# RF model

November 28, 2024

```
[38]: import os
      os.environ['HDF5_DISABLE_VERSION_CHECK'] = "1"
      import datetime as dt
      import numpy as np
      import pandas as pd
      import matplotlib.pyplot as plt
      import netCDF4 as nc
      import xarray as xr
      from sklearn import metrics
      from sklearn.model_selection import GridSearchCV
      from sklearn.ensemble import RandomForestRegressor
      from eofs.xarray import Eof
      from esem import rf_model
      from glob import glob
      from matplotlib import colors
      import matplotlib.pyplot as plt
      import cartopy.crs as ccrs
      from utils_rf import *
```

```
[39]: # path to save the net-cdf file path_output ='outputs_ssp245_prediction_ESEm.nc'
```

#### 0.0.1 Initial EDA to look at variables

```
[40]: inputs = ["./train_val/inputs_ssp126.nc", "./train_val/inputs_ssp370.nc","./

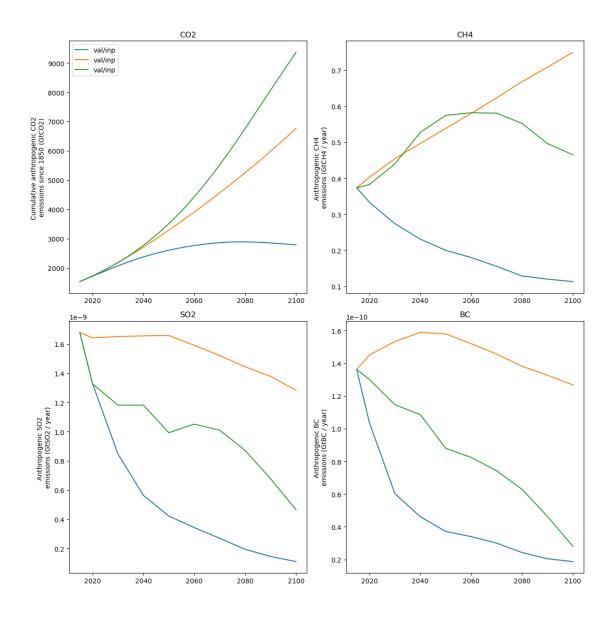
strain_val/inputs_ssp585.nc"]

SECONDS_IN_YEAR = 60*60*24*365

fig, axes = plt.subplots(2, 2, figsize=(12,12))
```

```
for input in inputs:
   label=input.split('_')[1][:-3]
   X = xr.open_dataset(input)
   x = range(2015, 2101)
   weights = np.cos(np.deg2rad(X.latitude))
   axes[0, 0].plot(x, X['CO2'].data, label=label)
   axes[0, 0].set_ylabel("Cumulative anthropogenic CO2 \nemissions since 1850_
 ⇔(GtCO2)")
   axes[0, 1].plot(x, X['CH4'].data, label=label)
   axes[0, 1].set_ylabel("Anthropogenic CH4 \nemissions (GtCH4 / year)")
    # FIXME: Not sure where this factor of 1000 comes from...! Maybe the CEDS__
 \rightarrow data is really g/m-2/s?
   axes[1, 0].plot(x, X['SO2'].weighted(weights).sum(['latitude',_
 axes[1, 0].set_ylabel("Anthropogenic SO2 \nemissions (GtSO2 / year)")
   axes[1, 1].plot(x, X['BC'].weighted(weights).sum(['latitude', 'longitude']).

data*SECONDS_IN_YEAR*1e-9, label=label)
   axes[1, 1].set_ylabel("Anthropogenic BC \nemissions (GtBC / year)")
axes[0, 0].set title('CO2')
axes[0, 1].set_title('CH4')
axes[1, 0].set_title('S02')
axes[1, 1].set_title('BC')
axes[0, 0].legend()
plt.tight_layout()
test_data_path= "./test"+'inputs_ssp245.nc'
```



