

APPENDIX

Table A1: Area of each biome, expressed in millions of km² and percentage, with a significant increase or decrease in each index (FWI, ERC, and IC) for each season (DJF, MAM, JJA, SON)

FIRE WEATHER INDEX (FWI)	DJF				MAM				JJA				SON			
	Area of Significant Increase (million km ²)	Area of Significant Increase (%)	Area of Significant Decrease (million km ²)	Area of Significant Decrease (%)	Area of Significant Increase (million km ²)	Area of Significant Increase (%)	Area of Significant Decrease (million km ²)	Area of Significant Decrease (%)	Area of Significant Increase (million km ²)	Area of Significant Increase (%)	Area of Significant Decrease (million km ²)	Area of Significant Decrease (%)	Area of Significant Increase (million km ²)	Area of Significant Increase (%)	Area of Significant Decrease (million km ²)	Area of Significant Decrease (%)
BIOME																
Boreal Forest/Taiga	1.15	3.93	0.75	2.56	7.72	26.28	0.17	0.57	3.16	10.75	0.3	1.02	4.48	15.26	0.01	0.05
Deserts & Xeric Shrublands	10.34	35.64	0.22	0.75	10.52	36.25	0.11	0.39	7.99	27.54	0.96	3.31	7.51	25.87	0.74	2.55
Mediterranean Forests, Woodlands & Scrubs	0.43	11.11	0.01	0.36	1.05	27.37	0	0.04	1.66	43.12	0.03	0.68	0.68	17.76	0.04	1
Temperate Broadleaf & Mixed Forests	1.67	9.94	0.04	0.23	6.69	39.76	0.17	1.02	5.72	34	0.07	0.4	6.18	36.69	0.02	0.1
Temperate Conifer Forests	0.5	9.68	0.05	0.97	1.91	36.64	0.03	0.53	2.28	43.75	0.02	0.46	1.55	29.69	0.01	0.13
Temperate Grasslands, Savannas & Shrublands	3.16	22.59	0.11	0.81	5.41	38.75	0.21	1.53	5.33	38.17	0.21	1.53	4.68	33.53	0.06	0.41
Tropical & Subtropical Coniferous Forests	0.16	21.26	0	0.1	0.24	32.44	0.02	2.2	0.14	18.66	0	0.5	0.04	5.19	0.03	3.99
Tropical & Subtropical Dry Broadleaf Forests	0.74	19.18	0.14	3.66	0.23	6.05	0.09	2.22	0.73	19.04	0.09	2.22	1.07	27.71	0.13	3.34
Tropical & Subtropical Grasslands, Savannas & Shrublands	7.79	37.18	0.3	1.45	6.38	30.46	0.12	0.58	10.95	52.25	0.1	0.48	9.2	43.9	0.78	3.71
Tropical & Subtropical Moist Broadleaf Forests	3.37	17.73	0.42	2.22	3.14	16.49	0.76	4.02	7.78	40.9	0.18	0.94	8.71	45.79	0.27	1.42
Flooded Grasslands & Savannas	0.48	39.2	0.02	1.77	0.47	37.9	0.01	0.41	0.46	37.25	0.01	0.65	0.85	68.77	0.05	4.25
Mangroves	0.03	11.54	0.01	4.33	0.03	9.38	0.01	2.64	0.03	11.06	0.01	1.68	0.05	15.14	0.02	5.53
Montane Grasslands & Shrublands	0.83	15.09	0.13	2.43	0.81	14.65	0.03	0.6	1.18	21.48	0.31	5.67	1.17	21.16	0.17	3.11
ENERGY RELEASE COMPONENT (ERC)																
BIOME																
Boreal Forest/Taiga	0	0	0	0	4.24	14.43	0.13	0.44	1.86	6.34	0.39	1.32	3.02	10.27	0.08	0.26
Deserts & Xeric Shrublands	3.4	11.7	0.24	0.84	3.13	10.79	0.05	0.19	2.22	7.66	0.14	0.48	2.25	7.77	0.2	0.69
Mediterranean Forests, Woodlands & Scrubs	0.15	3.98	0	0.08	0.39	10.18	0	0	0.57	14.86	0.02	0.57	0.32	8.39	0.01	0.21
Temperate Broadleaf & Mixed Forests	1.54	9.15	0	0	2.83	16.84	0.02	0.13	1.38	8.22	0	0	1.24	7.38	0.01	0.06
Temperate Conifer Forests	0.27	5.12	0	0	1.39	26.62	0.06	1.22	1.61	30.97	0.02	0.43	0.99	18.96	0.03	0.66
Temperate Grasslands, Savannas & Shrublands	0.82	5.88	0.02	0.16	1.79	12.81	0.28	2.04	1.72	12.3	0.02	0.16	1.2	8.58	0.06	0.44
Tropical & Subtropical Coniferous Forests	0.13	18.36	0	0	0.21	28.24	0.01	0.9	0.05	6.99	0	0.2	0.02	3.29	0.02	3.09
Tropical & Subtropical Dry Broadleaf Forests	0.1	2.67	0.04	1	0.05	1.29	0.01	0.27	0.02	0.63	0	0.04	0.15	3.79	0.05	1.21
Tropical & Subtropical Grasslands, Savannas & Shrublands	0.81	3.88	0.13	0.63	1.08	5.18	0.03	0.13	1.29	6.15	0.05	0.22	2.23	10.64	0.21	1.01
Tropical & Subtropical Moist Broadleaf Forests	0.91	4.79	0.19	0.98	0.63	3.32	0.12	0.62	2.1	11.05	0	0	1.33	6.99	0.02	0.08
Flooded Grasslands & Savannas	0.16	12.75	0	0.18	0.28	22.73	0	0	0.08	6.14	0	0	0.39	31.94	0.02	1.36
Mangroves	0	1.44	0	0.24	0	1.2	0	0.24	0.01	3.12	0	0	0	0.72	0	0
Montane Grasslands & Shrublands	0.45	8.09	0	0.04	0.23	4.1	0	0.03	0.29	5.18	0.01	0.2	0.43	7.71	0.02	0.37
IGNITION COMPONENT (IC)																
BIOME																
Boreal Forest/Taiga	0	0	0	0	2.25	7.67	0.06	0.21	1.46	4.95	0.06	0.22	1.01	3.45	0.01	0.02
Deserts & Xeric Shrublands	5.39	18.58	0.37	1.27	8.04	27.72	0.11	0.36	6.06	20.88	1.26	4.34	5.18	17.85	0.63	2.19
Mediterranean Forests, Woodlands & Scrubs	0.21	5.41	0.07	1.78	0.57	14.71	0.01	0.38	0.91	23.51	0.01	0.34	0.52	13.55	0	0.02
Temperate Broadleaf & Mixed Forests	1.17	6.95	0	0	2.42	14.36	0.01	0.06	1.44	8.53	0	0.01	0.76	4.5	0.01	0.08
Temperate Conifer Forests	0.19	3.55	0	0	1.14	21.81	0.03	0.55	1.54	29.63	0.02	0.46	0.87	16.62	0.01	0.13
Temperate Grasslands, Savannas & Shrublands	1.29	9.25	0.01	0.07	2.68	19.17	0.41	2.95	3.52	25.2	0.12	0.83	2.06	14.78	0.11	0.79
Tropical & Subtropical Coniferous Forests	0.18	24.45	0	0.1	0.23	31.04	0.01	1.2	0.08	10.58	0	0	0.03	4.29	0.02	2.5
Tropical & Subtropical Dry Broadleaf Forests	0.16	4.15	0.15	4	0.08	2.03	0.19	4.93	0.22	5.78	0.02	0.57	0.43	11.14	0.15	3.85
Tropical & Subtropical Grasslands, Savannas & Shrublands	2.38	11.33	0.29	1.37	2.91	13.87	0.04	0.2	3.92	18.71	0.03	0.15	4.96	23.67	0.99	4.73
Tropical & Subtropical Moist Broadleaf Forests	0.39	2.05	0.15	0.79	0.28	1.45	0.44	2.3	0.9	4.71	0.01	0.05	0.58	3.07	0.02	0.09
Flooded Grasslands & Savannas	0.19	15.29	0.01	0.53	0.25	20.54	0	0.06	0.19	15.29	0	0.06	0.47	37.9	0.06	4.66
Mangroves	0	1.2	0.01	1.92	0	0.96	0	0.48	0	0.72	0	0	0	0.72	0	0.24
Montane Grasslands & Shrublands	0.57	10.41	0	0.01	0.43	7.88	0	0.08	0.56	10.14	0.03	0.49	0.6	10.91	0.03	0.49

