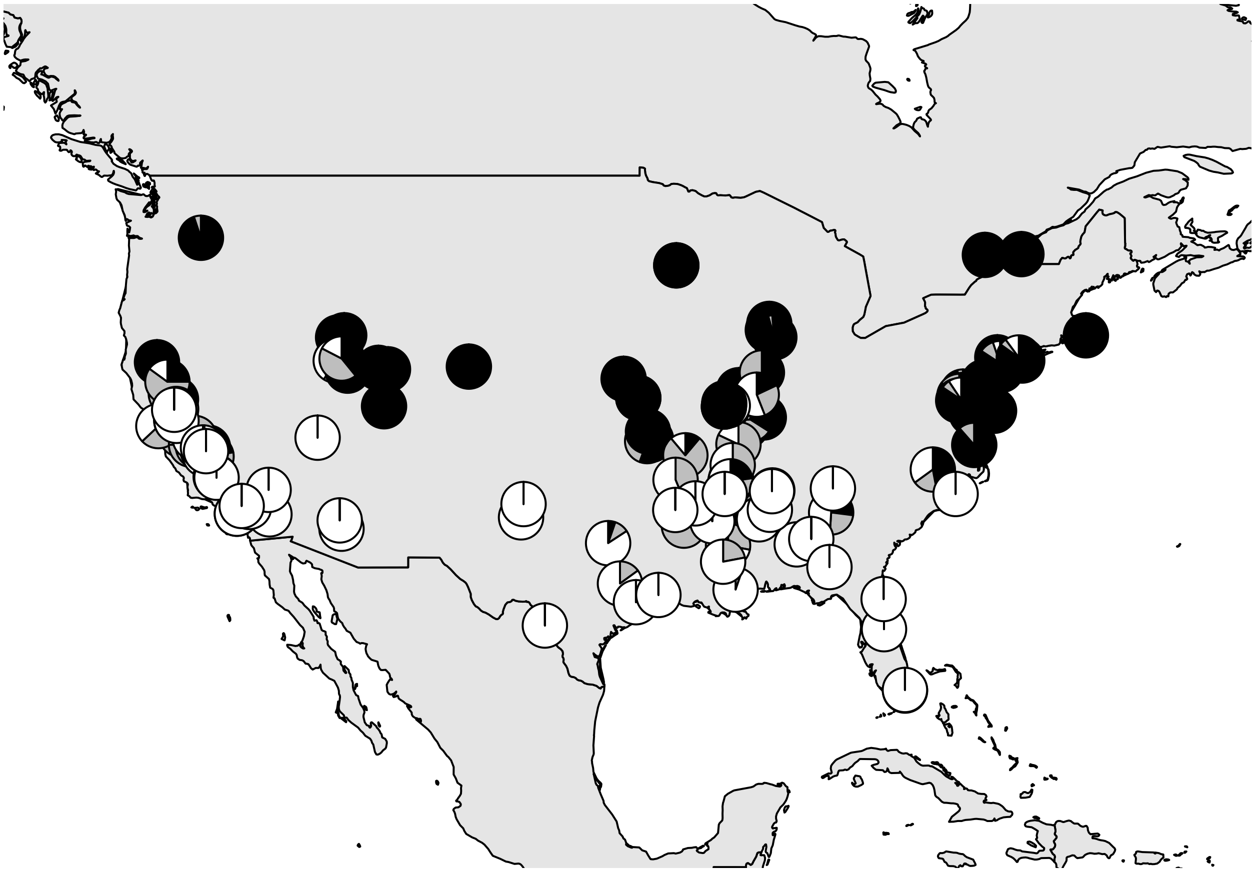
```r
map(add = T, col = "grey90", fill = TRUE)
points(coord,col="black",cex=1,pch=3)
```



Add pies to map following: "http://membres-timc.imag.fr/Olivier.Francois/Conversion.R"

```r
# Open PDF device
#pdf("../figs/ace2_pies_ThisBarrLit.pdf", width = 8, height = 6)

# Set xpd to NA to allow for plotting in the margins
par(xpd = NA)

# Determine plot order by descending h_index
#plot_order <- rev(order(countsAllDf$h_index))
plot_order <- rev(c(order(countsAllDf$h_index)[countsAllDf$year > 2021], order(countsAllDf$h_index)[cou
plot_order <- c(rev(order(countsAllDf$h_index)[countsAllDf$year <= 2021]), rev(order(countsAllDf$h_inde

# plot pies onto map
map("usa")
map(add = T, col = "grey90", fill = TRUE)
for (i in plot_order){
  add.pie(z = freqsDf[i,],
          x = coord[i,1],
          y = coord[i,2],
          clockwise=TRUE,
          labels = "",
          col = c("black","grey","white"),
```

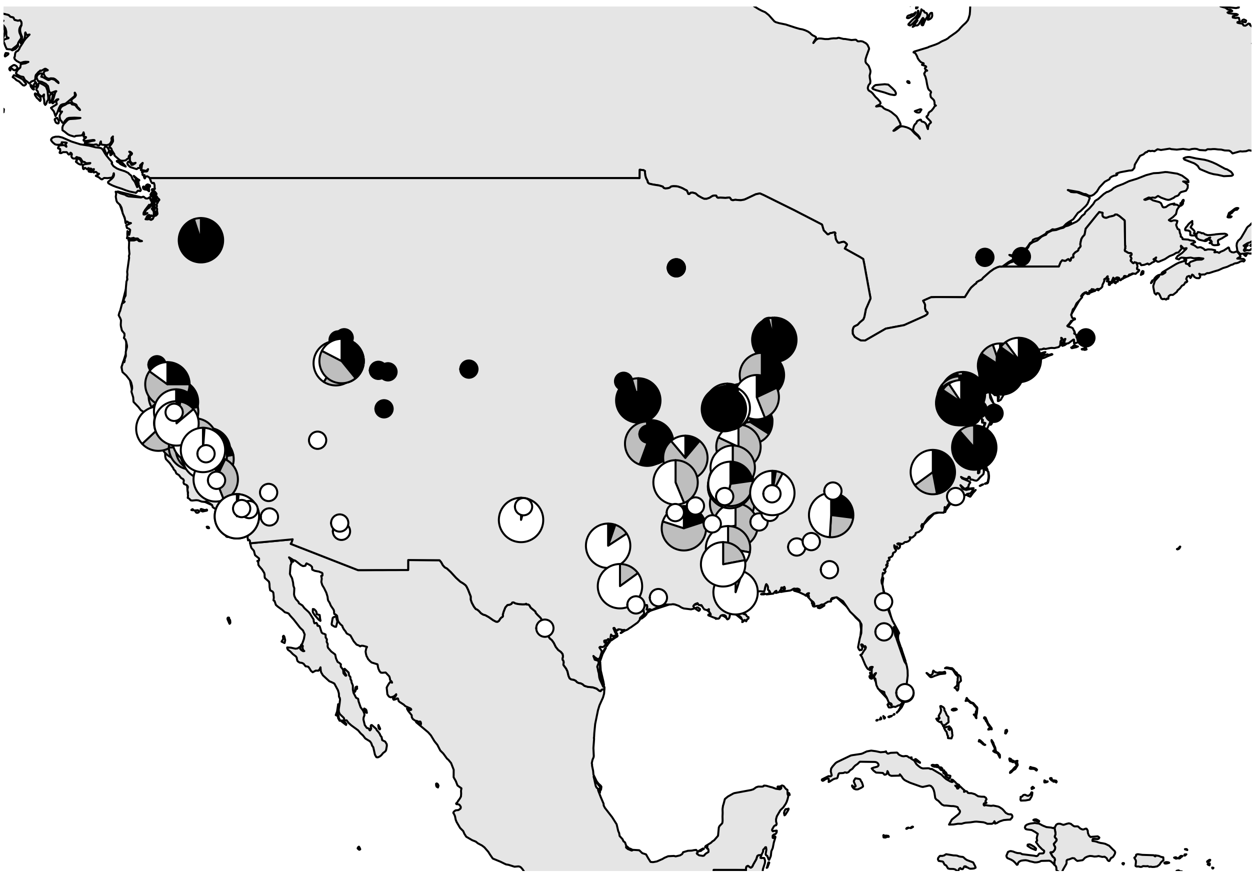
```
            cex = 1, radius = 1 )
}
```



```
#dev.off()
```

```
# Plot with small dots for fixed sites... but doesn't look great.

# Set xpd to NA to allow for plotting in the margins
par(xpd = NA)

# Add flag for fixed sites and what type of fixed (pp or qq)
freqs_fixed <- freqsDf[, 1] == 1 | freqsDf[, 3] == 1
freqs_fixed_type <- ifelse(freqsDf[, 1] == 1, "pp",
                           ifelse(freqsDf[, 3] == 1, "qq", NA))

# Plot map with expanded margins
map("usa")
map(add = TRUE, col = "grey90", fill = TRUE)

for (i in plot_order) {
  if (freqs_fixed[i]) {
    if (freqs_fixed_type[i] == "pp") {
      # Black dot
      points(coord[i,1], coord[i,2], pch = 21, bg = "black", col = "black", cex = 1.2)
    } else if (freqs_fixed_type[i] == "qq") {
      # White dot with black border
```

```
      points(coord[i,1], coord[i,2], pch = 21, bg = "white", col = "black", cex = 1.2)
    }
  } else {
    add.pie(z = freqsDf[i,],
          x = coord[i,1],
          y = coord[i,2],
          clockwise=TRUE,
          labels = "",
          col = c("black","grey","white"),
          cex = 1, radius = 1 )
  }
}
```