#### 0.0.2 Random Forest Regressor Model Building

```
[41]: train_files = [ "historical", "ssp585", "ssp126", "ssp370", ]
    # Create training and testing arrays
    X, solvers = create_predictor_data(train_files)
    Y = create_predictdand_data(train_files)

[42]: #parameters dictionary
    param_dict_tas = {
        'n_estimators': 250,
        'min_samples_split': 5,
        'min_samples_leaf': 7,
```

```
'max_depth': 5
      }
      param_dict_pr = {
          'n_estimators': 150,
          'min_samples_split': 15,
          'min_samples_leaf': 8,
          'max_depth': 40
      }
      param_dict_pr90 = {
          'n_estimators': 250,
          'min_samples_split': 15,
          'min_samples_leaf': 12,
          'max_depth': 25
      }
      param_dict_dtr = {
          'n_estimators': 300,
          'min_samples_split': 10,
          'min_samples_leaf': 12,
          'max_depth': 20
      }
[43]: rf_tas = rf_model(X, Y['tas'], random_state=0, bootstrap=True,__

max_features='sqrt', **param_dict_tas)

      rf_pr = rf_model(X, Y['pr'], random_state=0, bootstrap=True,_
       →max_features='sqrt', **param_dict_pr)
      rf_pr90 = rf_model(X, Y['pr90'], random_state=0, bootstrap=True,__
       →max_features='sqrt',**param_dict_pr90)
      rf_dtr = rf_model(X, Y["diurnal_temperature_range"], random_state=0,__
       ⇔bootstrap=True, max_features='sqrt',**param_dict_dtr)
      rf_tas.train()
      rf_pr.train()
      rf_pr90.train()
      rf_dtr.train()
[44]: ## Test on SSP245 pathway
      X_test = get_test_data('ssp245', solvers)
      Y_test = create_predictdand_data_test(['ssp245'])
      tas_truth = Y_test["tas"]
      pr_truth = Y_test["pr"]
      pr90_truth = Y_test["pr90"]
      dtr_truth = Y_test["diurnal_temperature_range"]
```

```
[45]: m_out_tas, _ = rf_tas.predict(X_test)
m_out_pr, _ = rf_pr.predict(X_test)
m_out_pr90, _ = rf_pr90.predict(X_test)
m_out_dtr, _ = rf_dtr.predict(X_test)
```

```
[46]: xr_output = xr.Dataset(dict(tas=m_out_tas, pr=m_out_pr, pr90=m_out_pr90,__
diurnal_temperature_range=m_out_dtr)).assign_coords(time=m_out_tas.sample +__
32014)

#save output to net-cdf file
xr_output.to_netcdf(path_output,'w')
```

#### 0.0.3 Testing out predictions with test set

```
[47]: print(f"RMSE: {get_rmse(tas_truth[35:], m_out_tas[35:]).mean()}")
    print(f"RMSE: {get_rmse(dtr_truth[35:], m_out_dtr[35:]).mean()}")
    print(f"RMSE: {get_rmse(pr_truth[35:], m_out_pr[35:]).mean()}")
    print(f"RMSE: {get_rmse(pr_truth[35:], m_out_pr[35:]).mean()}")
    print(f"RMSE: {get_rmse(pr90_truth[35:], m_out_pr90[35:]).mean()}")
```

RMSE: 0.6823172244093356

RMSE: 0.16537489851670092

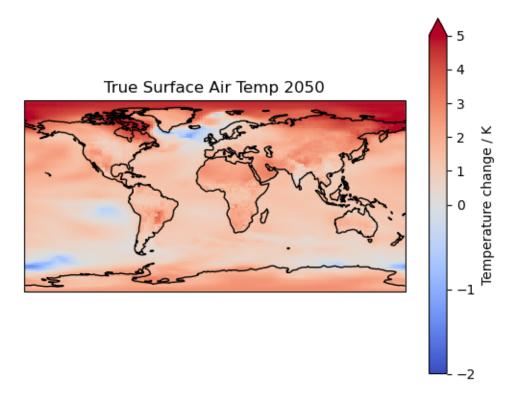
RMSE: 0.5578336782743653

RMSE: 1.5880423328622344

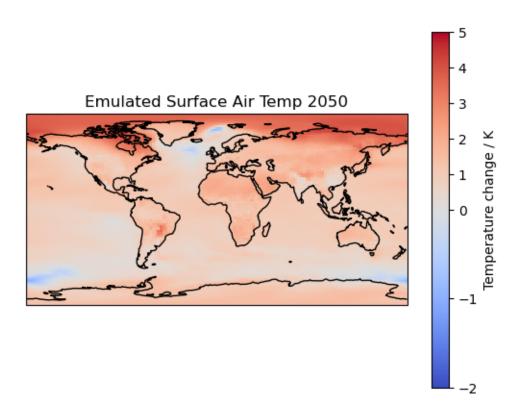
# 0.0.4 Comparing emulated results of RF model to True Results Graphically (Year 2050)