Table A2: Significant rate of increase in FWI, ERC, and IC, for each biome and season (DJF, MAM, JJA, SON), as well as the seasonal significant rate of increase for each index averaged across all biomes

BIOMES	FWI (FIRE DANGER POTENTIAL)				ERC (INTENSITY POTENTIAL)				IC (IGNITION POTENTIAL)			
	ROI DJF	ROI MAM	ROI JJA	ROI SON	ROI DJF	ROI MAM	ROI JJA	ROI SON	ROI DJF	ROI MAM	ROI JJA	ROI SON
Boreal Forest/Taiga	1.07	1.52	1.58	1.66	0.00	2.25	1.15	2.14	0.00	2.37	1.05	2.41
Deserts & Xeric Shrublands	0.77	0.61	0.64	0.65	1.78	0.74	0.65	0.81	1.27	0.72	0.75	0.84
Mediterranean Forests, Woodlands & Scrubs	1.07	1.19	0.90	1.05	1.35	1.00	0.63	0.74	0.84	1.00	0.86	0.99
Temperate Broadleaf & Mixed Forests	1.70	1.41	1.63	1.71	2.86	1.36	1.27	1.45	3.02	1.60	1.37	1.61
Temperate Conifer Forests	1.63	1.73	1.59	1.73	2.53	2.39	1.15	1.76	2.33	2.32	1.10	1.68
Temperate Grasslands, Savannas & Shrublands	1.80	1.48	1.57	1.67	2.67	1.44	1.17	1.60	2.02	1.69	1.32	1.66
Tropical & Subtropical Coniferous Forests	1.18	1.02	1.56	1.20	0.95	0.86	1.28	0.86	1.23	1.08	1.29	1.15
Tropical & Subtropical Dry Broadleaf Forests	1.43	1.02	1.17	1.35	0.78	0.58	0.80	0.76	1.37	1.27	1.40	1.25
Tropical & Subtropical Grasslands, Savannas & Shrublands	1.10	0.98	1.22	1.41	0.88	0.78	0.93	1.00	0.92	0.61	1.11	1.23
Tropical & Subtropical Moist Broadleaf Forests	1.79	1.78	2.16	2.19	1.38	1.87	1.75	1.87	1.46	1.19	2.63	1.64
Flooded Grasslands & Savannas	1.27	1.19	1.72	1.80	0.70	1.05	0.94	1.64	0.79	1.07	1.67	1.58
Mangroves	1.18	1.12	1.47	1.36	0.62	0.63	1.52	0.80	1.33	0.61	1.01	0.97
Montane Grasslands & Shrublands	1.69	1.33	1.39	1.79	1.91	1.08	0.84	1.29	2.08	1.21	0.89	1.58
Significant Rate of Increase Averaged over all biomes (%/yr)	1.36	1.26	1.43	1.51	1.42	1.23	1.08	1.29	1.43	1.29	1.27	1.43