1. Load and Process Species Distribution Models (SDMs)

```
# Load MaxEnt SDMs
sdm_pipiens <- raster("../gis/culex_pipiens_meansuitability.nc")
```

```
## Loading required namespace: ncdf4
```

```
sdm_quinque <- raster("../gis/culex_quinquefasciatus_meansuitability.nc")

# Threshold to binary
threshold <- 0.5
sdm_pipiens_bin <- sdm_pipiens >= threshold
```

```
sdm_quinque_bin <- sdm_quinque >= threshold
```

2. Convert SDMs to Polygons

```
# Raster to terra
sdm_pipiens_v <- terra::rast(sdm_pipiens_bin)
sdm_quinque_v <- terra::rast(sdm_quinque_bin)

# Raster to polygons
poly_pipiens <- terra::as.polygons(sdm_pipiens_v, dissolve = TRUE)
poly_quinque <- terra::as.polygons(sdm_quinque_v, dissolve = TRUE)

# Terra to sf
poly_pipiens_sf <- st_as_sf(poly_pipiens)
poly_quinque_sf <- st_as_sf(poly_quinque)

# Filter to presence only
names(poly_pipiens_sf)[1] <- "presence"
names(poly_quinque_sf)[1] <- "presence"
poly_pipiens_sf <- poly_pipiens_sf %>% filter(presence == 1)
poly_quinque_sf <- poly_quinque_sf %>% filter(presence == 1)
```

3. Project to Albers Equal Area and Calculate Overlap

```
# Define CRS
aea_crs <- st_crs("+proj=aea +lat_1=29.5 +lat_2=45.5 +lat_0=23 +lon_0=-96")

# Project
poly_pipiens_sf <- st_transform(poly_pipiens_sf, aea_crs)
poly_quinque_sf <- st_transform(poly_quinque_sf, aea_crs)

# Overlap
overlap_sf <- st_intersection(poly_pipiens_sf, poly_quinque_sf)

# Calculate areas (km²)
area_pipiens_km2 <- sum(st_area(poly_pipiens_sf)) / 1e6
area_quinque_km2 <- sum(st_area(poly_quinque_sf)) / 1e6
area_overlap_km2 <- sum(st_area(overlap_sf)) / 1e6
```

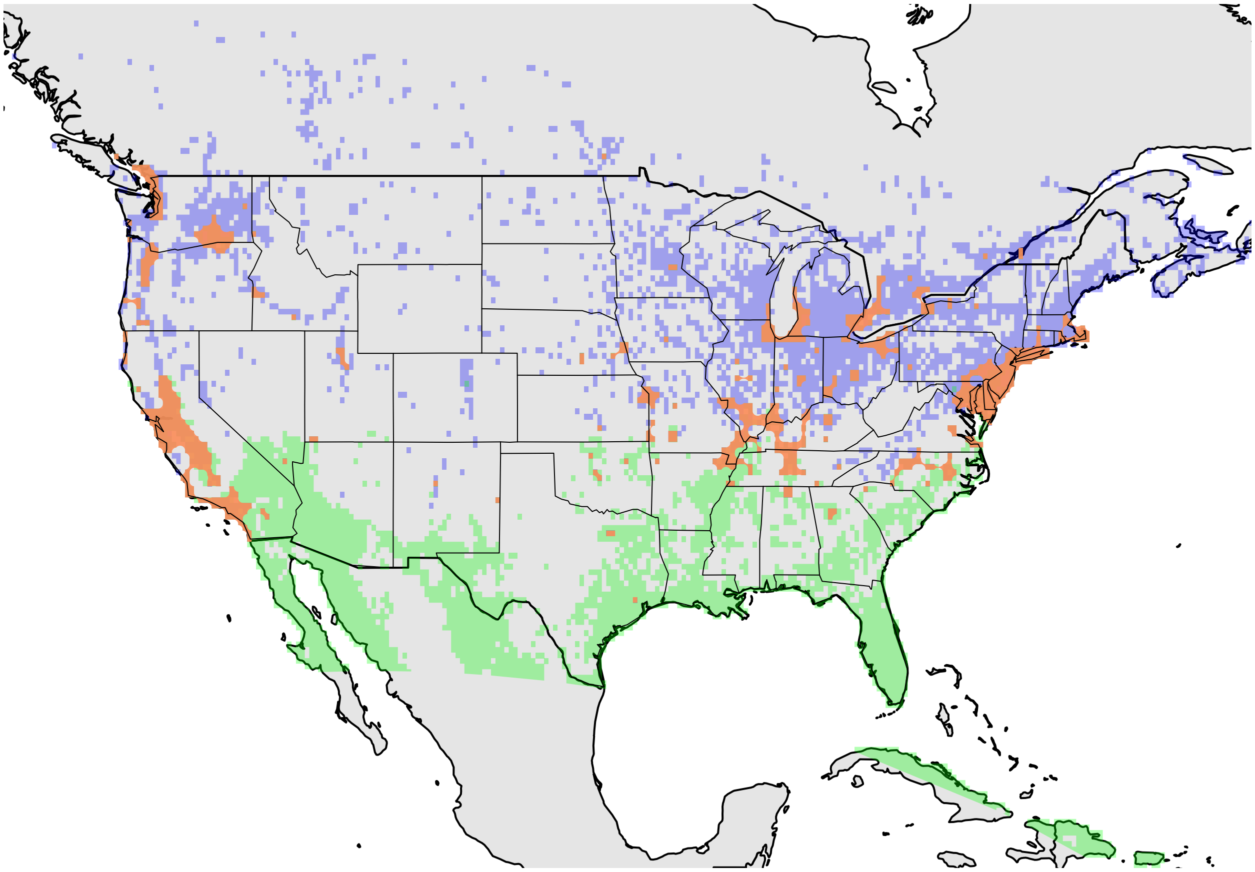
4. Clip to North America and Reproject to WGS84

```
# US base map
us_states <- st_as_sf(map("usa", plot = FALSE, fill = TRUE))
us_states <- st_transform(us_states, crs = aea_crs)

# Clip extent
bbox_na <- st_as_sfc(st_bbox(c(xmin = -170, xmax = -50, ymin = 5, ymax = 85), crs = st_crs(4326)))
bbox_na_sf <- st_transform(bbox_na, crs = aea_crs)

# Clip
```

```
poly_pipiens_sf <- st_intersection(st_make_valid(poly_pipiens_sf), bbox_na_sf)
poly_quinque_sf <- st_intersection(st_make_valid(poly_quinque_sf), bbox_na_sf)
overlap_sf <- st_intersection(st_make_valid(overlap_sf), bbox_na_sf)

# Reproject to WGS84
poly_pipiens_ll <- st_transform(poly_pipiens_sf, 4326)
poly_quinque_ll <- st_transform(poly_quinque_sf, 4326)
overlap_ll <- st_transform(overlap_sf, 4326)
```

6. Merge Nearby Overlapping zones

```
# Reproject overlap
overlap_ll_proj <- st_transform(overlap_ll, aea_crs)

# Make valid and extract polygons
overlap_valid <- st_make_valid(overlap_ll_proj)
overlap_polygons <- st_collection_extract(overlap_valid, "POLYGON")
overlap_parts <- st_cast(overlap_polygons, "POLYGON")

# Buffer outward
buffer_dist_meters <- 25000
overlap_buffered <- st_buffer(overlap_parts, dist = buffer_dist_meters)
overlap_buffered <- st_make_valid(overlap_buffered)

# Merge touching patches
overlap_combined <- st_union(overlap_buffered)
overlap_combined <- st_make_valid(overlap_combined)

# Buffer inward
overlap_combined <- st_buffer(overlap_combined, dist = -buffer_dist_meters)
overlap_combined <- st_make_valid(overlap_combined)

# Finalize
overlap_combined <- st_cast(overlap_combined, "MULTIPOLYGON")
overlap_combined <- st_transform(overlap_combined, 4326)

#pdf("../figs/overlap_SDM_ThisBarrLit.pdf", width = 8, height = 6)
par(xpd = NA)
map("usa")
map(add = TRUE, col = "grey90", fill = TRUE)

plot(st_geometry(poly_pipiens_ll), col = rgb(0, 0, 1, 0.3), border = NA, add = TRUE)
plot(st_geometry(poly_quinque_ll), col = rgb(0, 1, 0, 0.3), border = NA, add = TRUE)
plot(st_geometry(overlap_combined), col = adjustcolor("#fc8d59", alpha.f = 0.9), border = NA, add = TRUI

map("state", add = TRUE, col = "black", lwd = 0.5)
```



```
# Add sampling points, but looks messy:
# points(coord,col="black",cex=1,pch=3)

#dev.off()
```

