GAM_spatial_SD_Prior_Simulation

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Priors for the spatial variance in GAM parameters

The stratum-level population trajectories are fit using a spatially explicit, hierarchical GAM smooth. This spatial hierarchical structure allows the model to share information on the shape of the population trajectory among neighbouring strata and across the full range of the sites monitored for a given species. The variation among strata in the shape of the population trajectory is estimated using an intrinsic conditional autoregressive (iCAR) structure. This iCAR component of the model estimates the parameters of the GAM smooth as drawn from a normal distribution centered on the means of the parameter values in the neighbouring strata and with an estimated standard deviation (SD). The value of the SD controls the amount of variation in the shape of the trajectories among strata.

An appropriate prior for the SD parameter is not intuitive, because the GAM parameters do not directly reflect a biological process for which prior knowledge might provide an informative prior. Priors on variance parameters can be unintentionally informative if they put substantial prior mass at improbable levels of variation ((Gelman 2006; Lemoine 2019; Wesner and Pomeranz 2021)). Therefore, we conducted a prior simulation to translate the SD priors into a variation in long-term population trends, for which we do have some biological intuition. The simulation was designed to ensure that the prior on the spatial SD was largely uninformative, allowing for a reasonably broad variation in long-term (1966-2019 USGS analyses) and short-term (2007-2017 CWS analyses) population trend estimates across a species range, and that it did not contain substantial prior mass at highly improbable levels of variation.

We compared the variation in stratum-level trends under the alternative priors to observed variation in trends from a collection of realised long-term trend estimates from a different statistical model applied to the North American Breeding Bird Survey ((Link, Sauer, and Niven 2020)).

We compared three possible prior distributions for the Standard Deviation of the among-stratum variance on the GAM parameters.

1. half-normal
2. half-t-distribution with 3 degrees of freedom
3. gamma with shape parameter = 2

And, for each of the prior distributions, we compared 5 different values to set the prior-scale (or the rate parameter, the inverse of the scale, for the gamma distributions): 0.5, 1, 2, 3, and 4. Given the log-link in the trend model and the basis function scaling of the low-rank thin-plate regression spline with identifiability constraints ((Wood 2020)), these 5-values of prior-scales should cover the range of plausible parameter values.

Selected prior

We suggest a half t-distribution, with a scale parameter = 1, fits the realised distributions of the SD in long-term trends among regions for most bird species surveyed by the BBS (i.e., most bird species with the best information on population trends at continental scales and for ~50 years). In addition, a half-normal prior with scale parameter = 2, or a gamma parameter with shape = 2 and rate = 2, also seem to fit similarly well. The half-t prior results in prior distribution of SD in long-term trends that fit the realized distributions and includes long tails that cover the range of plausible trend estimates without including large amounts of prior probability mass at implausibly extreme values. For the short-term trends, the half t-distribution with scale = 1 includes some prior mass above the maximum realised values in the BBS data, although less than 1%. As such, this prior may be slightly more informative than desired in some situations. However, given the relatively close fit to the realised data and the general desirability of a mild regularizing effect on among-strata variation in trends, we suggest that this prior is sufficient for our purposes here.