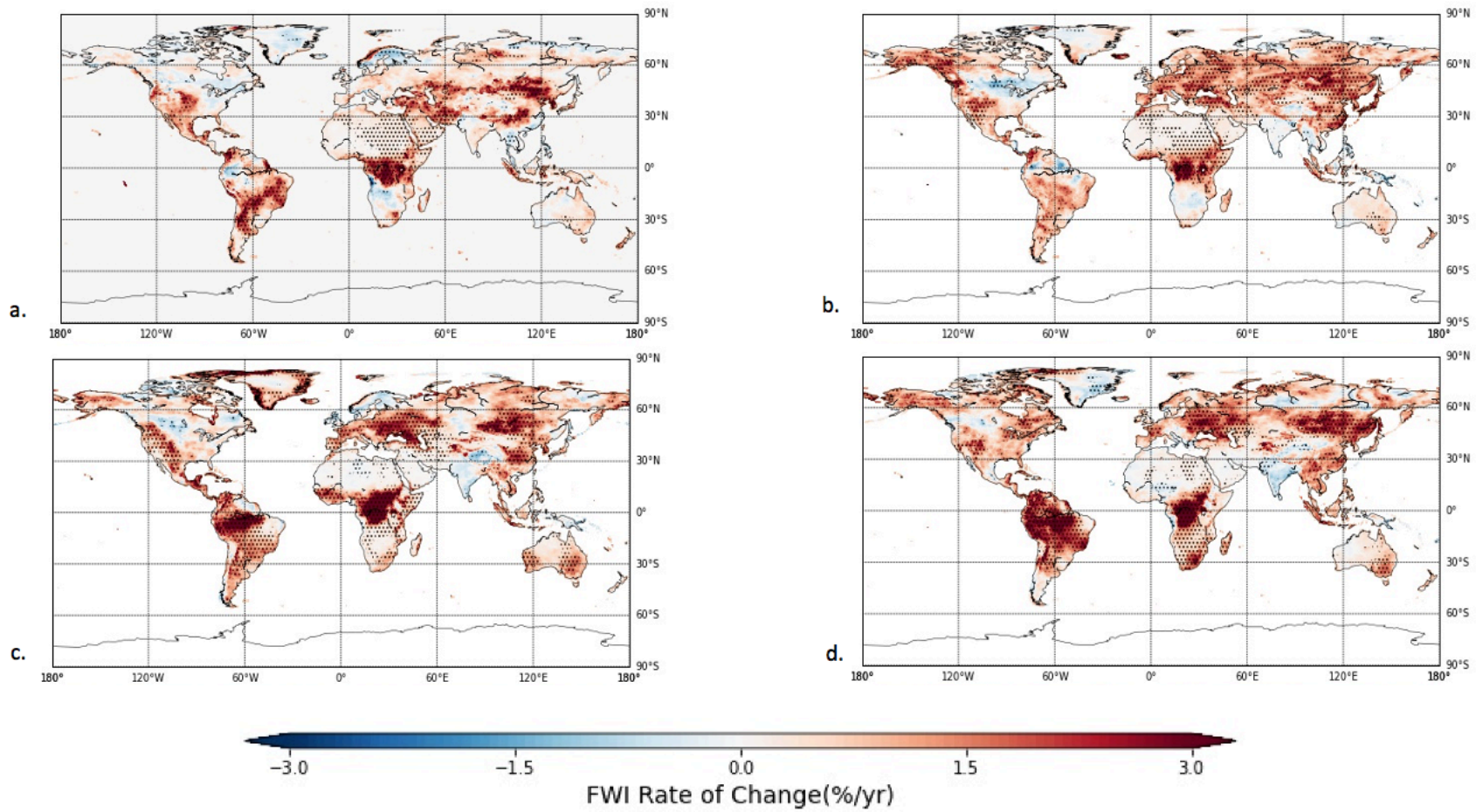


Figure A1: Rate of increase (red) and decrease (blue) in fire danger potential (FWI) (%/yr) for (a) DJF, (b) MAM, (c) JJA, (d) SON, with black dots representing areas with significant changes at the 95% confidence level