Predicted level of overlapping suitable habitat?

```
# ---------------------------------------------
# Quantify predicted overlap around each sample point
# ---------------------------------------------

# Step 1: Make sample points an sf object
samples_sf <- st_as_sf(countsAllDf, coords = c("longitude", "latitude"), crs = 4326)

# Step 2: Reproject sample points to Albers Equal Area CRS
samples_sf <- st_transform(samples_sf, crs = aea_crs)

# Step 3: Buffer each point by 30 km (30,000 meters)
sample_buffers <- st_buffer(samples_sf, dist = 30000)

# Step 4: Prepare overlap_combined layer in same CRS
overlap_combined_proj <- st_transform(overlap_combined, crs = aea_crs)

# Step 5: Calculate proportion of buffer area that overlaps
predicted_overlap_prop <- sapply(1:nrow(sample_buffers), function(i) {
  buf <- sample_buffers[i,]
  intersection <- st_intersection(buf, overlap_combined_proj)
```

```
  if (nrow(intersection) == 0) {
    # No overlap
    overlap_area <- 0
  } else {
    # Sum all overlapping parts
    overlap_area <- sum(st_area(intersection))
  }

  buffer_area <- st_area(buf)

  # Return proportion
  as.numeric(overlap_area) / as.numeric(buffer_area)
})

# Step 6: Add predicted overlap to countsAllDf
countsAllDf$predicted_overlap <- predicted_overlap_prop
```

Predicted H-index

Now, add directionality with 0 = quinq, 1 = pip, to estimate "predicted_h_index"