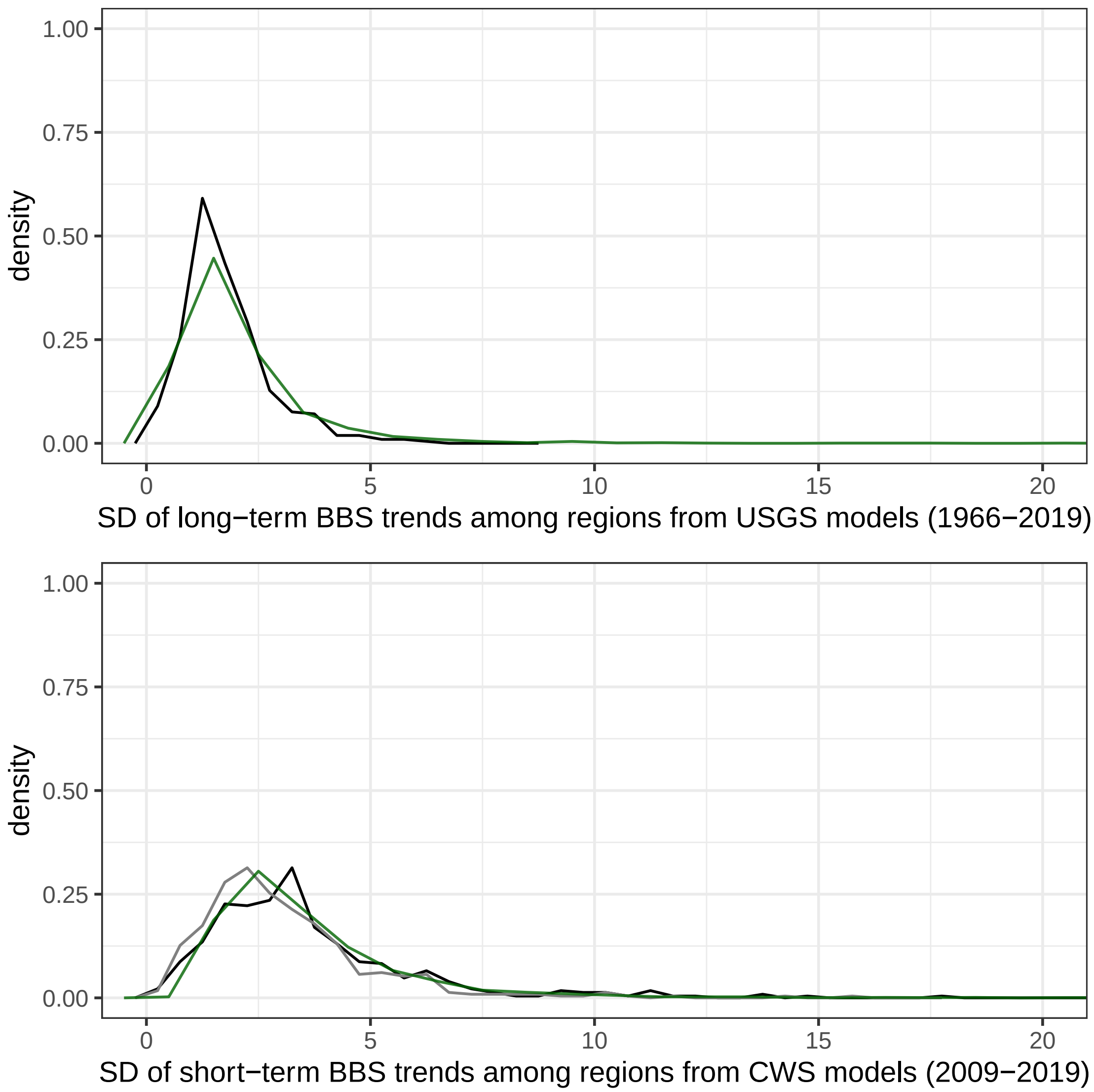

Figure 1: Observed distributions of the SD of long-term population trends from the BBS data using non-GAM models (in black), and the simulated prior distribution (in green) of long- and short-term trends from the spline smooth basis used in this paper, with a half-t (df = 3 and scale parameter = 1) prior distribution on the standard deviation of the spline parameters

Table 1: Prior simulated distribution quantiles for the standard deviation of long-term trends among strata within species and proportion of the distributions greater than the realised maximum values from a separate analysis of the BBS data for > 400 species. Prior simulations for three prior distributions with 5 different scales (normal and t) or rates (gamma)

Distribution	Prior Scale (normal, t) or Rate (gamma)	Median Prior Predicted Distribution	80th percentile	90th percentile	99th percentile	Proportion of prior distribution > realised maximum value
gamma	0.5	6.173	9.222	11.705	19.687	0.218
gamma	1.0	3.220	4.689	5.944	9.733	0.019
gamma	2.0	1.524	2.269	2.836	4.472	0.000
gamma	3.0	1.048	1.514	1.906	3.266	0.000
gamma	4.0	0.783	1.174	1.436	2.399	0.000
norm	0.5	0.626	0.971	1.230	1.880	0.000
norm	1.0	1.278	1.942	2.313	3.791	0.000
norm	2.0	2.464	3.891	4.933	8.696	0.009
norm	3.0	3.876	5.738	6.940	11.377	0.035
norm	4.0	5.003	7.857	9.611	15.827	0.124
t	0.5	0.817	1.386	1.833	3.913	0.002
t	1.0	1.633	2.693	3.632	8.884	0.010
t	2.0	3.300	5.587	7.479	17.461	0.065
t	3.0	4.986	8.172	11.240	26.530	0.167
t	4.0	6.690	11.203	14.886	36.298	0.322

Summary of the quantiles of the prior simulated distributions for the long-term trends.

Table 2: Prior simulated distribution quantiles for the standard deviation of short-term trends among strata within species and proportion of the distributions greater than the realised maximum values from a separate analysis of the BBS data for > 400 species. Prior simulations for three prior distributions with 5 different scales (normal and t) or rates (gamma)