#### True vs Emulated Surface Air Temperature

[48]: <cartopy.mpl.feature\_artist.FeatureArtist at 0x15396cf6d420>

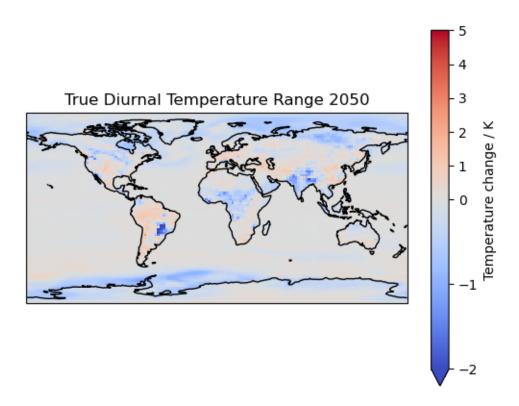


[49]: <cartopy.mpl.feature\_artist.FeatureArtist at 0x15396484faf0>

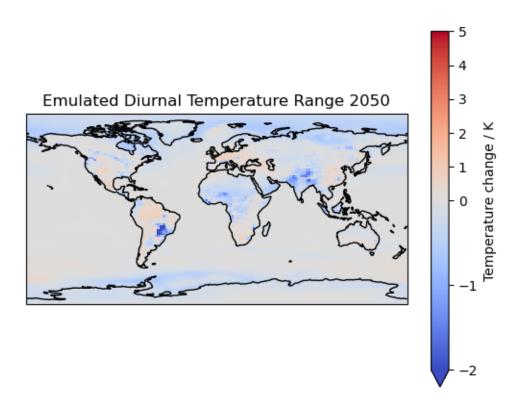


## True vs Emulated Diurnal Temperature Range

[50]: <cartopy.mpl.feature\_artist.FeatureArtist at 0x15396467b0a0>

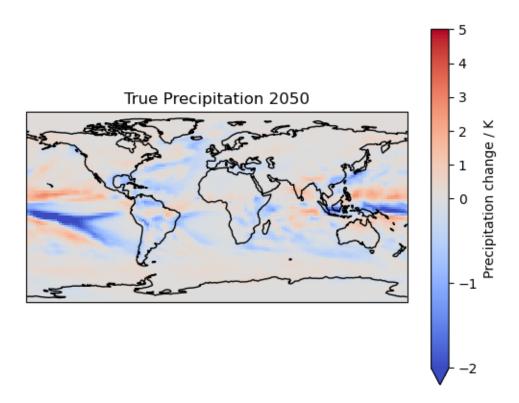


[51]: <cartopy.mpl.feature\_artist.FeatureArtist at 0x153964727970>

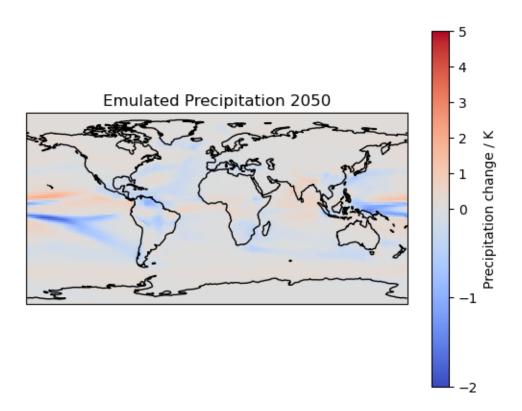


### True vs Emulated Percipitation

[52]: <cartopy.mpl.feature\_artist.FeatureArtist at 0x1539645de4d0>

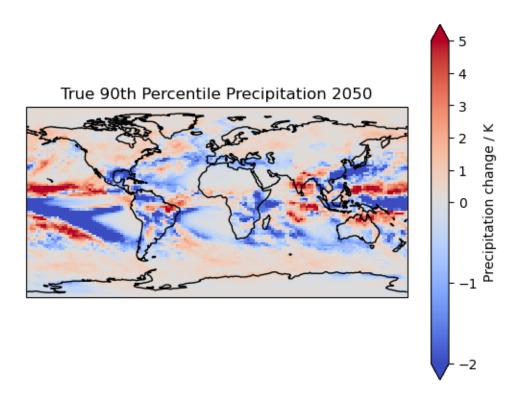


[53]: <cartopy.mpl.feature\_artist.FeatureArtist at 0x15396460bcd0>

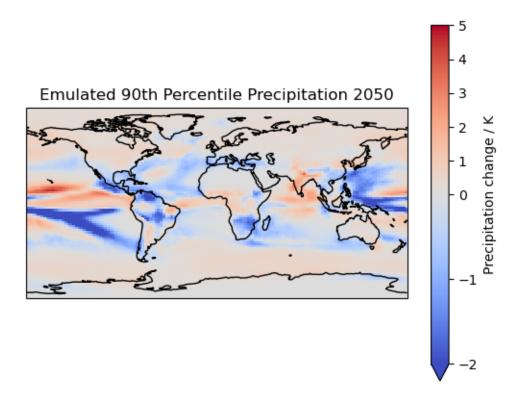


#### True vs Emulated 90th Percentile Percipitation

[54]: <cartopy.mpl.feature\_artist.FeatureArtist at 0x153964366fb0>



[55]: <cartopy.mpl.feature\_artist.FeatureArtist at 0x153964422f20>



### 0.0.5 Running models Again After Grid Search

```
# Loop over each target variable
# Uncomment out everything under this to run grid search
# Commented for now to reduce # of pages in pdf output of file
# for target in targets:
     print(f"Running GridSearchCV for {target}...")
      # Get training data
      Y_train = Y[target].mean(dim=["lat", "lon"]).values
#
      X train = X
      # GridSearchCV
#
#
      grid_search = GridSearchCV(
#
          estimator=base model,
#
          param_grid=param_grid,
#
          cv=3.
          scoring='neg_root_mean_squared_error',
#
#
          verbose=2,
          n_{jobs}=-1
#
      )
      # Fit the model
      grid_search.fit(X_train, Y_train)
#
      # results
      best_params[target] = grid_search.best_params_
#
      best_scores[target] = -qrid_search.best_score_
      print(f"Best parameters for {target}: {qrid search.best params }")
      print(f"Best score for {target} (neg MSE): {qrid_search.best_score }")
# results_df = pd.DataFrame({
      'Variable': targets,
      'Best Parameters': [best_params[target] for target in targets],
      'Best Negative MSE': [best_scores[target] for target in targets]
# })
# print("\nGrid Search Summary:")
# print(results df)
```