Predicted h_index based on **Current** SDM habitat MaxEnt models also included, although I wonder about the logic of this, since climate HAS changed?

```
# ---------------------------------------------
# New: Predict directional hybrid index from habitat around each sampling site
# ---------------------------------------------

# Step 1: Prepare the pipiens-only and quinque-only polygons
# (We already have poly_pipiens_ll and poly_quinque_ll, but need to transform)
poly_pipiens_proj <- st_transform(poly_pipiens_ll, crs = aea_crs)
poly_quinque_proj <- st_transform(poly_quinque_ll, crs = aea_crs)
overlap_combined_proj <- st_transform(overlap_combined, crs = aea_crs)  # already done above

# Step 2: Create pip-only and quinque-only polygons (remove overlap area)
pip_only <- st_difference(poly_pipiens_proj, overlap_combined_proj)
quinque_only <- st_difference(poly_quinque_proj, overlap_combined_proj)

# Step 3: Calculate areas for each sample buffer
library(units)  # make sure units package is loaded
```

```
## udunits database from /usr/share/xml/udunits/udunits2.xml
```

```
predicted_h_index <- sapply(1:nrow(sample_buffers), function(i) {
  buf <- sample_buffers[i, ]

  pip_intersect <- st_intersection(buf, pip_only)
  quinque_intersect <- st_intersection(buf, quinque_only)
  overlap_intersect <- st_intersection(buf, overlap_combined_proj)

  pip_area <- if (nrow(pip_intersect) == 0) units::set_units(0, "m^2") else sum(st_area(pip_intersect))
  quinque_area <- if (nrow(quinque_intersect) == 0) units::set_units(0, "m^2") else sum(st_area(quinque_
  overlap_area <- if (nrow(overlap_intersect) == 0) units::set_units(0, "m^2") else sum(st_area(overlap_
```

```r
  total_area <- pip_area + quinque_area + overlap_area

  if (as.numeric(total_area) == 0) {
    return(NA)  # no habitat found
  } else {
    pred_h <- (pip_area + 0.5 * overlap_area) / total_area
    return(as.numeric(pred_h))  # strip units at the end
  }
})
# Step 4: Add predicted_h_index to countsAllDf
countsAllDf$predicted_h_index <- predicted_h_index

# Step 5: Quick check and save
(summary_table <- countsAllDf[, c("site", "latitude", "longitude", "h_index", "predicted_overlap", "pred
```

```
##                                site latitude  longitude h_index predicted_overlap
## 001.ByroWA.2023   001.ByroWA.2023 46.19300 -119.89900    0.97       0.841121564
## 002.StAnQC.1944   002.StAnQC.1944 45.45600  -73.63100    1.00       0.361104399
## 003.OttaON.1957   003.OttaON.1957 45.42090  -75.69010    1.00       0.192520104
## 004.StPaMN.1953   004.StPaMN.1953 44.94970  -93.09310    1.00       0.311265050
## 005.StPaMN.1953   005.StPaMN.1953 44.94970  -93.09310    1.00       0.311265050
## 006.GreaIL.1944   006.GreaIL.1944 42.30930  -87.84970    1.00       0.687216478
## 007.CookIL.2023   007.CookIL.2023 42.03176  -87.93087    1.00       0.999322243
## 008.CachUT.2023   008.CachUT.2023 41.79696 -111.82005    1.00       0.000000000
## 009.BarnMA.2023   009.BarnMA.2023 41.79362  -69.99427    1.00       0.824884441
## 010.TrumIL.2012   010.TrumIL.2012 41.70490  -87.56440    0.97       0.794448383
## 011.BoxEUT.2024   011.BoxEUT.2024 41.69945 -112.16386    1.00       0.000000000
## 012.OgdeUT.2024   012.OgdeUT.2024 41.20359 -112.04803    1.00       0.475093146
## 013.OxfoNJ.1953   013.OxfoNJ.1953 40.80320  -74.98960    1.00       0.008691163
## 014.FortNY.2007   014.FortNY.2007 40.79600  -73.77800    0.87       1.000000000
## 015.SaltUT.2023   015.SaltUT.2023 40.74805 -111.96788    0.38       0.485085123
## 015.SaltUT.2018   015.SaltUT.2018 40.74805 -111.96788    0.93       0.485085123
## 016.SaltUT.2021   016.SaltUT.2021 40.74750 -111.96760    0.61       0.484910810
## 017.GoveNY.1953   017.GoveNY.1953 40.69150  -74.01240    1.00       1.000000000
## 018.SaltUT.1957   018.SaltUT.1957 40.66320 -111.91030    1.00       0.470535723
## 019.FreeNY.1953   019.FreeNY.1953 40.65760  -73.58360    1.00       0.895548023
## 020.BensUT.2021   020.BensUT.2021 40.64940 -112.29680    0.30       0.086471138
## 021.ReddCA.2003   021.ReddCA.2003 40.58040 -122.37710    1.00       0.000000000
## 022.HuntNJ.2023   022.HuntNJ.2023 40.53959  -74.83462    0.89       0.427789251
## 023.SomeNJ.2023   023.SomeNJ.2023 40.53358  -74.58610    0.90       0.695388858
## 024.FortCO.2023   024.FortCO.2023 40.38428 -104.78940    1.00       0.000000000
## 025.UteTUT.2024   025.UteTUT.2024 40.32890 -109.89110    1.00       0.000000000
## 026.VernUT.2024   026.VernUT.2024 40.26180 -109.35110    1.00       0.000000000
## 027.TrenNJ.2007   027.TrenNJ.2007 40.23300  -74.76600    0.98       0.987008509
## 028.ProvUT.2024   028.ProvUT.2024 40.20065 -111.62731    1.00       0.186683924
## 029.ChamIL.2005   029.ChamIL.2005 40.11700  -88.26500    0.80       0.000000000
## 030.SeneKS.1951   030.SeneKS.1951 39.83420  -96.06420    1.00       0.000000000
## 031.ChicCA.1992   031.ChicCA.1992 39.70000 -121.79000    0.55       0.790033112
## 032.NewaDE.1953   032.NewaDE.1953 39.68280  -75.75160    1.00       0.676133581
## 033.RaymIL.1939   033.RaymIL.1939 39.31950  -89.57200    1.00       0.000000000
## 034.ClarMD .2020 034.ClarMD .2020 39.25640  -76.92760    0.98       0.891844198
## 035.SuttCA.2023   035.SuttCA.2023 39.16647 -121.59845    0.72       0.914493895
## 036.EffiIL.2005   036.EffiIL.2005 39.11800  -88.55700    0.31       0.000000000
## 037.Old MD.2020   037.Old MD.2020 39.09920  -77.00180    0.95       0.961456368
```

```
## 038.RockMD.2023   038.RockMD.2023 39.05775  -77.13055    0.93         0.874845423
## 039.LawrKS.1955   039.LawrKS.1955 38.97190  -95.23590    0.98         0.422164069
## 040.LawrKS.1951   040.LawrKS.1951 38.97190  -95.23590    1.00         0.422164069
## 041.LincCA.2023   041.LincCA.2023 38.90447 -121.30633    0.98         0.855749203
## 042.DistDC.2019   042.DistDC.2019 38.89130  -77.02600    0.88         1.000000000
## 043.FairVA.2007   043.FairVA.2007 38.85400  -77.19500    0.92         0.959820119
## 044.AnacDC.2020   044.AnacDC.2020 38.84720  -77.01180    0.89         1.000000000
## 045.BadeMO.1952   045.BadeMO.1952 38.72870  -90.21780    0.92         0.966786790
## 046.StAnMO.1952   046.StAnMO.1952 38.72810  -90.38790    1.00         0.882733698
## 047.NortMO.1952   047.NortMO.1952 38.70490  -90.21740    1.00         0.933525874
## 048.UnivMO.1952   048.UnivMO.1952 38.65690  -90.31030    1.00         0.799896752
## 049.RichMO.1952   049.RichMO.1952 38.62830  -90.31910    1.00         0.731860647
## 050.StLoMO.1952   050.StLoMO.1952 38.62800  -90.19100    0.73         0.791288629
## 051.StLoMO.1953   051.StLoMO.1953 38.62800  -90.19100    0.08         0.791288629
## 052.EastIL.1944   052.EastIL.1944 38.62690  -90.15970    0.95         0.788980118
## 053.EastIL.1943   053.EastIL.1943 38.62690  -90.15970    1.00         0.788980118
## 054.MoabUT.2024   054.MoabUT.2024 38.59597 -109.57376    1.00         0.000000000
## 055.KirkMO.1952   055.KirkMO.1952 38.58010  -90.40690    1.00         0.562205677
## 056.KirkMO.1952   056.KirkMO.1952 38.58010  -90.40690    1.00         0.562205677
## 057.CambMA.1945   057.CambMA.1945 38.57150  -76.07630    1.00         0.992826084
## 058.CahoIL.1943   058.CahoIL.1943 38.56620  -90.17940    0.50         0.654560902
## 059.SacrCA.1947   059.SacrCA.1947 38.47320 -121.29810    0.41         0.895758193
## 060.KingCA.1957   060.KingCA.1957 38.43640 -121.40830    0.00         0.992391977
## 061.BainMD.1945   061.BainMD.1945 38.39180  -75.17350    1.00         0.677493194
## 062.PatuMD.1945   062.PatuMD.1945 38.28680  -76.44360    1.00         0.384456761
## 063.CarmIL.1941   063.CarmIL.1941 38.09090  -88.15860    1.00         0.838270062
## 064.OaklCA.1992   064.OaklCA.1992 38.00000 -121.73800    0.70         1.000000000
## 065.BentIL.2005   065.BentIL.2005 38.00000  -88.92400    0.54         0.999558899
## 066.StocCA.1957   066.StocCA.1957 37.95770 -121.29080    0.50         1.000000000
## 067.SanJCA.1957   067.SanJCA.1957 37.93730 -121.27740    0.08         1.000000000
## 068.CrabIL.1942   068.CrabIL.1942 37.70770  -89.12470    1.00         0.673832475
## 069.AlamCA.1992   069.AlamCA.1992 37.70000 -122.30000    0.51         0.972419966
## 070.FronKS.1951   070.FronKS.1951 37.45560  -94.68910    1.00         0.362863363
## 071.NewmCA.1992   071.NewmCA.1992 37.30000 -121.01700    0.62         1.000000000
## 072.StGeUT.2023   072.StGeUT.2023 37.17900 -113.32000    0.00         0.304021108
## 073.ChowCA.1991   073.ChowCA.1991 37.16700 -120.25000    0.11         0.799629650
## 074.JoplMO.1952   074.JoplMO.1952 37.08420  -94.51330    0.85         0.531934812
## 075.BaxtKS.1957   075.BaxtKS.1957 37.02360  -94.73520    0.78         0.334707893
## 076.SikeMO.2005   076.SikeMO.2005 36.88200  -89.58700    0.41         0.844358543
## 077.FireCA.1952   077.FireCA.1952 36.85880 -120.45600    0.50         1.000000000
## 078.MadeCA.1992   078.MadeCA.1992 36.85000 -120.07800    0.45         0.976789348
## 079.NorfVA.1957   079.NorfVA.1957 36.84940  -76.29000    0.94         0.653304608
## 080.KermCA.1992   080.KermCA.1992 36.78300 -120.06600    0.35         1.000000000
## 081.FresCA.1953   081.FresCA.1953 36.73940 -119.78480    0.01         0.922491087
## 082.CentCA.2000   082.CentCA.2000 36.73390 -119.49830    0.67         0.483149003
## 083.ReedCA.2000   083.ReedCA.2000 36.66670 -119.83330    0.34         0.980749996
## 084.SelmCA.1953   084.SelmCA.1953 36.57080 -119.61210    0.00         0.796428028
## 085.FresCA.2005   085.FresCA.2005 36.42700 -119.68900    0.27         0.976260559
## 086.BullAR.1957   086.BullAR.1957 36.38400  -92.58160    0.50         0.000000000
## 087.VisaCA.1992   087.VisaCA.1992 36.33300 -119.30300    0.39         0.480897839
## 088.BlytAR.2005   088.BlytAR.2005 35.94000  -89.91100    0.32         0.746968916
## 089.RaleNC.2007   089.RaleNC.2007 35.74300  -78.62600    0.56         0.395767799
## 092.BakeCA.1992   092.BakeCA.1992 35.41600 -119.06600    0.26         0.725368806
## 093.BakeCA.1953   093.BakeCA.1953 35.37390 -119.01950    0.00         0.729994833
```

```
## 094.ShelTN.2002   094.ShelTN.2002 35.31520  -90.00620    0.56        0.308644133
## 095.RussAR.1957   095.RussAR.1957 35.27840  -93.13380    0.22        0.000000000
## 096.MempTN.2002   096.MempTN.2002 35.21220  -90.03840    0.38        0.441559622
## 097.MempTN.2002   097.MempTN.2002 35.11310  -90.05720    0.36        0.447261866
## 098.ShelTN.2005   098.ShelTN.2005 35.07700  -90.06000    0.49        0.446873395
## 099.LakeGA.1955   099.LakeGA.1955 34.88900  -84.26130    0.00        0.000000000
## 100.SanBCA.1951   100.SanBCA.1951 34.82530 -116.08330    0.00        0.000000000
## 101.FlorAL.1954   101.FlorAL.1954 34.79980  -87.67730    0.05        0.000000000
## 102.ShefAL.1953   102.ShefAL.1953 34.76510  -87.69860    0.00        0.000000000
## 103.TuniMS.1945   103.TuniMS.1945 34.63990  -90.36240    0.00        0.000000000
## 104.CaLeNC.1957   104.CaLeNC.1957 34.63970  -77.34180    0.00        0.000000000
## 105.BateMS.2005   105.BateMS.2005 34.32400  -89.94500    0.44        0.000000000
## 106.PineAR.1957   106.PineAR.1957 34.21570  -92.01400    0.00        0.000000000
## 107.PlaiTX.1953   107.PlaiTX.1953 34.18480 -101.70680    0.00        0.000000000
## 108.CucaCA.1957   108.CucaCA.1957 34.09920 -117.60220    0.00        0.888801175
## 109.RedlCA.1951   109.RedlCA.1951 34.05500 -117.18270    0.00        0.556155598
## 110.LomaCA.1957   110.LomaCA.1957 34.05380 -117.26110    1.00        0.687196135
## 111.WinfAL.1957   111.WinfAL.1957 33.92820  -87.81630    0.00        0.000000000
## 112.GurdAR.1957   112.GurdAR.1957 33.91820  -93.14880    0.00        0.000000000
## 113.AtlaGA.2007   113.AtlaGA.2007 33.80700  -84.36000    0.39        0.666059179
## 114.OranCA.1953   114.OranCA.1953 33.75060 -117.87220    0.01        1.000000000
## 115.OranCA.1953   115.OranCA.1953 33.75060 -117.87220    0.01        1.000000000
## 116.RiveCA.1957   116.RiveCA.1957 33.72200 -116.03720    0.00        0.319824055
## 117.LubbTX.1953   117.LubbTX.1953 33.58560 -101.84700    0.02        0.000000000
## 118.ColuMS.1944   118.ColuMS.1944 33.49570  -88.42730    0.00        0.000000000
## 119.PhoeAZ.2024   119.PhoeAZ.2024 33.44844 -112.07414    0.00        0.000000000
## 120.GreeMS.1957   120.GreeMS.1957 33.41110  -91.06360    0.00        0.000000000
## 121.VaidMS.2005   121.VaidMS.2005 33.33300  -89.75300    0.36        0.000000000
## 122.ElDoAR.1953   122.ElDoAR.1953 33.21150  -92.66500    0.50        0.000000000
## 123.MariAZ.2023   123.MariAZ.2023 33.07362 -111.97377    0.00        0.000000000
## 124.DalFTX.2024   124.DalFTX.2024 32.42235  -96.93698    0.11        0.000000000
## 125.AubuAL.1957   125.AubuAL.1957 32.60990  -85.48080    0.00        0.000000000
## 126.MontAL.1957   126.MontAL.1957 32.36700  -86.30060    0.00        0.000000000
## 127.JackMS.2005   127.JackMS.2005 32.31100  -90.17400    0.14        0.000000000
## 128.BrooMS.2005   128.BrooMS.2005 31.58600  -90.45200    0.11        0.000000000
## 129.BakeGA.1953   129.BakeGA.1953 31.34390  -84.45550    0.00        0.000000000
## 130.CollTX.2023   130.CollTX.2023 30.60044  -96.26893    0.08        0.000000000
## 131.SlidLA.2024   131.SlidLA.2024 30.32700  -89.74900    0.03        0.000000000
## 132.BeauTX.1954   132.BeauTX.1954 30.08600  -94.10180    0.00        0.000000000
## 133.AnasFL.2023   133.AnasFL.2023 29.90311  -81.40074    0.00        0.000000000
## 134.HousTX.1957   134.HousTX.1957 29.75890  -95.36770    0.00        0.235793000
## 135.EaglTX.1953   135.EaglTX.1953 28.70840 -100.50390    0.00        0.000000000
## 136.OrlaFL.1957   136.OrlaFL.1957 28.54210  -81.37900    0.00        0.000000000
## 137.MiDaFL.2023   137.MiDaFL.2023 25.80141  -80.19909    0.00        0.000000000
## 138.MiamFL.1957   138.MiamFL.1957 25.77420  -80.19360    0.00        0.000000000
##                  predicted_h_index
## 001.ByroWA.2023          0.5208546
## 002.StAnQC.1944          0.8184089
## 003.OttaON.1957          0.9036682
## 004.StPaMN.1953          0.8443658
## 005.StPaMN.1953          0.8443658
## 006.GreaIL.1944          0.5584620
## 007.CookIL.2023          0.5003389
## 008.CachUT.2023          1.0000000
```

```
## 009.BarnMA.2023          0.5000000
## 010.TrumIL.2012          0.5425679
## 011.BoxEUT.2024          1.0000000
## 012.OgdeUT.2024          0.7051933
## 013.OxfoNJ.1953          0.9954287
## 014.FortNY.2007          0.5000000
## 015.SaltUT.2023          0.7010417
## 015.SaltUT.2018          0.7010417
## 016.SaltUT.2021          0.7010898
## 017.GoveNY.1953          0.5000000
## 018.SaltUT.1957          0.6879793
## 019.FreeNY.1953          0.5000000
## 020.BensUT.2021          0.9321020
## 021.ReddCA.2003          1.0000000
## 022.HuntNJ.2023          0.7861053
## 023.SomeNJ.2023          0.6523055
## 024.FortCO.2023          1.0000000
## 025.UteTUT.2024          1.0000000
## 026.VernUT.2024          1.0000000
## 027.TrenNJ.2007          0.5064957
## 028.ProvUT.2024          0.8433461
## 029.ChamIL.2005          1.0000000
## 030.SeneKS.1951                 NA
## 031.ChicCA.1992          0.4068169
## 032.NewaDE.1953          0.6619332
## 033.RaymIL.1939          1.0000000
## 034.ClarMD .2020         0.5540776
## 035.SuttCA.2023          0.4925264
## 036.EffiIL.2005          1.0000000
## 037.Old MD.2020          0.5192716
## 038.RockMD.2023          0.5586669
## 039.LawrKS.1955          0.6634387
## 040.LawrKS.1951          0.6634387
## 041.LincCA.2023          0.4591176
## 042.DistDC.2019          0.5000000
## 043.FairVA.2007          0.5200899
## 044.AnacDC.2020          0.5000000
## 045.BadeMO.1952          0.5166066
## 046.StAnMO.1952          0.5583703
## 047.NortMO.1952          0.5332371
## 048.UnivMO.1952          0.5984681
## 049.RichMO.1952          0.6295175
## 050.StLoMO.1952          0.6043557
## 051.StLoMO.1953          0.6043557
## 052.EastIL.1944          0.6055099
## 053.EastIL.1943          0.6055099
## 054.MoabUT.2024                 NA
## 055.KirkMO.1952          0.6968042
## 056.KirkMO.1952          0.6968042
## 057.CambMA.1945          0.5000000
## 058.CahoIL.1943          0.6727195
## 059.SacrCA.1947          0.4697888
## 060.KingCA.1957          0.4961960
## 061.BainMD.1945          0.5000000
```

```
## 062.PatuMD.1945           0.5000000
## 063.CarmIL.1941           0.5023048
## 064.OaklCA.1992           0.5000000
## 065.BentIL.2005           0.5002206
## 066.StocCA.1957           0.5000000
## 067.SanJCA.1957           0.5000000
## 068.CrabIL.1942           0.6216752
## 069.AlamCA.1992           0.5000000
## 070.FronKS.1951           0.5000000
## 071.NewmCA.1992           0.5000000
## 072.StGeUT.2023           0.4154164
## 073.ChowCA.1991           0.5000000
## 074.JoplMO.1952           0.3894218
## 075.BaxtKS.1957           0.2937069
## 076.SikeMO.2005           0.4221798
## 077.FireCA.1952           0.5000000
## 078.MadeCA.1992           0.5000000
## 079.NorfVA.1957           0.3727732
## 080.KermCA.1992           0.5000000
## 081.FresCA.1953           0.4811033
## 082.CentCA.2000           0.3687577
## 083.ReedCA.2000           0.4919062
## 084.SelmCA.1953           0.4146860
## 085.FresCA.2005           0.4881303
## 086.BullAR.1957           0.0000000
## 087.VisaCA.1992           0.2709736
## 088.BlytAR.2005           0.3734854
## 089.RaleNC.2007           0.2218396
## 092.BakeCA.1992           0.4386534
## 093.BakeCA.1953           0.4614086
## 094.ShelTN.2002           0.1543237
## 095.RussAR.1957                  NA
## 096.MempTN.2002           0.2207813
## 097.MempTN.2002           0.2236339
## 098.ShelTN.2005           0.2234390
## 099.LakeGA.1955                  NA
## 100.SanBCA.1951           0.0000000
## 101.FlorAL.1954           0.0000000
## 102.ShefAL.1953           0.0000000
## 103.TuniMS.1945           0.0000000
## 104.CaLeNC.1957           0.0000000
## 105.BateMS.2005           0.0000000
## 106.PineAR.1957           0.0000000
## 107.PlaiTX.1953                  NA
## 108.CucaCA.1957           0.4444006
## 109.RedlCA.1951           0.3239416
## 110.LomaCA.1957           0.3695397
## 111.WinfAL.1957                  NA
## 112.GurdAR.1957           0.0000000
## 113.AtlaGA.2007           0.3330306
## 114.OranCA.1953           0.5000000
## 115.OranCA.1953           0.5000000
## 116.RiveCA.1957           0.1599133
## 117.LubbTX.1953           0.0000000
```

```
## 118.ColuMS.1944          0.0000000
## 119.PhoeAZ.2024          0.0000000
## 120.GreeMS.1957          0.0000000
## 121.VaidMS.2005          0.0000000
## 122.ElDoAR.1953          0.0000000
## 123.MariAZ.2023          0.0000000
## 124.DalFTX.2024          0.0000000
## 125.AubuAL.1957          0.0000000
## 126.MontAL.1957          0.0000000
## 127.JackMS.2005          0.0000000
## 128.BrooMS.2005          0.0000000
## 129.BakeGA.1953          0.0000000
## 130.CollTX.2023          0.0000000
## 131.SlidLA.2024          0.0000000
## 132.BeauTX.1954          0.0000000
## 133.AnasFL.2023          0.0000000
## 134.HousTX.1957          0.1178991
## 135.EaglTX.1953          0.0000000
## 136.OrlaFL.1957          0.0000000
## 137.MiDaFL.2023          0.0000000
## 138.MiamFL.1957          0.0000000
```

```
# Save as CSV
# write.csv(summary_table, file = "../data/summary_hindex_prediction.csv", row.names = FALSE)
```