Distribution	Prior Scale (normal, t) or Rate (gamma)	Median Prior Predicted Distribution	80th percentile	90th percentile	99th percentile	Proportion of prior distribution > realised maximum value	Proportion of prior distribution > realised maximum value based on slope
gamma	0.5	11.059	15.330	18.206	27.998	0.041	0.117
gamma	1.0	5.592	7.520	8.842	13.398	0.000	0.002
gamma	2.0	2.755	3.659	4.330	6.167	0.000	0.000
gamma	3.0	1.811	2.481	2.886	4.439	0.000	0.000
gamma	4.0	1.387	1.858	2.229	3.188	0.000	0.000
norm	0.5	1.132	1.562	1.840	2.501	0.000	0.000
norm	1.0	2.263	3.055	3.592	5.119	0.000	0.000
norm	2.0	4.524	6.262	7.423	11.570	0.000	0.000
norm	3.0	6.911	9.365	10.740	15.641	0.000	0.004
norm	4.0	9.162	12.634	14.900	21.595	0.010	0.040
t	0.5	1.520	2.346	2.958	5.654	0.002	0.002
t	1.0	3.015	4.697	6.024	13.058	0.003	0.005
t	2.0	6.080	9.315	12.137	26.805	0.018	0.032
t	3.0	9.165	14.103	18.647	47.280	0.066	0.113
t	4.0	12.546	19.316	25.255	73.649	0.139	0.246

And the same for the short-term trends.

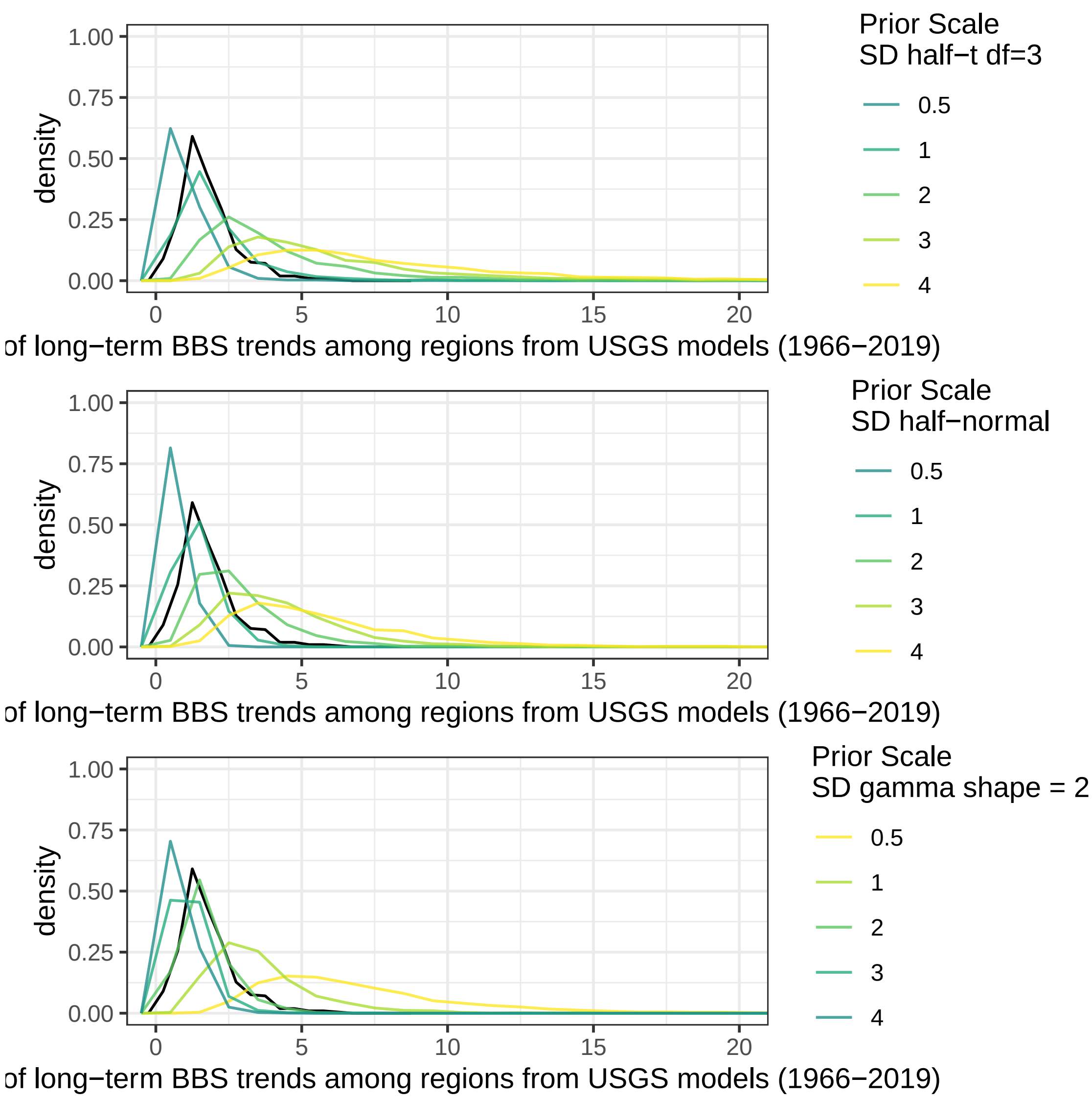

Figure 2: Observed distributions of the SD of long-term population trends from the BBS data using non-GAM models (in black), and the simulated prior distributions (in viridis palette) of long-term trends from the spline smooth basis used in this paper, with a half-t (df = 3), half-normal, and gamma(shape = 2) prior distributions on the standard deviation of the spline parameters. The colours of the simulated prior distributions reflect alternative scale parameters (normal and t) and alternative rate parameters (gamma)