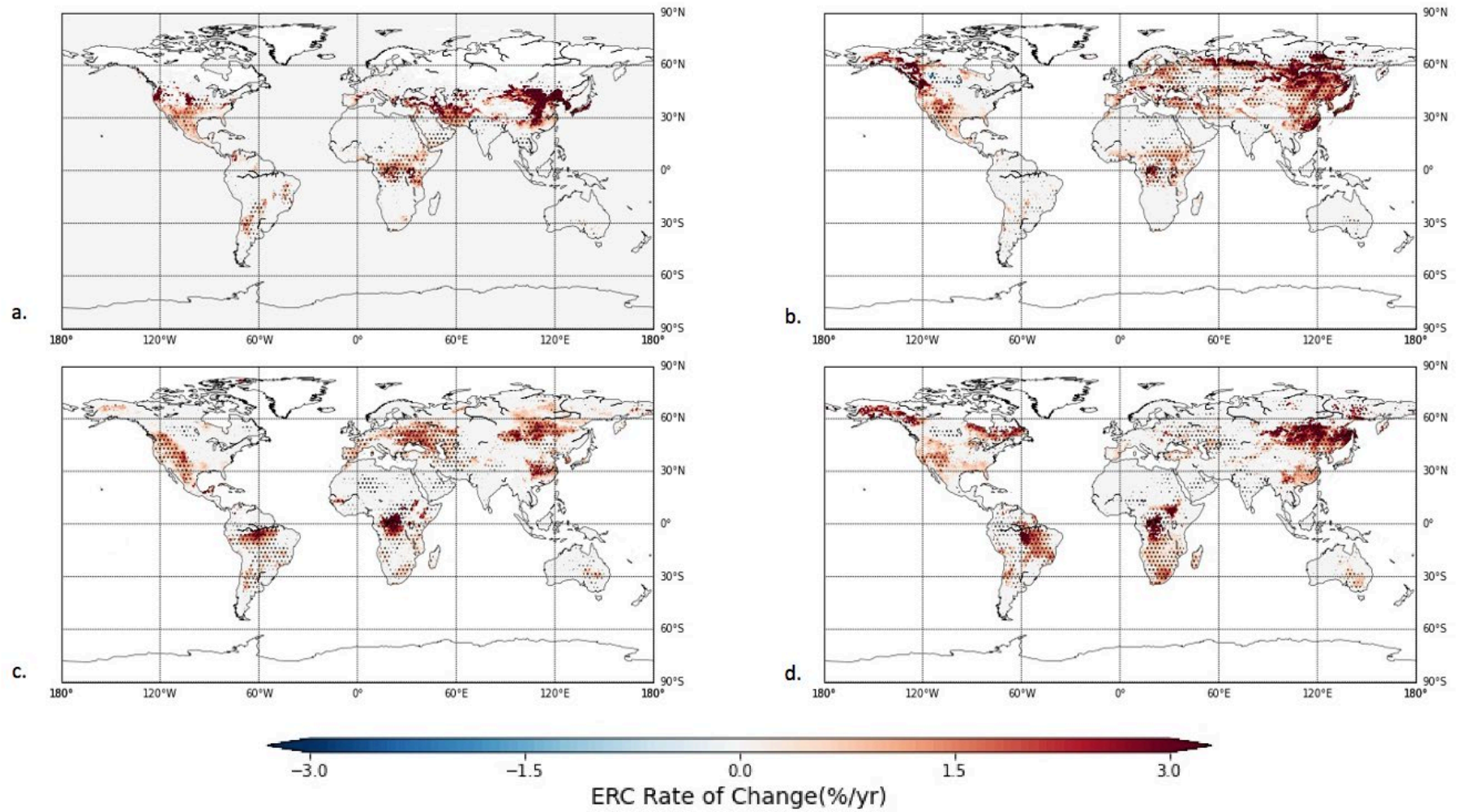


Figure A2: Rate of increase (red) and decrease (blue) in the fire intensity potential (ERC) (%/yr) for (a) DJF, (b) MAM, (c) JJA, (d) SON, with black dots representing areas with significant changes at the 95% confidence level