Plot h_index versus predicted_h_index, latitude, etc…

By Zone: H-index versus Predicted H-index and Latitude

```
library(ggplot2)
library(dplyr)
library(patchwork)
```

```
##
## Attaching package: 'patchwork'

## The following object is masked from 'package:terra':
##
##     area

## The following object is masked from 'package:raster':
##
##     area
```

```
# Define hybrid zones:

countsAllDf$zone <- NULL
countsAllDf$zone <- case_when(
  grepl("CA|OR|WA", countsAllDf$site) ~ "West Coast",
  grepl("NJ|MD|MA|DE|CT|NY|VA|FL|QC|DC|TN|GA|NC", countsAllDf$site) ~ "East Coast",
  grepl("TX|LA|IL|LA|MN|ON|KS|MO|AR|AL|MS", countsAllDf$site) ~ "Central",
  grepl("UT|CO|AZ", countsAllDf$site) ~ "Mtn/Southwest"
)

# Control order by making it a factor
```

```r
countsAllDf$zone <- factor(countsAllDf$zone, levels = c("West Coast", "Mtn/Southwest", "Central", "East

# Define zone color palette
zone_colors <- c(
   "Mtn/Southwest" = "#d73027",
   "Central" =   "#6a3d9a",
   "West Coast" = "#e6b800",
   "East Coast" ="#1f78b4"
)

# Create shared color scale
zone_scale <- scale_color_manual(values = zone_colors, name = "Zone:")

# Shared theme for both plots
shared_theme <- theme_minimal(base_size = 10) +
  theme(
    plot.title = element_text(size = 12, face = "bold"),
    legend.position = "bottom",  # <-- Legend at bottom
    axis.title = element_text(size = 10),
    axis.text = element_text(size = 8),
    plot.margin = margin(10, 10, 10, 10)
  )

# ---------------------------------------
# H-index vs Predicted H-index
# ---------------------------------

r2_pred <- countsAllDf %>%
  group_by(zone) %>%
  summarise(r2 = summary(lm(predicted_h_index ~ h_index))$r.squared)

p2 <- ggplot(countsAllDf, aes(x = h_index, y = predicted_h_index, color = zone)) +
  geom_point(size = 3, alpha = 0.5, shape = 16) +
  geom_smooth(method = "lm", formula = y ~ x, se = FALSE, linewidth = 1.2) +
  geom_text(data = r2_pred, aes(x = 0.05, y = 0.95 - as.numeric(zone) * 0.05,
                                label = paste0("R² = ", round(r2, 2)), color = zone),
            hjust = 0, size = 3.5, inherit.aes = FALSE) +
  theme_minimal() +
  labs(x = "H-index", y = "Predicted H-index (from SDM)", title = "Predicted H-index", color = "Zone:")
  xlim(0, 1) +
  ylim(0, 1) +
  scale_color_manual(values = zone_colors)
  guides(color = guide_legend(override.aes = list(alpha = 1, shape = NA, linetype = 1)))
```