Details on the prior simulations

Here's the full, not-yet well-annotated code that runs the simulations in Stan.

```r
### prior simulation of spatial GAM sd

library(bbsBayes)
library(tidyverse)
library(cmdstanr)
library(patchwork)

setwd("C:/GitHub/GAMYE_Elaboration")


# fit model with fixed data for all parameters except the local sm --------

species <- "Yellow-headed Blackbird"
species_f <- gsub(species,pattern = " ",replacement = "_")


bbs_trends <- read.csv("data_basic/All BBS trends 2017 w reliab.csv")

sd_trends_short <- bbs_trends %>%
  filter(trendtype == "short-term",
         trendtime == "full",
         region.type == "Stratum") %>%
  group_by(species) %>%
  summarise(sd_trends = sd(trend),
            min_trend = min(trend),
            max_trend = max(trend),
            uci_trend = quantile(trend,0.95),
            lci_trend = quantile(trend,0.05)) %>%
  mutate(range_trend = max_trend - min_trend,
         span_90_trend = uci_trend-lci_trend) %>%
  filter(!is.na(sd_trends)) %>%
  arrange(-span_90_trend)

# hist(sd_trends_short$range_trend)
# hist(sd_trends_short$span_90_trend)

G_short_canada <- max(sd_trends_short$sd_trends,na.rm = T)

realised_short_bbs_hist <- ggplot(data = sd_trends_short,
                                  aes(sd_trends,after_stat(density)))+
  geom_freqpoly(breaks = seq(0,G_short_canada,0.5),center = 0)+
  xlab("SD of short-term BBS trends among regions from CWS models (2009-2019)")+
  theme_bw()+
  scale_y_continuous(limits = c(0,1))
print(realised_short_bbs_hist)



# slope based CWS trends --------------------------------------------------
```