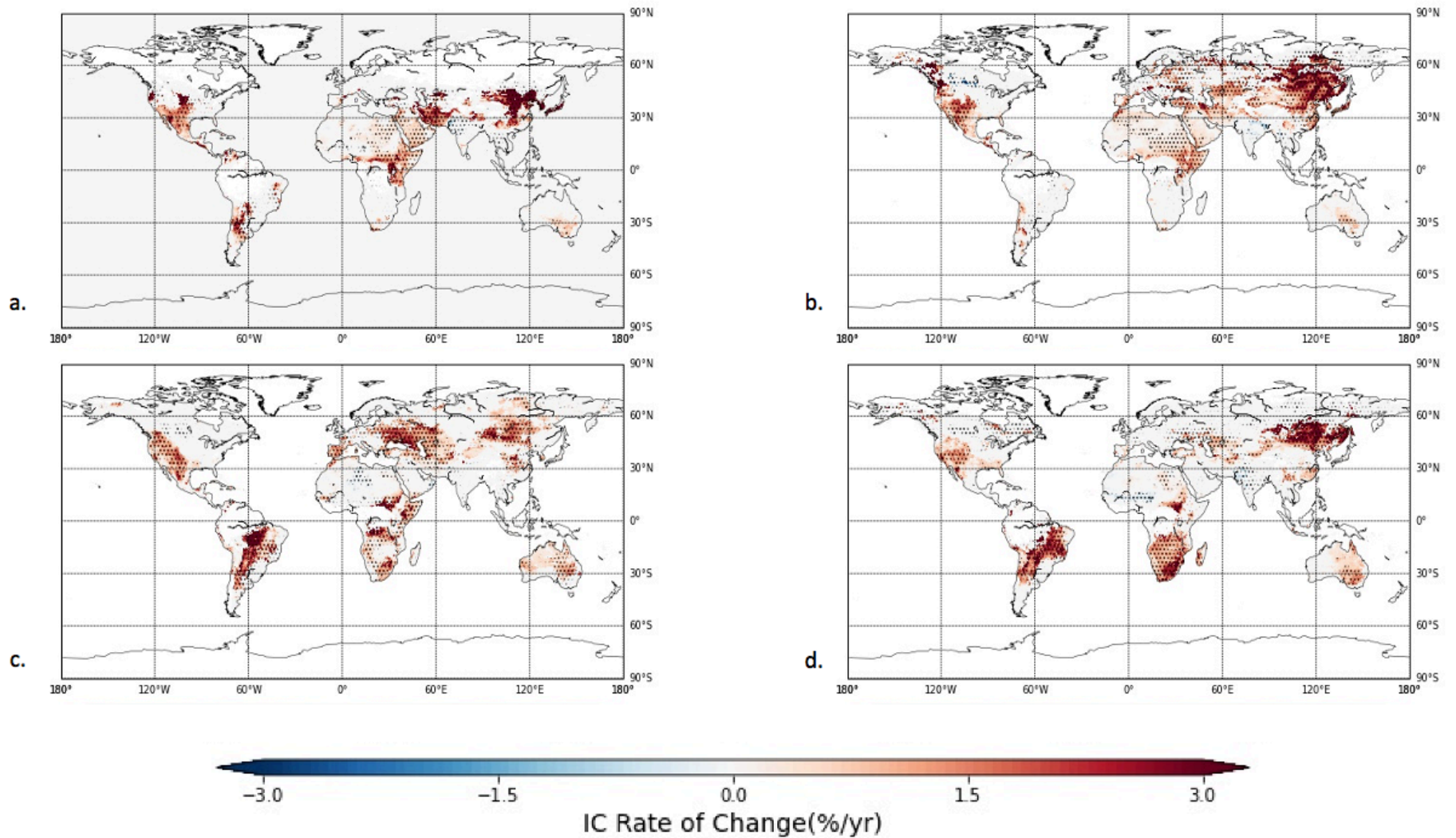


Figure A3: Rate of increase (red) and decrease (blue) in the ignition potential (IC) (%/yr) for (a) DJF, (b) MAM, (c) JJA, (d) SON, with black dots representing areas with significant changes at the 95% confidence level

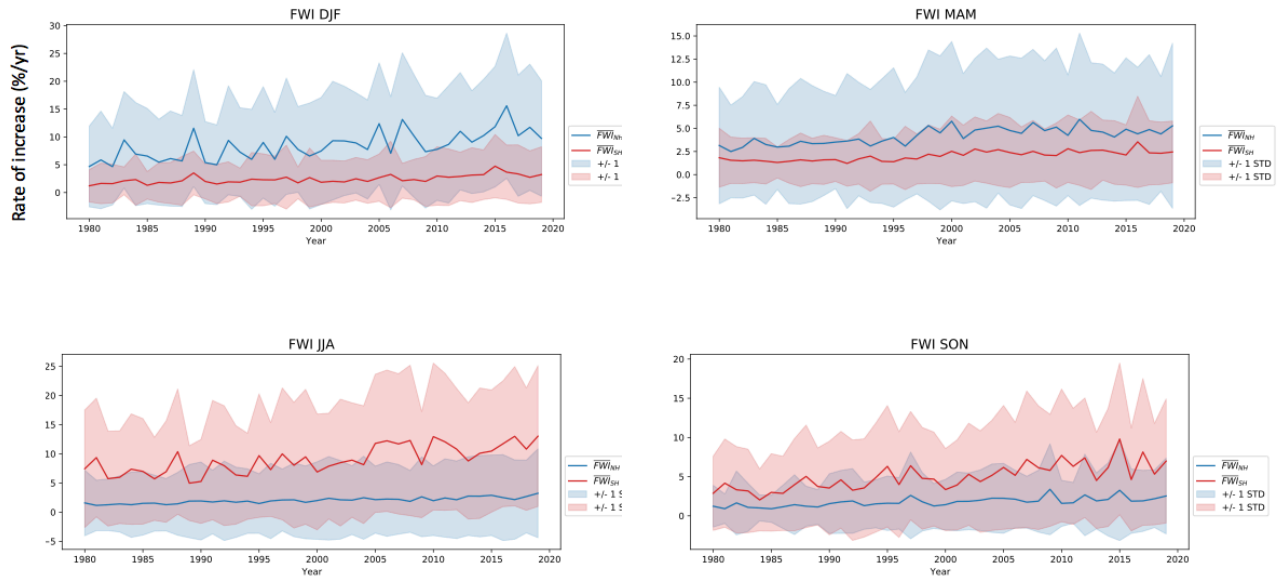


Figure A4: The 1980-2019 timeseries of the average rate of increase in fire danger potential (FWI) for all pixels within the Tropical and Subtropical Moist Broadleaf Biome within the Northern Hemisphere (blue) and the Southern Hemispheres (red) that show a significant increase at the 95% confidence level, where the blue shade and red shade represent the standard deviation in the Northern Hemisphere and Southern Hemisphere, respectively (each season labeled in the title)