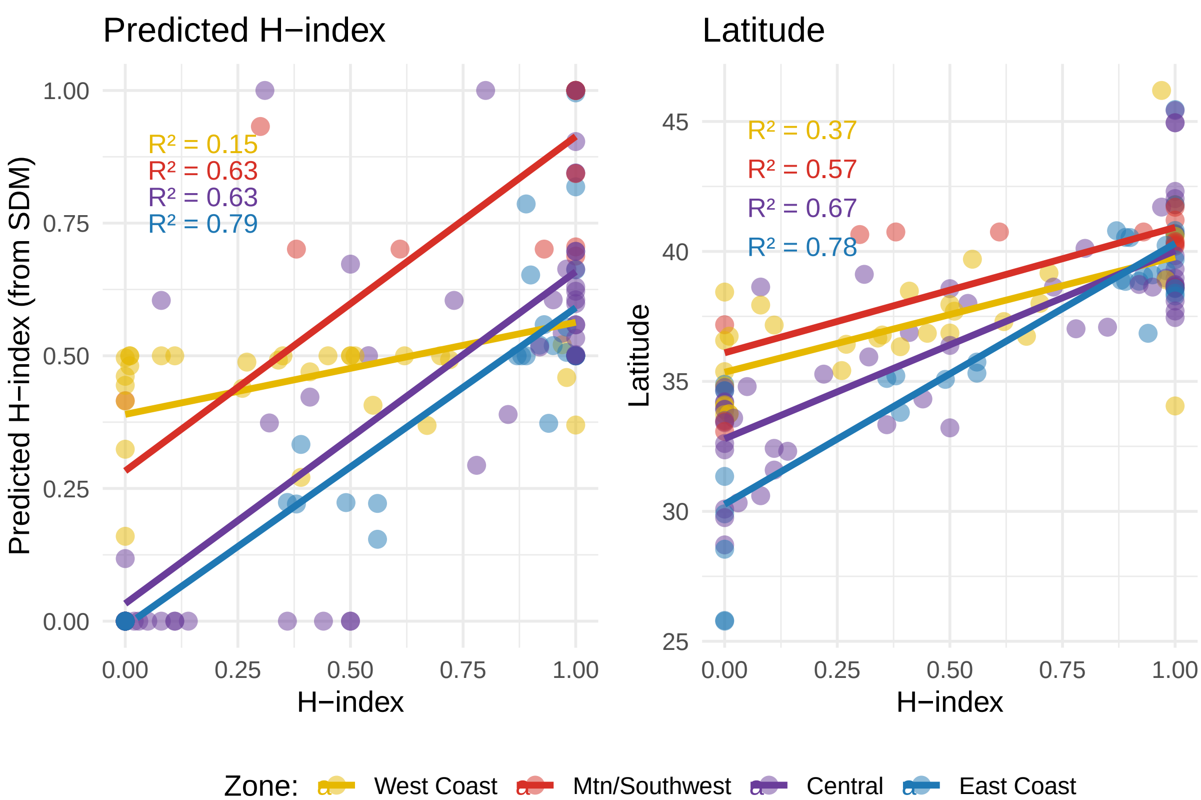
```
## <Guides[1] ggproto object>
##
## colour : <GuideLegend>
```

```r
# ---------------------------------------
#  H-index vs Latitude
# ---------------------------------------
r2_lat <- countsAllDf %>%
  group_by(zone) %>%
  summarise(r2 = summary(lm(latitude ~ h_index))$r.squared)
```

```r
p1 <- ggplot(countsAllDf, aes(x = h_index, y = latitude, color = zone)) +
  geom_point(size = 3, alpha = 0.5, shape = 16) +
  geom_smooth(method = "lm", formula = y ~ x, se = FALSE, linewidth = 1.2) +
  geom_text(data = r2_lat, aes(x = 0.05, y = max(countsAllDf$latitude, na.rm = TRUE) - as.numeric(zone)
                              label = paste0("R² = ", round(r2, 2)), color = zone),
            hjust = 0, size = 3.5, inherit.aes = FALSE) +
  theme_minimal() +
  labs(x = "H-index", y = "Latitude", title = "Latitude", color = "Zone:") +
  xlim(0, 1) +
  scale_color_manual(values = zone_colors)
  guides(color = guide_legend(override.aes = list(alpha = 1, shape = NA, linetype = 1)))
```

```
## <Guides[1] ggproto object>
##
## colour : <GuideLegend>
```

```r
# ---------------------------------------
# Combine plots with unified legend at bottom
# ---------------------------------------

# Define the plot object
final_plot  <- (p2 | p1) + plot_layout(guides = 'collect') & theme(legend.position = "bottom")

  final_plot
```



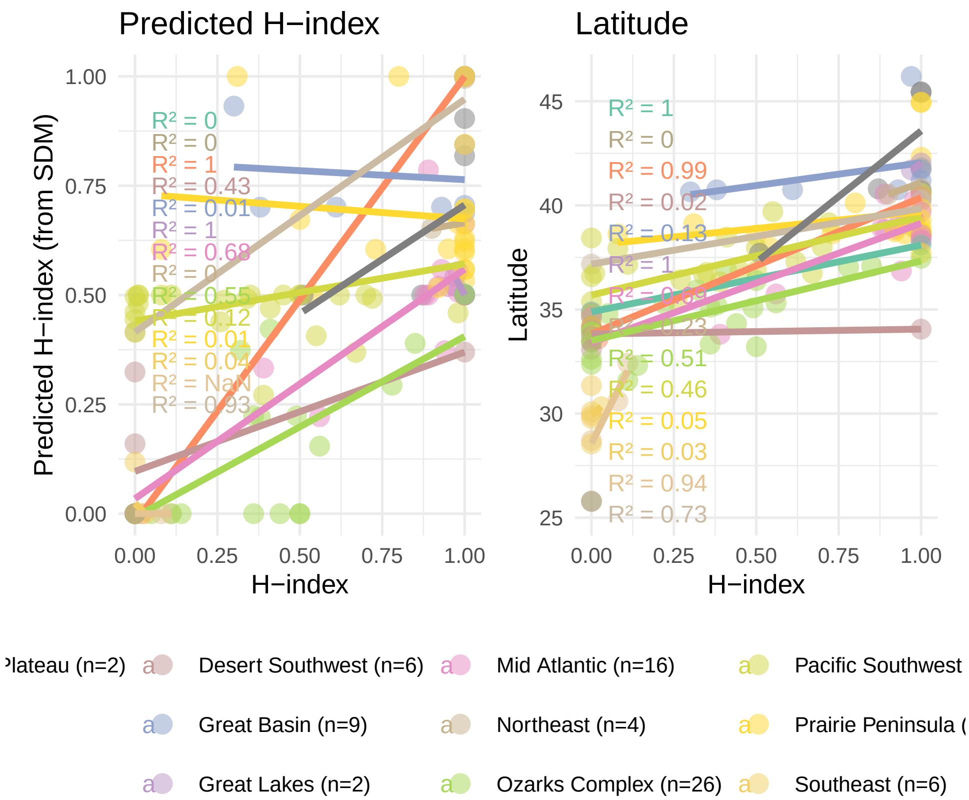

```r
# Save as PDF with specific width and height (in inches)
#ggsave("../figs/h_index_lm_all_by_zone.pdf", plot = final_plot, width = 7, height = 4, units = "in")
```