[82]: '\nUncomment out everything under this to run grid search \nCommented for now to reduce # of pages in pdf output of file \n'

```
[67]: # new parameter values based on grid search
      param_dict_tas_opt = {
          'n_estimators': 250,
          'min_samples_split': 15,
          'min_samples_leaf': 5,
          'max_depth': 10
      }
      param_dict_pr_opt = {
          'n_estimators': 250,
          'min samples split': 15,
          'min_samples_leaf': 5,
          'max_depth': 20
      }
      param_dict_pr90_opt = {
          'n_estimators': 200,
          'min_samples_split': 15,
          'min_samples_leaf': 5,
          'max_depth': 10
      }
      param_dict_dtr_opt = {
          'n estimators': 250,
          'min_samples_split': 10,
          'min samples leaf': 5,
          'max_depth': 20
      }
[68]: # Used log2 instead of sqrt for max features, training on grid search parameter.
       \hookrightarrow tuning
      rf_tas = rf_model(X, Y['tas'], random_state=0, bootstrap=True,_
       →max_features='log2', **param_dict_tas_opt)
      rf_pr = rf_model(X, Y['pr'], random_state=0, bootstrap=True,__
       →max_features='log2', **param_dict_pr_opt)
      rf_pr90 = rf_model(X, Y['pr90'], random_state=0, bootstrap=True,_
       max_features='log2',**param_dict_pr90_opt)
      rf_dtr = rf_model(X, Y["diurnal_temperature_range"], random_state=0,__
       ⇔bootstrap=True, max_features='log2',**param_dict_dtr_opt)
      rf tas.train()
      rf_pr.train()
      rf_pr90.train()
      rf_dtr.train()
```

```
[69]: ## Test on SSP245
      X_test = get_test_data('ssp245', solvers)
      Y_test = create_predictdand_data_test(['ssp245'])
      tas_truth = Y_test["tas"]
      pr truth = Y test["pr"]
      pr90_truth = Y_test["pr90"]
      dtr_truth = Y_test["diurnal_temperature_range"]
[70]: # predictions for each variable
      m_out_tas, _ = rf_tas.predict(X_test)
      m_out_pr, _ = rf_pr.predict(X_test)
      m_out_pr90, _ = rf_pr90.predict(X_test)
      m_out_dtr, _ = rf_dtr.predict(X_test)
[71]: path_output = "outputs_ssp245_prediction_hyper_change.nc"
      xr_output = xr.Dataset(dict(tas=m_out_tas, pr=m_out_pr, pr90=m_out_pr90,_

→diurnal_temperature_range=m_out_dtr)).assign_coords(time=m_out_tas.sample +

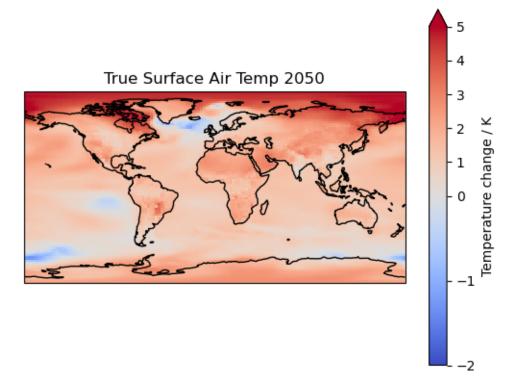
□
       <sup>4</sup>2014)
      #save output to net-cdf file
      xr_output.to_netcdf(path_output,'w')
     0.0.6 Testing out predictions with test set
[72]: print(f"RMSE: {get_rmse(tas_truth[35:], m_out_tas[35:]).mean()}")
      print("\n")
      print(f"RMSE: {get_rmse(dtr_truth[35:], m_out_dtr[35:]).mean()}")
      print("\n")
      print(f"RMSE: {get rmse(pr truth[35:], m out pr[35:]).mean()}")
      print("\n")
      print(f"RMSE: {get_rmse(pr90_truth[35:], m_out_pr90[35:]).mean()}")
     RMSE: 0.6614993057851092
     RMSE: 0.16673128377739266
     RMSE: 0.5548657390705033
```

RMSE: 1.5955868266285376

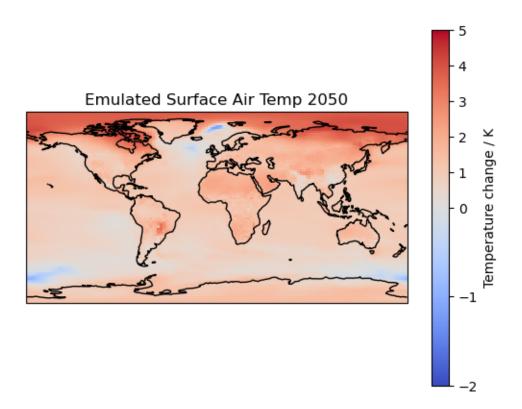
# 0.0.7 Comparing emulated results of New RF model to True Results Graphically (Year 2050)

