RF model

November 26, 2024

```
[1]: 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 *
```

2024-11-26 21:35:30.263076: E

external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:477] Unable to register cuFFT factory: Attempting to register factory for plugin cuFFT when one has already been registered

WARNING: All log messages before absl::InitializeLog() is called are written to STDERR

E0000 00:00:1732682130.282512 52358 cuda_dnn.cc:8310] Unable to register cuDNN factory: Attempting to register factory for plugin cuDNN when one has already been registered

E0000 00:00:1732682130.288266 52358 cuda_blas.cc:1418] Unable to register cuBLAS factory: Attempting to register factory for plugin cuBLAS when one has

already been registered 2024-11-26 21:35:30.347514: I tensorflow/core/platform/cpu_feature_guard.cc:210] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.

To enable the following instructions: AVX2 AVX512F FMA, in other operations,

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

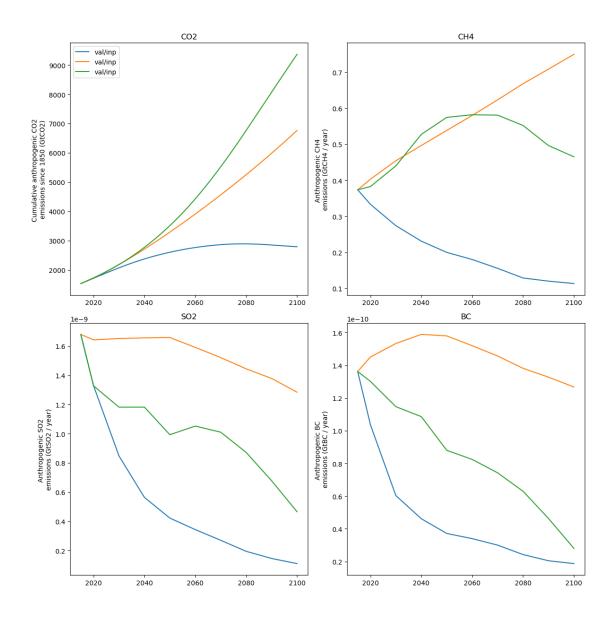
0.0.1 Initial EDA to look at variables

rebuild TensorFlow with the appropriate compiler flags.

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

→train 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_
      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
     \hookrightarrow 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

```
[4]: train_files = [ "historical", "ssp585", "ssp126", "ssp370", ]

# Create training and testing arrays

X, solvers = create_predictor_data(train_files)

Y = create_predictdand_data(train_files)
```

```
[5]: #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
}
```

2024-11-26 21:35:36.893152: E external/local_xla/xla/stream_executor/cuda/cuda_driver.cc:152] failed call to cuInit: INTERNAL: CUDA error: Failed call to cuInit: CUDA_ERROR_NO_DEVICE: no CUDA-capable device is detected

```
[7]: ## 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"]
8]: m_out_tas, _ = rf_tas.predict(X_test)
```

```
[8]: 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)
```