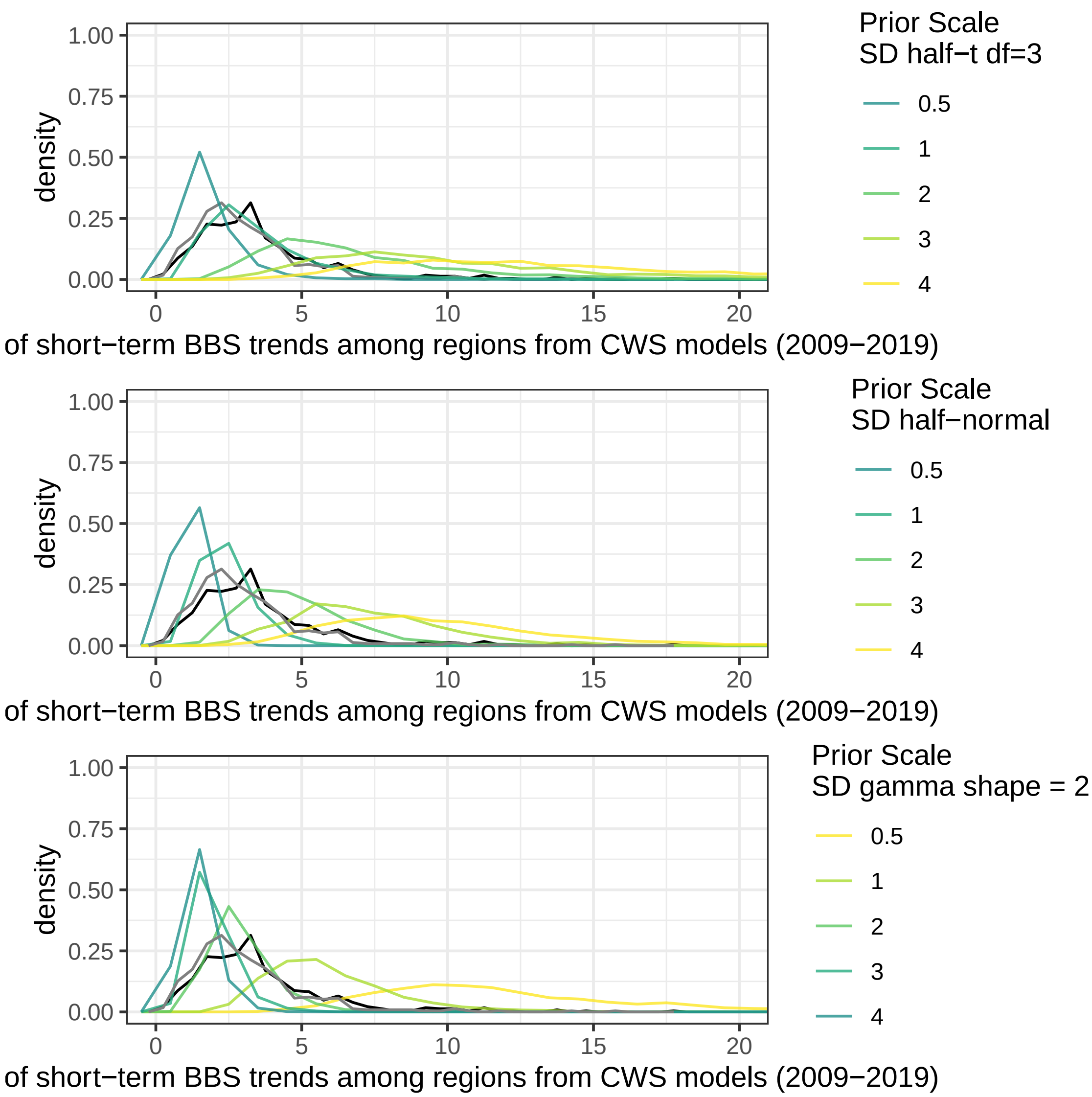

Figure 3: Observed distributions of the SD of short-term population trends from the BBS data using non-GAM models (in black for end-point trends and in grey for slope-based estimates that reduce the influence of annual fluctuations), and the simulated prior distributions (in viridis palette) of short-term trends from the spline smooth basis used in this paper, with a half-t (df = 3), half-normal, and gamma(shape = 2) prior distributions on the standard deviation of the spline parameters. The colours of the simulated prior distributions reflect alternative scale parameters (normal and t) and alternative rate parameters (gamma)

```r
sd_slope_trends_short <- bbs_trends %>%
  filter(trendtype == "short-term",
         trendtime == "full",
         region.type == "Stratum") %>%
  group_by(species) %>%
  summarise(sd_trends = sd(slope.trend),
            min_trend = min(slope.trend),
            max_trend = max(slope.trend),
            uci_trend = quantile(slope.trend,0.95),
            lci_trend = quantile(slope.trend,0.05)) %>%
  mutate(range_trend = max_trend - min_trend,
         span_90_trend = uci_trend-lci_trend) %>%
  filter(!is.na(sd_trends)) %>%
  arrange(-span_90_trend)


G_short_slope_canada <- max(sd_slope_trends_short$sd_trends,na.rm = T)

realised_slope_short_bbs_hist <- ggplot(data = sd_slope_trends_short,
                                 aes(sd_trends,after_stat(density)))+
  geom_freqpoly(breaks = seq(0,G_short_canada,0.5),center = 0)+
  xlab("SD of short-term BBS trends among regions from CWS models (2009-2019)")+
  theme_bw()+
  scale_y_continuous(limits = c(0,1))
print(realised_slope_short_bbs_hist)

# USGS trends -------------------------------------------------------------
# download_bbs_data(sb_id = sb_items[6,2],
#                   bbs_dir = "data/")



bbs_trends_usgs <- read.csv("data/BBS_1966-2019_core_best_trend.csv")

sd_trends_long_usgs <- bbs_trends_usgs %>%
  filter(Region.Name != "Survey-Wide",
         Region.Name != "CA1",
         Region.Name != "US1",
         !grepl(pattern = "^unid",Species.Name)) %>%
  group_by(Species.Name) %>%
  summarise(sd_trends = sd(Trend),
            min_trend = min(Trend),
            max_trend = max(Trend),
            uci_trend = quantile(Trend,0.95),
            lci_trend = quantile(Trend,0.05)) %>%
  mutate(range_trend = max_trend - min_trend,
         span_90_trend = uci_trend-lci_trend) %>%
  arrange(-span_90_trend)


G_long_usgs <- max(sd_trends_long_usgs$sd_trends)

realised_long_bbs_hist <- ggplot(data = sd_trends_long_usgs,
```

```r
                                 aes(sd_trends,after_stat(density)))+
  geom_freqpoly(breaks = seq(0,G_long_usgs,0.5),center = 0)+
  xlab("SD of long-term BBS trends among regions from USGS models (1966-2019)")+
  theme_bw()+
  scale_y_continuous(limits = c(0,1))
print(realised_long_bbs_hist)



for(pp in c("gamma","norm","t")){
  for(prior_scale in c(0.5,1,2,3,4)){

    tp = paste0(pp,"_rate_",prior_scale)

    #STRATA_True <- log(2)
    output_dir <- "output/"
    out_base <- paste0(species_f,"_sim_",tp,"_BBS")
    csv_files <- paste0(out_base,"-",1:3,".csv")

    if(pp == "gamma"){
      pnorm <- 0
    }
    if(pp == "norm"){
      pnorm <- 1
    }
    if(pp == "t"){
      pnorm <- 2
    }

    if(!file.exists(paste0(output_dir,csv_files[1]))){

      load(paste0("Data/Real_data_",species_f,"_BBS.RData"))

      tmp_data = original_data_df

      nstrata = max(strata_df$Stratum_Factored)
      nyears = max(tmp_data$Year_Index)


      N_edges = neighbours$N_edges
      node1 = neighbours$node1
      node2 = neighbours$node2

      nknots_year = GAM_year$nknots_Year
      year_basis = GAM_year$Year_basis

      stan_data = list(#scalar indicators
        nstrata = nstrata,
        nyears = nyears,


        #spatial structure
        N_edges = N_edges,
```

```
  node1 = node1,
  node2 = node2,

  #GAM structure
  nknots_year = nknots_year,
  year_basis = year_basis,

  prior_scale = prior_scale,
  pnorm = pnorm
)




# Fit model ---------------------------------------------------------------

print(paste("beginning",tp,Sys.time()))