By NEON Ecozone: H-index vs Predicted H-index and Latitude

```r
## By NEON Ecozone
library(sf)
library(RColorBrewer)
library(patchwork)

# Load NEON ecozones
neon_domains <- st_read("~/git/ace2/gis/NEON_Domains.shp", quiet = TRUE)

# Join sampling sites to NEON ecozones
df_sf <- st_as_sf(countsAllDf, coords = c("longitude", "latitude"), crs = 4326)
df_sf <- st_transform(df_sf, st_crs(neon_domains))
df_joined <- st_join(df_sf, neon_domains)

# Extract coordinates back out for plotting
df_joined$longitude <- st_coordinates(df_joined)[,1]
df_joined$latitude  <- st_coordinates(df_joined)[,2]

# Pick ecozone field
if ("domainName" %in% names(df_joined)) {
  df_joined$ecozone <- df_joined$domainName
} else {
  df_joined$ecozone <- df_joined$domainID
}

# Sample counts per ecozone for legend labels
eco_counts <- df_joined %>%
  group_by(ecozone) %>%
  summarise(n = n(), .groups = "drop")

eco_labels <- setNames(
  paste0(eco_counts$ecozone, " (n=", eco_counts$n, ")"),
  eco_counts$ecozone
)

# Color palette
eco_levels <- eco_counts$ecozone
ecozone_colors <- setNames(
  colorRampPalette(brewer.pal(8, "Set2"))(length(eco_levels)),
  eco_levels
)

# ----------------------------------------
# H-index vs Predicted H-index
# ----------------------------------------
r2_pred <- df_joined %>%
  group_by(ecozone) %>%
  summarise(r2 = summary(lm(predicted_h_index ~ h_index))$r.squared)

p2 <- ggplot(df_joined, aes(x = h_index, y = predicted_h_index, color = ecozone)) +
  geom_point(size = 3, alpha = 0.5) +
  geom_smooth(method = "lm", se = FALSE, linewidth = 1.2, show.legend = FALSE) +
  geom_text(data = r2_pred,
```

```r
            aes(x = 0.05, y = 0.95 - as.numeric(factor(ecozone)) * 0.05,
                label = paste0("R² = ", round(r2, 2)), color = ecozone),
            hjust = 0, size = 3.2, inherit.aes = FALSE) +
  labs(x = "H-index", y = "Predicted H-index (from SDM)",
       title = "Predicted H-index", color = "Ecozone:") +
  xlim(0, 1) + ylim(0, 1) +
  scale_color_manual(values = ecozone_colors, labels = eco_labels) +
  theme_minimal(base_size = 10)

# ----------------------------------------
# H-index vs Latitude
# ----------------------------------------
r2_lat <- df_joined %>%
  group_by(ecozone) %>%
  summarise(r2 = summary(lm(latitude ~ h_index))$r.squared)

p1 <- ggplot(df_joined, aes(x = h_index, y = latitude, color = ecozone)) +
  geom_point(size = 3, alpha = 0.5) +
  geom_smooth(method = "lm", se = FALSE, linewidth = 1.2, show.legend = FALSE) +
  geom_text(data = r2_lat,
            aes(x = 0.05,
                y = max(df_joined$latitude, na.rm = TRUE) - as.numeric(factor(ecozone)) * 1.5,
                label = paste0("R² = ", round(r2, 2)), color = ecozone),
            hjust = 0, size = 3.2, inherit.aes = FALSE) +
  labs(x = "H-index", y = "Latitude",
       title = "Latitude", color = "Ecozone:") +
  xlim(0, 1) +
  scale_color_manual(values = ecozone_colors, labels = eco_labels) +
  theme_minimal(base_size = 10)

# ----------------------------------------
# Combine plots with unified legend
# ----------------------------------------
final_plot <- (p2 | p1) + plot_layout(guides = 'collect') & theme(legend.position = "bottom")

final_plot
```

```
## `geom_smooth()` using formula = 'y ~ x'
## `geom_smooth()` using formula = 'y ~ x'
```




```
ggsave("../figs/h_index_lm_all_by_neon.pdf", plot = final_plot, width = 7, height = 4, units = "in")
```

```
## `geom_smooth()` using formula = 'y ~ x'
## `geom_smooth()` using formula = 'y ~ x'
```

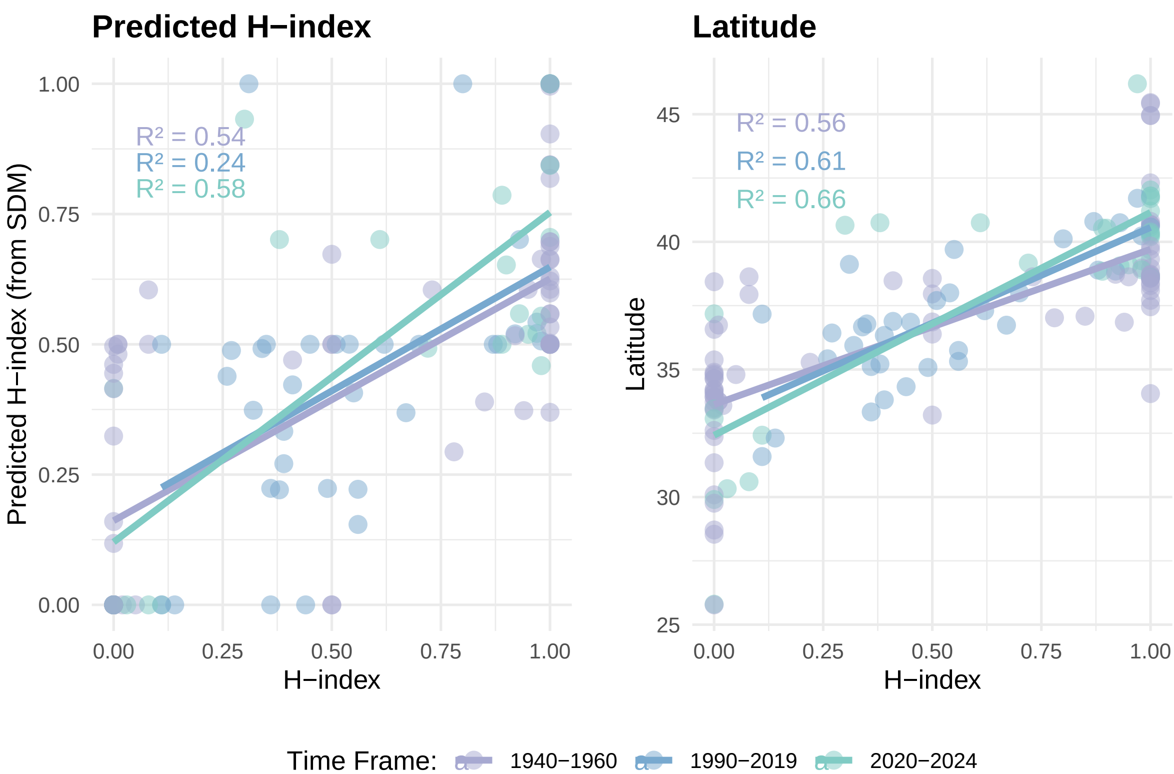
We tested whether NEON ecozones provided greater ecological resolution than broad latitudinal/region bins. However, most ecozones contained very few samples (often n < 5), leading to unstable slopes, inconsistent R^2 values, and plots that were not interpretable (see directly above). Because finer ecological stratification fragments the dataset and reduces statistical power, we present results using broader East/West/Central/Mountain zones, which provide more robust inference.

By Year: H-index vs Predicted H-index and Latitude

```
library(ggplot2)
library(dplyr)
library(patchwork)

countsAllDf <- countsAllDf %>%
  mutate(time_frame = case_when(
    year >= 1939 & year <= 1961 ~ "1940-1960",
    year >= 1989 & year <= 2019 ~ "1990-2019",
    year >= 2020 & year <= 2024 ~ "2020-2024",
    TRUE ~ "Other"
  ))

# Optional: Make time_frame a factor to control order
countsAllDf$time_frame <- factor(countsAllDf$time_frame,
                                 levels = c("1940-1960", "1990-2019", "2020-2024"))
```

```r
time_frame_colors <- c("1940-1960" = "#A7A9D1",  # muted lavender/blue
                       "1990-2019" = "#78A9CF",  # moderate blue
                       "2020-2024" = "#80CBC4")  # aqua-green, clearly distinct

time_frame_scale <- scale_color_manual(values = time_frame_colors, name = "Time Frame:")

# Shared theme
shared_theme <- theme_minimal(base_size = 10) +
  theme(
    plot.title = element_text(size = 12, face = "bold"),
    legend.position = "bottom",
    axis.title = element_text(size = 10),
    axis.text = element_text(size = 8),
    plot.margin = margin(10, 10, 10, 10)
  )

# ---------------------------------------
# H-index vs Predicted H-index
# ---------------------------------------

r2_pred <- countsAllDf %>%
  group_by(time_frame) %>%
  summarise(r2 = summary(lm(predicted_h_index ~ h_index))$r.squared)

p2 <- ggplot(countsAllDf, aes(x = h_index, y = predicted_h_index, color = time_frame)) +
  geom_point(size = 3, alpha = 0.5, shape = 16) +
  geom_smooth(method = "lm", formula = y ~ x, se = FALSE, linewidth = 1.2) +
  geom_text(data = r2_pred, aes(x = 0.05, y = 0.95 - as.numeric(time_frame) * 0.05,
                                label = paste0("R² = ", round(r2, 2)), color = time_frame),
            hjust = 0, size = 3.5, inherit.aes = FALSE) +
  shared_theme +
  labs(x = "H-index", y = "Predicted H-index (from SDM)", title = "Predicted H-index", color = "Time Fra
  xlim(0, 1) +
  ylim(0, 1) +
  time_frame_scale


# ---------------------------------------
#  H-index vs Latitude
# ---------------------------------------

r2_lat <- countsAllDf %>%
  group_by(time_frame) %>%
  summarise(r2 = summary(lm(latitude ~ h_index))$r.squared)

p1 <- ggplot(countsAllDf, aes(x = h_index, y = latitude, color = time_frame)) +
  geom_point(size = 3, alpha = 0.5, shape = 16) +
  geom_smooth(method = "lm", formula = y ~ x, se = FALSE, linewidth = 1.2) +
  geom_text(data = r2_lat, aes(x = 0.05, y = max(countsAllDf$latitude, na.rm = TRUE) - as.numeric(time_
                               label = paste0("R² = ", round(r2, 2)), color = time_frame),
            hjust = 0, size = 3.5, inherit.aes = FALSE) +
  shared_theme +
  labs(x = "H-index", y = "Latitude", title = "Latitude", color = "Time Frame:") +
```

```
  xlim(0, 1) +
  time_frame_scale


# ---------------------------------------
# Combine plots with unified legend at bottom
# ---------------------------------------

# Define the plot object
final_plot  <- (p2 | p1) + plot_layout(guides = 'collect') & theme(legend.position = "bottom")

final_plot
```




```
# Save as PDF with specific width and height (in inches)
#ggsave("../figs/h_index_lm_all_by_time.pdf", plot = final_plot, width = 7, height = 4, units = "in")
```