#### True vs Emulated Surface Air Temperature

[73]: <cartopy.mpl.feature\_artist.FeatureArtist at 0x1539647c9b70>

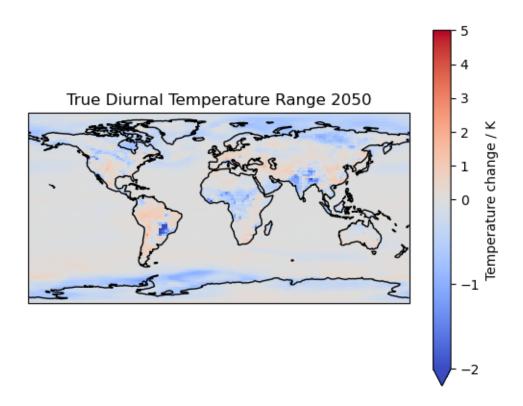


[74]: <cartopy.mpl.feature\_artist.FeatureArtist at 0x153964cdfd30>

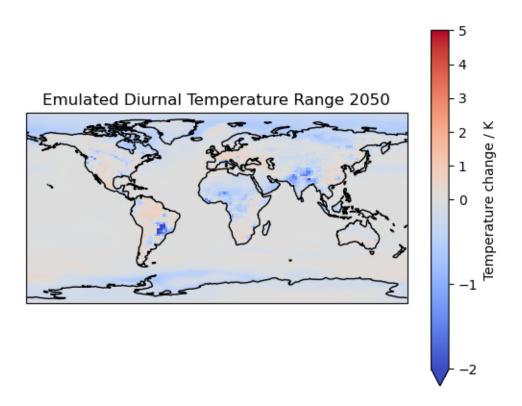


## True vs Emulated Diurnal Temperature Range

[75]: <cartopy.mpl.feature\_artist.FeatureArtist at 0x15396df89990>

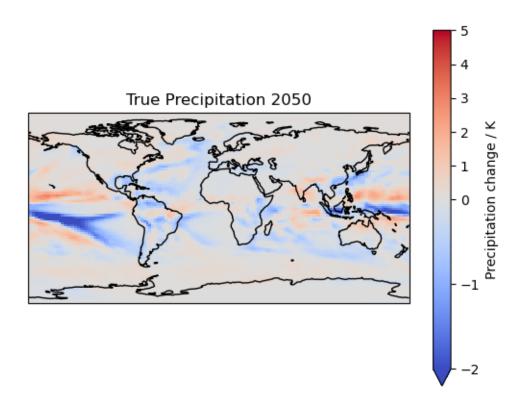


[76]: <cartopy.mpl.feature\_artist.FeatureArtist at 0x1539763aada0>

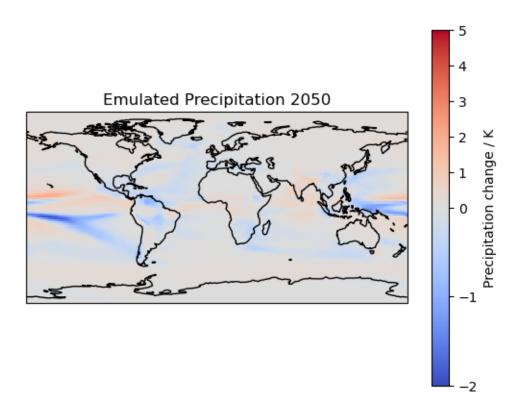


### True vs Emulated Precipitation

[77]: <cartopy.mpl.feature\_artist.FeatureArtist at 0x1539641dded0>

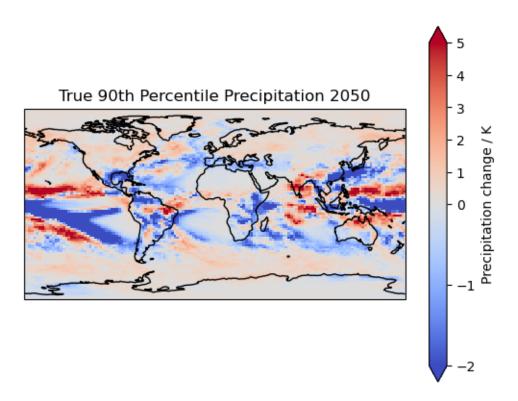


[78]: <cartopy.mpl.feature\_artist.FeatureArtist at 0x1539763a88b0>



#### True vs Emulated 90th Percentile Precipitation

[79]: <cartopy.mpl.feature\_artist.FeatureArtist at 0x1539763a93f0>



[80]: <cartopy.mpl.feature\_artist.FeatureArtist at 0x153963e72ad0>