mod.file = "models/gamye_iCAR_sd_prior_sim.stan"

## compile model
model <- cmdstan_model(mod.file)


# Initial Values ----------------------------------------------------------


init_def <- function(){ list(sdbeta = runif(nknots_year,0.01,0.1),
                             beta_raw = matrix(rnorm(nknots_year*nstrata,0,0.01),nrow = nstrata,n

stanfit <- model$sample(
  data=stan_data,
  refresh=100,
  chains=2, iter_sampling=1000,
  iter_warmup=500,
  parallel_chains = 2,
  #pars = parms,
  adapt_delta = 0.8,
  max_treedepth = 14,
  seed = 123,
  init = init_def,
  output_dir = output_dir,
  output_basename = out_base)


#stanfit1 <- as_cmdstan_fit(files = paste0(output_dir,csv_files))


save(list = c("stanfit","stan_data","csv_files",
              "out_base"),
     file = paste0(output_dir,"/",out_base,"_gamye_iCAR.RData"))
```

```r
    }

  }#end prior_scale loop
}#end pp loop



# post model summary of priors --------------------------------------------

source("Functions/posterior_summary_functions.R")

nsmooth_out <- NULL
trends_out <- NULL
summ_out <- NULL

for(pp in c("gamma","norm","t")){
  for(prior_scale in c(0.5,1,2,3,4)){

    tp = paste0(pp,"_rate_",prior_scale)

    #STRATA_True <- log(2)
    output_dir <- "output/"
    out_base <- paste0(species_f,"_sim_",tp,"_BBS")


    load(paste0(output_dir,"/",out_base,"_gamye_iCAR.RData"))

    summ = stanfit$summary()

    summ <- summ %>%
      mutate(prior_scale = prior_scale,
             distribution = pp)


    nsmooth_samples <- posterior_samples(stanfit,
                                         parm = "nsmooth",
                                         dims = c("Stratum_Factored","Year_Index"))

    nsmooth <- nsmooth_samples %>%
      posterior_sums(.,
                     dims = c("Stratum_Factored","Year_Index"))%>%
      mutate(prior_scale = prior_scale,
             distribution = pp)


    nyears = max(nsmooth_samples$Year_Index)
    # function to calculate a %/year trend from a count-scale trajectory
    trs <- function(y1,y2,ny){
      tt <- (((y2/y1)^(1/ny))-1)*100
    }

    for(tl in c(11,nyears)){ #estimating all possible 1-year, 10-year, and full trends
      ny = tl-1
```

```r
      yrs1 <- seq(1,(nyears-ny),by = ny)
      yrs2 <- yrs1+ny
      for(j in 1:length(yrs1)){
        y2 <- yrs2[j]
        y1 <- yrs1[j]

        nyh2 <- paste0("Y",y2)
        nyh1 <- paste0("Y",y1)
        trends <- nsmooth_samples %>%
          filter(Year_Index %in% c(y1,y2)) %>%
          select(.draw,.value,Stratum_Factored,Year_Index) %>%
          pivot_wider(.,names_from = Year_Index,
                      values_from = .value,
                      names_prefix = "Y") %>%
          rename_with(.,~gsub(pattern = nyh2,replacement = "YE", .x)) %>%
          rename_with(.,~gsub(pattern = nyh1,replacement = "YS", .x)) %>%
          group_by(.draw,Stratum_Factored) %>%
          summarise(trend = trs(YS,YE,ny))%>%
          mutate(prior_scale = prior_scale,
                 distribution = pp,
                 first_year = y1,
                 last_year = y2,
                 nyears = ny)
        trends_out <- bind_rows(trends_out,trends)
      }
    }



    nsmooth_out <- bind_rows(nsmooth_out,nsmooth)
    summ_out <- bind_rows(summ_out,summ)
    print(paste(pp,prior_scale))

  }#prior_scale
}# pp

save(file = "output/prior_sim_summary.RData",
     list = c("nsmooth_out",
              "trends_out",
              "summ_out"))




# summarise ---------------------------------------------------------------

load("output/prior_sim_summary.RData")


trends_sd <- trends_out %>%
  group_by(.draw,prior_scale,distribution,nyears) %>%
  summarise(sd_trends = sd(trend),
            min_trend = min(trend),
            max_trend = max(trend),
```

```
            lci95 = quantile(trend,0.025),
            uci95 = quantile(trend,0.975),
            span_95 = uci95 - lci95,
            range_trend = max_trend - min_trend) %>%
  mutate(scale_factor = factor(prior_scale,levels = c(0.5,1,2,3,4),ordered = TRUE))

save(list = "trends_sd",
     file = "data/long_term_trendsd_prior_sim.RData")


trends_sd_t <- trends_sd %>%
  filter(distribution == "t",