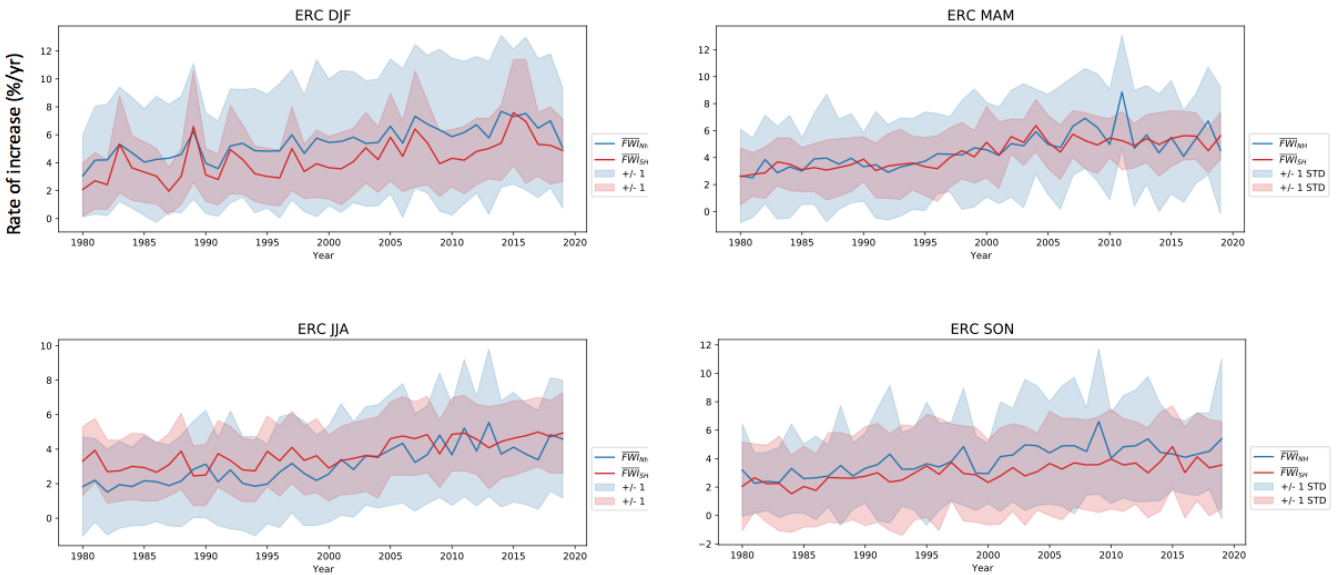


Figure A5: The 1980-2019 timeseries of the average rate of increase in fire intensity potential (ERC) for all pixels within the Tropical and Subtropical Moist Broadleaf Biome within the Northern Hemisphere (blue) and the Southern Hemispheres (red) that show a significant increase at the 95% confidence level, where the blue shade and red shade represent the standard deviation in the Northern Hemisphere and Southern Hemisphere, respectively (each season labeled in the title)