ANCOVA (Analysis of Covariance)

This allows you to test:

Whether slopes differ significantly by zone vs. time.

Whether overall fit is better when grouping by zone vs. by time.

You can compare models using AIC or adjusted R^2.

```
# Model 1: Zone as factor
mod_zone <- lm(latitude ~ h_index * zone, data = countsAllDf)

# Model 2: Time Frame as factor
```

```r
mod_time <- lm(latitude ~ h_index * time_frame, data = countsAllDf)

# Compare model fits
AIC(mod_zone, mod_time)
```

```
##          df      AIC
## mod_zone  9 606.2853
## mod_time  7 634.8123
```

```r
summary(mod_zone)
```

```
##
## Call:
## lm(formula = latitude ~ h_index * zone, data = countsAllDf)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.7368 -1.3649 -0.2123  1.2204  6.5356
##
## Coefficients:
##                           Estimate Std. Error t value Pr(>|t|)
## (Intercept)                35.3504     0.5674  62.299  < 2e-16 ***
## h_index                     4.4403     1.1366   3.906 0.000150 ***
## zoneMtn/Southwest           0.7480     1.2113   0.618 0.537990
## zoneCentral                -2.5602     0.7207  -3.552 0.000534 ***
## zoneEast Coast             -5.0792     0.9214  -5.512 1.85e-07 ***
## h_index:zoneMtn/Southwest   0.3864     1.7441   0.222 0.825009
## h_index:zoneCentral         2.7914     1.3134   2.125 0.035466 *
## h_index:zoneEast Coast      5.5966     1.4757   3.792 0.000228 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.134 on 129 degrees of freedom
## Multiple R-squared:  0.6899, Adjusted R-squared:  0.6731
## F-statistic:    41 on 7 and 129 DF,  p-value: < 2.2e-16
```

```r
summary(mod_time)
```

```
##
## Call:
## lm(formula = latitude ~ h_index * time_frame, data = countsAllDf)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -7.8521 -1.3168  0.0515  1.0134  5.7474
##
## Coefficients:
##                             Estimate Std. Error t value Pr(>|t|)
## (Intercept)                  33.6263     0.4111  81.800   <2e-16 ***
## h_index                       6.0822     0.6029  10.088   <2e-16 ***
## time_frame1990-2019          -0.5602     1.0190  -0.550   0.5835
## time_frame2020-2024          -1.2066     0.9115  -1.324   0.1879
## h_index:time_frame1990-2019   1.4157     1.6986   0.833   0.4061
## h_index:time_frame2020-2024   2.6501     1.2068   2.196   0.0298 *
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.385 on 131 degrees of freedom
## Multiple R-squared:  0.6068, Adjusted R-squared:  0.5918
## F-statistic: 40.43 on 5 and 131 DF,  p-value: < 2.2e-16
```

Repeat with SDM predicted H-index

```r
# Model with zone
mod_pred_zone <- lm(predicted_h_index ~ h_index * zone, data = countsAllDf)
summary(mod_pred_zone)
```

```
##
## Call:
## lm(formula = predicted_h_index ~ h_index * zone, data = countsAllDf)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.38964 -0.09067 -0.02205  0.07831  0.77307
##
## Coefficients:
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)                 0.38964    0.04690   8.308 1.50e-13 ***
## h_index                     0.17351    0.09394   1.847  0.06715 .
## zoneMtn/Southwest          -0.10653    0.10017  -1.064  0.28963
## zoneCentral                -0.35659    0.06098  -5.848 4.20e-08 ***
## zoneEast Coast             -0.39905    0.07919  -5.039 1.63e-06 ***
## h_index:zoneMtn/Southwest   0.45668    0.14571   3.134  0.00216 **
## h_index:zoneCentral         0.45191    0.10979   4.116 7.00e-05 ***
## h_index:zoneEast Coast      0.42657    0.12434   3.431  0.00082 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1764 on 123 degrees of freedom
##   (6 observations deleted due to missingness)
## Multiple R-squared:  0.6763, Adjusted R-squared:  0.6578
## F-statistic: 36.71 on 7 and 123 DF,  p-value: < 2.2e-16
```

```r
# Model with time frame
mod_pred_time <- lm(predicted_h_index ~ h_index * time_frame, data = countsAllDf)
summary(mod_pred_time)
```

```
##
## Call:
## lm(formula = predicted_h_index ~ h_index * time_frame, data = countsAllDf)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.39367 -0.16157 -0.06731  0.14973  0.67969
##
## Coefficients:
##                              Estimate Std. Error t value Pr(>|t|)
## (Intercept)                   0.16157    0.03932   4.109 7.14e-05 ***
## h_index                       0.46421    0.05654   8.210 2.33e-13 ***
## time_frame1990-2019           0.01136    0.09302   0.122    0.903
## time_frame2020-2024          -0.04102    0.08343  -0.492    0.624
```

```
## h_index:time_frame1990-2019  0.01119    0.15431   0.073    0.942
## h_index:time_frame2020-2024  0.16857    0.11110   1.517    0.132
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2156 on 125 degrees of freedom
##   (6 observations deleted due to missingness)
## Multiple R-squared:  0.5084, Adjusted R-squared:  0.4887
## F-statistic: 25.85 on 5 and 125 DF,  p-value: < 2.2e-16
```

```
# Compare model fits
AIC(mod_pred_zone, mod_pred_time)
```

```
##               df       AIC
## mod_pred_zone  9 -73.05279
## mod_pred_time  7 -22.33187
```

```
summary(mod_pred_zone)
```

```
##
## Call:
## lm(formula = predicted_h_index ~ h_index * zone, data = countsAllDf)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.38964 -0.09067 -0.02205  0.07831  0.77307
##
## Coefficients:
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)                 0.38964    0.04690   8.308 1.50e-13 ***
## h_index                     0.17351    0.09394   1.847  0.06715 .
## zoneMtn/Southwest          -0.10653    0.10017  -1.064  0.28963
## zoneCentral                -0.35659    0.06098  -5.848 4.20e-08 ***
## zoneEast Coast             -0.39905    0.07919  -5.039 1.63e-06 ***
## h_index:zoneMtn/Southwest   0.45668    0.14571   3.134  0.00216 **
## h_index:zoneCentral         0.45191    0.10979   4.116 7.00e-05 ***
## h_index:zoneEast Coast      0.42657    0.12434   3.431  0.00082 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1764 on 123 degrees of freedom
##   (6 observations deleted due to missingness)
## Multiple R-squared:  0.6763, Adjusted R-squared:  0.6578
## F-statistic: 36.71 on 7 and 123 DF,  p-value: < 2.2e-16
```

```
summary(mod_pred_time)
```

```
##
## Call:
## lm(formula = predicted_h_index ~ h_index * time_frame, data = countsAllDf)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.39367 -0.16157 -0.06731  0.14973  0.67969
##
## Coefficients:
```

```
##                              Estimate Std. Error t value Pr(>|t|)    
## (Intercept)                   0.16157    0.03932   4.109 7.14e-05 ***
## h_index                       0.46421    0.05654   8.210 2.33e-13 ***
## time_frame1990-2019           0.01136    0.09302   0.122    0.903    
## time_frame2020-2024          -0.04102    0.08343  -0.492    0.624    
## h_index:time_frame1990-2019   0.01119    0.15431   0.073    0.942    
## h_index:time_frame2020-2024   0.16857    0.11110   1.517    0.132    
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2156 on 125 degrees of freedom
##   (6 observations deleted due to missingness)
## Multiple R-squared:  0.5084, Adjusted R-squared:  0.4887 
## F-statistic: 25.85 on 5 and 125 DF,  p-value: < 2.2e-16
```