         nyears == 53)


overp_t <- realised_long_bbs_hist +
  geom_freqpoly(data = trends_sd_t,
                aes(sd_trends,after_stat(density),
                    colour = scale_factor),
                breaks = seq(0,100,1),center = 0,
                alpha = 0.8)+
  scale_colour_viridis_d(begin = 0.5,alpha = 0.8,
                         "Prior Scale\nSD half-t df=3")+
  coord_cartesian(xlim = c(0,20))

print(overp_t)


trends_sd_norm <- trends_sd %>%
  filter(distribution == "norm",
         nyears == 53)


overp_norm <- realised_long_bbs_hist +
  geom_freqpoly(data = trends_sd_norm,
                aes(sd_trends,after_stat(density),
                    colour = scale_factor),
                breaks = seq(0,100,1),center = 0,
                alpha = 0.8)+
  scale_colour_viridis_d(begin = 0.5,alpha = 0.8,
                         "Prior Scale\nSD half-normal")+
  coord_cartesian(xlim = c(0,20))

print(overp_norm)



trends_sd_gamma <- trends_sd %>%
  filter(distribution == "gamma",
         nyears == 53)


overp_gamma <- realised_long_bbs_hist +
```

```
  geom_freqpoly(data = trends_sd_gamma,
                aes(sd_trends,after_stat(density),
                    colour = scale_factor),
                breaks = seq(0,100,1),center = 0,
                alpha = 0.8)+
  scale_colour_viridis_d(begin = 0.5,alpha = 0.8,direction = -1,
                         "Prior Scale\nSD gamma shape = 2")+
  coord_cartesian(xlim = c(0,20))

print(overp_gamma)

print(overp_t/overp_gamma/overp_norm)



trends_sd_t1 <- trends_sd_t %>%
  filter(prior_scale == 1)
trends_sd_norm1 <- trends_sd_norm %>%
  filter(prior_scale == 1)
trends_sd_gamma1 <- trends_sd_gamma %>%
  filter(prior_scale == 2)


overp_t1 <- realised_long_bbs_hist +
  geom_freqpoly(data = trends_sd_t1,
                aes(sd_trends,after_stat(density)),
                    colour = "darkgreen",
                breaks = seq(0,100,1),center = 0,
                alpha = 0.8)+
  coord_cartesian(xlim = c(0,20))

print(overp_t1)

overp_norm1 <- realised_long_bbs_hist +
  geom_freqpoly(data = trends_sd_norm1,
                aes(sd_trends,after_stat(density)),
                    colour = "darkgreen",
                breaks = seq(0,100,1),center = 0,
                alpha = 0.8)+
  coord_cartesian(xlim = c(0,20))

print(overp_norm1)

overp_gamma1 <- realised_long_bbs_hist +
  geom_freqpoly(data = trends_sd_gamma1,
                aes(sd_trends,after_stat(density)),
                colour = "darkgreen",
                breaks = seq(0,100,1),center = 0,
                alpha = 0.8)+
  coord_cartesian(xlim = c(0,20))

print(overp_gamma1)
```

```
save(list = c("overp_gamma1","overp_norm1","overp_t1"),
     file = "data/sd_GAM_spatial_saved_long-term.RData")

trends_long <- trends_sd %>%
  filter(nyears == 53)

quant_long_tends <- trends_long %>%
  group_by(distribution,prior_scale) %>%
  summarise(median_sim_sd_trends = median(sd_trends),
            sim_80th = quantile(sd_trends,0.80),
            sim_90th = quantile(sd_trends,0.90),
            sim_99th = quantile(sd_trends,0.99),
            proportion_sim_GT_max = length(which(sd_trends > G_long_usgs))/length(sd_trends))


kable(quant_long_tends, booktabs = TRUE,
      digits = 3,
      caption = "Prior simulated distribution quantiles and proportion of the distributions greater thar
      format.args = list(width = 7),
      col.names = c("Distribution",
                    "Prior Scale (normal t) or Rate (gamma)",
                    "Median Prior Predicted Distribution",
                    "80th percentile",
                    "90th percentile",
                    "99th percentile",
                    "Proportion of prior distribution > realised maximum value")) %>%
  kable_styling(font_size = 8)%>%
column_spec(column = 1:7,width = "2cm")

# Short-term comparison ---------------------------------------------------



trends_sd_t_short <- trends_sd %>%
  filter(distribution == "t",
         nyears == 10)


overp_t_short <- realised_short_bbs_hist +
  geom_freqpoly(data = sd_slope_trends_short,
                breaks = seq(0,G_short_slope_canada,0.5),center = 0,
                colour = grey(0.5))+