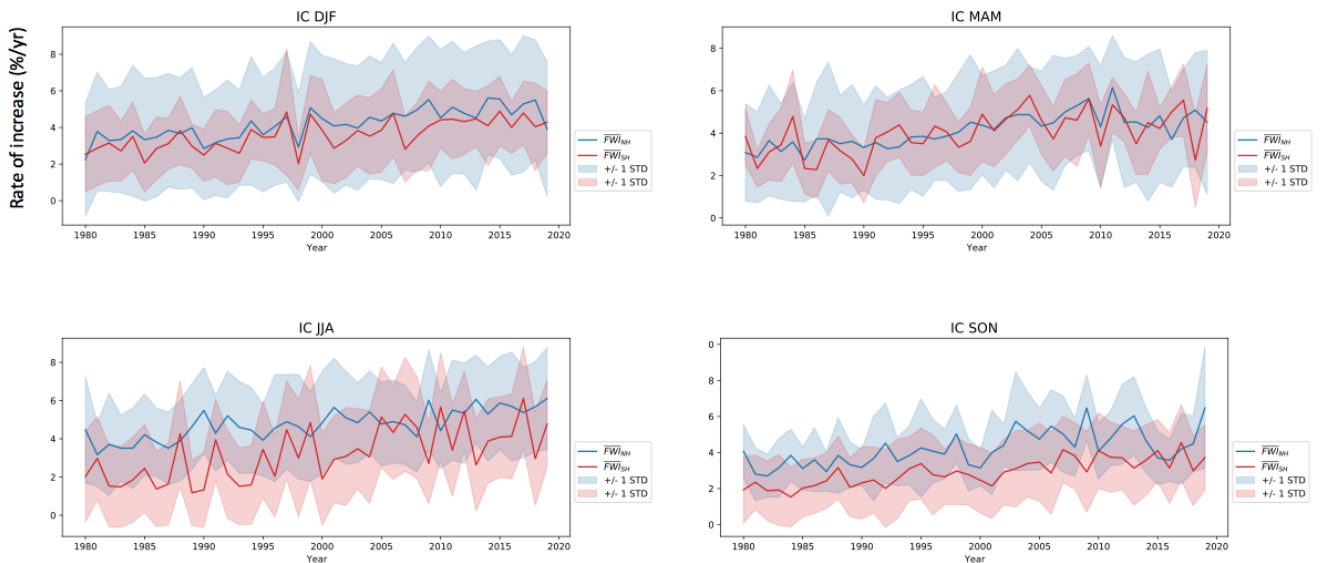


Figure A6: The 1980-2019 timeseries of the average rate of increase in ignition potential (IC) for all pixels within the Tropical and Subtropical Moist Broadleaf Biome within the Northern Hemisphere (blue) and the Southern Hemispheres (red) that show a significant increase at the 95% confidence level, where the blue shade and red shade represent the standard deviation in the Northern Hemisphere and Southern Hemisphere, respectively (each season labeled in the title)

Example Code

```
In [3572]: import numpy as np
import pandas as pd
import glob, os
import matplotlib.pyplot as plt
from numpy.polynomial.polynomial import polyfit
from netCDF4 import Dataset, num2date
from mpl_toolkits.basemap import Basemap, addcyclic, shiftgrid
from scipy import stats
import pymannkendall as mk
import warnings
warnings.filterwarnings("ignore", category=FutureWarning)
import geopandas as gpd
import cartopy.io.shapereader as shpreader
import regionmask
```

```
In [3573]: # This function plots the global map of data on Robin projection
def Map_Plots2(lats,lons,proj,data,alpha,ax,cmap,levels,num_lev,title=None,cbar=False,unit=None):
    m = Basemap(projection=proj,lon_0=0,resolution='c', ax=ax)
    data,lons = shiftgrid(180.,data,lons,start=False)
    lon2d, lat2d = np.meshgrid(lons, lats)
    x, y = m(lon2d, lat2d)

    cs = m.contourf(x, y, data, alpha=alpha, cmap=cmap, extend='both', levels=levels)

    if title is not None:
        ax.set_title(title,fontsize=16)

    m.drawcoastlines(linewidth=0.5)
    m.drawmapboundary()
    parallels = np.arange(-90.,91,30.)
    # labels = [left,right,top,bottom]
    m.drawparallels(parallels,labels=[False,True,True,False])
    meridians = np.arange(0.,361.,60.)
    m.drawmeridians(meridians,labels=[True,False,False,True])

    if cbar:
        cbar = m.colorbar(cs,size='1.5%',pad=0.15,extend='both',location='right')
        cbar.set_label(unit)
        cbar.set_ticks(np.linspace(levels[0],levels[-1],num_lev))
    return cs
```

```
In [3574]: # This function plots the global map of data on Robin projection
def Map_Plots(lats,lons,data,alpha,ax,cmap,levels,num_lev,title=None,cbar=False,unit=None):
    m = Basemap(projection='cea',lon_0=0,resolution='c', ax=ax)
    data,lons = shiftgrid(180.,data,lons,start=False)
    lon2d, lat2d = np.meshgrid(lons, lats)
    x, y = m(lon2d, lat2d)

    cs = m.contourf(x, y, data, alpha=alpha, cmap=cmap, extend='both', levels=levels)

    if title is not None:
        ax.set_title(title,fontsize=16)

    m.drawcoastlines(linewidth=0.5)
    m.drawmapboundary()
    parallels = np.arange(-90.,91,30.)
    # labels = [left,right,top,bottom]
    m.drawparallels(parallels,labels=[False,True,True,False])
    meridians = np.arange(0.,361.,60.)
    m.drawmeridians(meridians,labels=[True,False,False,True])

    if cbar:
        cbar = m.colorbar(cs,size='1.5%',pad=0.15,extend='both',location='right')
        cbar.set_label(unit)
        cbar.set_ticks(np.linspace(levels[0],levels[-1],num_lev))
    return cs
```



```
In [3575]: # This function loads data from NetCDF into python
```

```
def ReadNetCDFfile(ncfile, var):  
    # Load NetCDF data and get datetime  
    nc_fid = Dataset(ncfile, 'r')  
    data = nc_fid.variables[var][:]  
    time = nc_fid.variables['time']  
    lats = nc_fid.variables['latitude'][:]  
    lons = nc_fid.variables['longitude'][:]  
    units = time.units  
    #calendar = time.calendar  
  
    time_convert = num2date(time[:], units)  
    nptimes = time_convert.astype('datetime64[ns]')  
    datetime = pd.to_datetime(nptimes)  
    month = np.array(datetime.month)  
    year = np.array(datetime.year)  
  
    return lats, lons, data, month, year
```

```
In [3576]: def MannKendallTest(data):
```

```
T,M,N = data.shape  
data_mean = np.squeeze( np.mean(data, axis=0) ) # Get the mean in 2D for masking purpose  
  
# Initialize 2D array for slope and pvalue  
slope_map = np.nan * np.zeros((M,N))  
pval_map = np.nan * np.zeros((M,N))  
  
x = np.linspace(1,T,T)  
for j in range(M):  
    for i in range(N):  
        # We only run Mann-Kendall test at pixel that are lands. Ocean cells are masked, ignore them  
        if not np.ma.is_masked(data_mean[j,i]):  
            y = data[:,j,i]  
            trend, h, p, z, Tau, s, var_s, slope, intercept = mk.original_test(y, alpha=0.1)  
            slope_map[j,i] = stats.theilslopes(y, x, 0.9)[0] # Slope at each pixel  
            pval_map[j,i] = p # p-value of MK test at each pixel  
    return slope_map, pval_map
```

```
In [3769]: # Loading data
ncfile = 'KBDI_TIMESERIES_1980_2019_JJA.nc'
lats,lons,data,months,years = ReadNetCDFfile(ncfile,'kmdi')
```

```
In [3578]: # MK and Sen slop tests
slope_map,pval_map = MannKendallTest(data)
```

```
In [3579]: # fig,ax = plt.subplots(1,2,figsize=(14,6),sharex=True,sharey=True) # 2 subplots 1x2 grid

## First plot - slope_map
# cb0 = ax[0].pcolor(slope_map, cmap=plt.cm.jet,vmax=0.1,vmin=0)
# ax[0].set_xlabel('Longitude')
# ax[0].set_ylabel('Latitude')
# ax[0].set_title('Bi')
# fig.colorbar(cb0, ax=ax[0])

## Second plot - pval_map
# cb0 = ax[1].pcolor(pval_map, cmap=plt.cm.jet,vmax=1,vmin=0)
# ax[1].set_xlabel('Longitude')
# ax[1].set_ylabel('Latitude')
# ax[1].set_title('p-value')
# fig.colorbar(cb0, ax=ax[1])

# plt.tight_layout()
# plt.show()

## plt.savefig()
```