  geom_freqpoly(data = trends_sd_t_short,
                aes(sd_trends,after_stat(density),
                    colour = scale_factor),
                breaks = seq(0,100,1),center = 0,
                alpha = 0.8)+
  scale_colour_viridis_d(begin = 0.5,alpha = 0.8,
                         "Prior Scale\nSD half-t df=3")+
  coord_cartesian(xlim = c(0,20))

print(overp_t_short)
```

```
trends_sd_norm_short <- trends_sd %>%
  filter(distribution == "norm",
         nyears == 10)


overp_norm_short <- realised_short_bbs_hist +
  geom_freqpoly(data = trends_sd_norm_short,
                aes(sd_trends,after_stat(density),
                    colour = scale_factor),
                breaks = seq(0,100,1),center = 0,
                alpha = 0.8)+
  geom_freqpoly(data = sd_slope_trends_short,
                breaks = seq(0,G_short_slope_canada,0.5),center = 0,
                colour = grey(0.5))+
  scale_colour_viridis_d(begin = 0.5,alpha = 0.8,
                         "Prior Scale\nSD half-normal")+
  coord_cartesian(xlim = c(0,20))

print(overp_norm_short)



trends_sd_gamma_short <- trends_sd %>%
  filter(distribution == "gamma",
         nyears == 10)


overp_gamma_short <- realised_short_bbs_hist +
  geom_freqpoly(data = trends_sd_gamma_short,
                aes(sd_trends,after_stat(density),
                    colour = scale_factor),
                breaks = seq(0,100,1),center = 0,
                alpha = 0.8)+
  geom_freqpoly(data = sd_slope_trends_short,
                breaks = seq(0,G_short_slope_canada,0.5),center = 0,
                colour = grey(0.5))+
  scale_colour_viridis_d(begin = 0.5,alpha = 0.8,direction = -1,
                         "Prior Scale\nSD gamma shape = 2")+
  coord_cartesian(xlim = c(0,20))

print(overp_gamma_short)

print(overp_t_short/overp_gamma_short/overp_norm_short)

trends_short <- trends_sd %>%
  filter(nyears == 10)

quant_short_tends <- trends_short %>%
  group_by(distribution,prior_scale) %>%
  summarise(median_sim_sd_trends = median(sd_trends),
            sim_80th = quantile(sd_trends,0.80),
            sim_90th = quantile(sd_trends,0.90),
            sim_99th = quantile(sd_trends,0.99),
```

```
            proportion_sim_GT_max = length(which(sd_trends > G_short_canada))/length(sd_trends),
            proportion_sim_GT_max_slope = length(which(sd_trends > G_short_slope_canada))/length(sd_tre

kable(quant_short_tends, booktabs = TRUE,
      digits = 3,
      caption = "Prior simulated distribution quantiles for short-term trend variation and proportion o
      format.args = list(width = 7),
      col.names = c("Distribution",
                    "Prior Scale (normal t) or Rate (gamma)",
                    "Median Prior Predicted Distribution",
                    "80th percentile",
                    "90th percentile",
                    "99th percentile",
                    "Proportion of prior distribution > realised maximum value",
                    "Proportion of prior distribution > realised maximum value based on slope trends"))
  kable_styling(font_size = 8)%>%
column_spec(column = 1:8,width = "1.8cm")

trends_sd_t_short1 <- trends_sd_t_short %>%
  filter(prior_scale == 1)
overp_t_short1 <- realised_short_bbs_hist +
  geom_freqpoly(data = sd_slope_trends_short,
              breaks = seq(0,G_short_slope_canada,0.5),center = 0,
              colour = grey(0.5))+
  geom_freqpoly(data = trends_sd_t_short1,
              aes(sd_trends,after_stat(density)),
              colour = "darkgreen",
              breaks = seq(0,100,1),center = 0,
              alpha = 0.8)+
  scale_colour_viridis_d(begin = 0.5,alpha = 0.8,
                       "Prior Scale\nSD half-t df=3")+
  coord_cartesian(xlim = c(0,20))

print(overp_t_short1)
save(list = c("quant_short_tends",
              "overp_t1",
              "overp_t_short",
              "overp_gamma_short",
              "overp_norm_short",
              "overp_t_short1",
              "quant_long_tends",
              "overp_t",
              "overp_gamma",
              "overp_norm"),
     file = "data/SD_prior_sim_graphs.RData")
```

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