- Large p-value in MK test mean the trend is not significant or no trend
- Cells at large p-values thus show zero slope
- You can choose p-value threshold 0.1 for 90% CI or 0.05 for 95% CI

```
In [3770]: slope_filename= 'slope_kbdi_jja_1980_2019'
sig_filename= 'sig_kbdi_jja_1980_2019'

#np.save(slope_filename,slope_map) #####comment this out - but add back if changing initial .nc file
#np.save(sig_filename,pval_map)
```

```
In [3771]: slope=np.load(slope_filename+'.npy')
sig=np.load(sig_filename+'.npy')
```

```
In [3772]: # fig,ax = plt.subplots(1,2,figsize=(14,6),sharex=True,sharey=True)
# ax[0].imshow(slope_BI_8)
# # ax[1].imshow(sig_BI_8)
```

```
In [3773]: fig,ax = plt.subplots(1,2,figsize=(20,10),sharex=True,sharey=True)
Map_Plots(lats,lons,slope,1,ax[0],plt.cm.RdYlGn_r,np.linspace(-0.2,0.2,11),11,title='Trend in 1980-2019 September Fine
Map_Plots(lats,lons,sig,1,ax[1],plt.cm.hot,np.linspace(0,0.1,11),11,title='Significance in 1980-2019 September Fine Fue
```

```
In [3584]: # Mask the land cells
fp = 'Biomes2017_Diss15.shp'
shp_cont = gpd.read_file(fp)
shape_cont = list(shpreader.Reader(fp).geometries())
mask_cont = regionmask.mask_geopandas(shp_cont,lons,lats,wrap_lon=True)
mask_regions = mask_cont.copy().data
```

```
In [3774]: data_mean=np.mean(data,axis=0)
norm_slope = slope/data_mean*100
```

```
In [3955]: biomes_ind = 3
sub_norm_slope = norm_slope.copy()
sub_data_mean = data_mean.copy()
sub_sig = sig.copy()
sub_norm_slope[mask_regions!=biomes_ind] = np.nan # #ind_change index
sub_data_mean[mask_regions!=biomes_ind] = np.nan # #ind_change index
sub_sig[mask_regions!=biomes_ind] = np.nan # #ind_change index
```

```
In [3956]: #pair of row and columns that is significant
Index_sig=np.where(sub_sig<=0.05)
Index_sig_positive=np.where((sub_sig<=0.05) & (sub_norm_slope>0))
Index_sig_negative=np.where((sub_sig<=0.05) & (sub_norm_slope<0))
```

```
In [3957]: num_cells_biomes = np.where(mask_regions!=biomes_ind)[0].shape[0]
```

```
In [3958]: num_cells_biomes ##I ADDED THIS TO SEE THE NUMBER OF CELLS IN THE BIOME
```

```
Out[3958]: 1037824
```

```
In [3959]: #Number of cells that are significant *both positive and negative* over the domain that are land
Index_sig[0].size
```

```
Out[3959]: 50
```

```
In [3960]: num_sig_pos = Index_sig_positive[0].size
num_sig_neg = Index_sig_negative[0].size
```

```
In [3963]: Index_sig_positive[0].size
```

```
Out[3963]: 31
```

```
In [3964]: Index_sig_negative[0].size
```

```
Out[3964]: 19
```

```
In [3965]: np.mean(sub_norm_slope[Index_sig_positive])
```

```
Out[3965]: 0.9498492953667149
```

```
In [3966]: np.mean(sub_norm_slope[Index_sig_negative])
```

```
Out[3966]: -0.9872331486904571
```

```
In [3967]: Index_sig_positive[0].size/num_cells_biomes*100
```

```
Out[3967]: 0.002987018993586581
```

```
In [3968]: Index_sig_negative[0].size/num_cells_biomes*100
```

```
Out[3968]: 0.001830753576714356
```