0.0.3 Testing out predictions with test set

```
[10]: 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

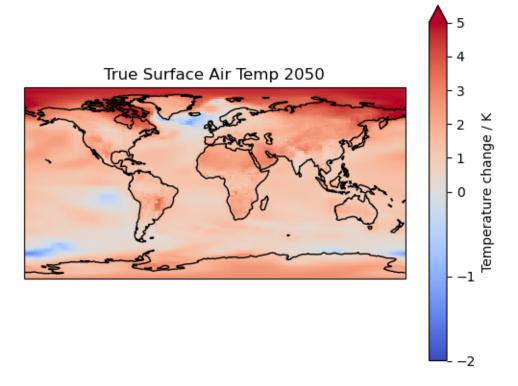
RMSE: 0.5578336782743653

RMSE: 1.5880423328622344

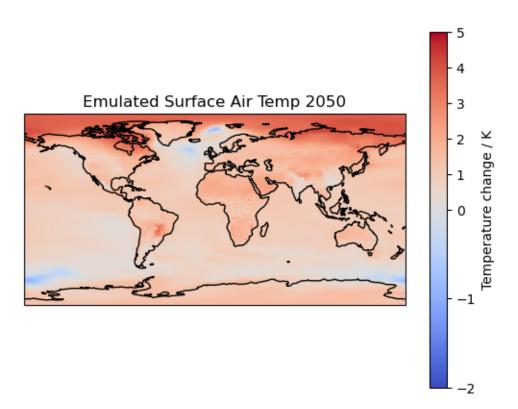
0.0.4 Comparing emulated results of RF model to True Results Graphically (Year 2050)

True vs Emulated Surface Air Temperature

[11]: <cartopy.mpl.feature_artist.FeatureArtist at 0x15396cf6fd00>

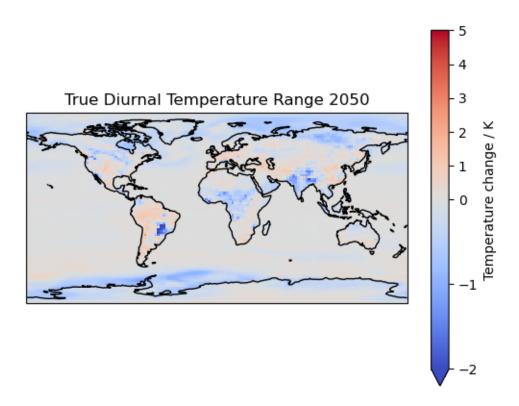


[12]: <cartopy.mpl.feature_artist.FeatureArtist at 0x15396c671420>

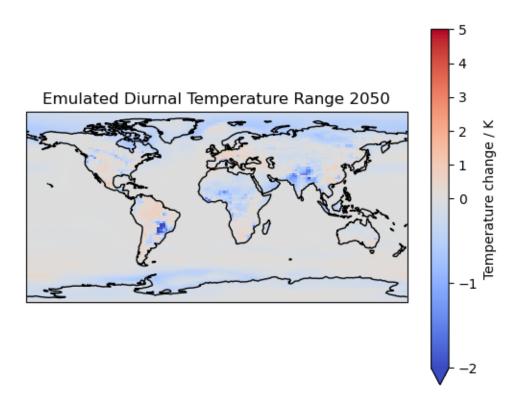


True vs Emulated Diurnal Temperature Range

[13]: <cartopy.mpl.feature_artist.FeatureArtist at 0x15396c52a380>

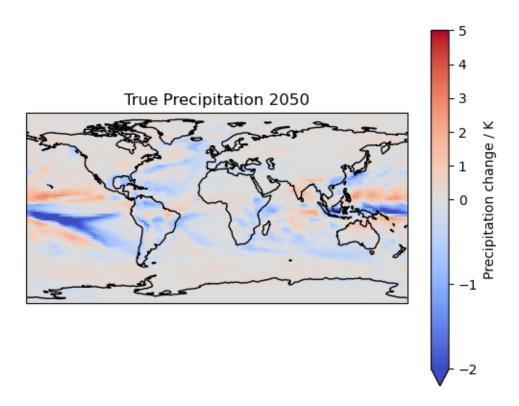


[14]: <cartopy.mpl.feature_artist.FeatureArtist at 0x15396c5e39d0>

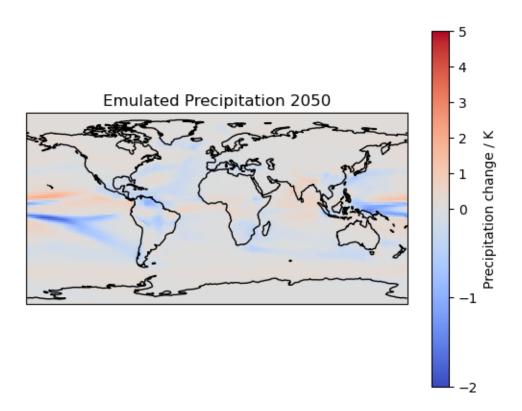


True vs Emulated Percipitation

[15]: <cartopy.mpl.feature_artist.FeatureArtist at 0x15396c39e980>

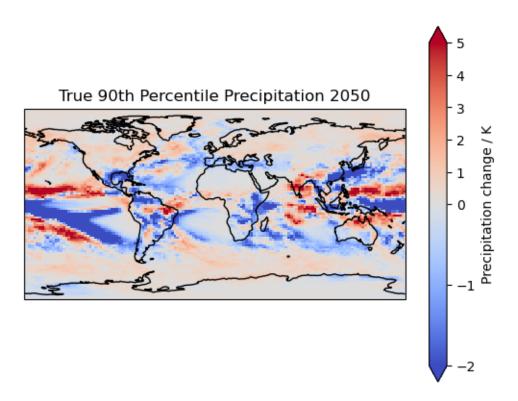


[16]: <cartopy.mpl.feature_artist.FeatureArtist at 0x15396c4a0f70>

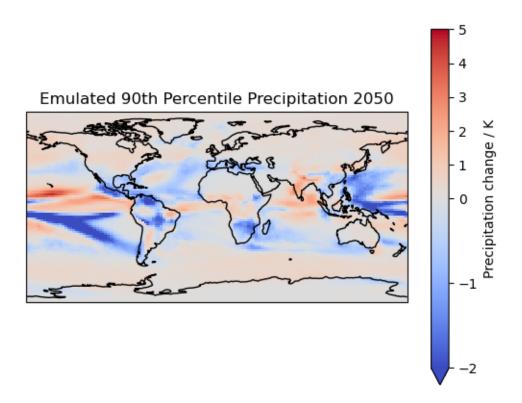


True vs Emulated 90th Percentile Percipitation

[17]: <cartopy.mpl.feature_artist.FeatureArtist at 0x15396c5071c0>



[18]: <cartopy.mpl.feature_artist.FeatureArtist at 0x15396c2de2c0>



0.0.5 Running models again with more optimized hyperparameter inputs

```
[19]: X, solvers = create_predictor_data(train_files)
Y = create_predictdand_data(train_files)
```

```
[20]: # only changed tas and pr parameters as others got worse
      param_dict_tas_opt = {
          'n_estimators': 250,
          'min_samples_split': 15,
          'min_samples_leaf': 10,
          'max_depth': 10
      }
      param_dict_pr_opt = {
          'n_estimators': 250,
          'min_samples_split': 20,
          'min_samples_leaf': 10,
          'max_depth': 45
      }
      param_dict_pr90_opt = {
          'n_estimators': 250,
          'min_samples_split': 15,
```

```
'min_samples_leaf': 12,
          'max_depth': 25
      }
      param_dict_dtr_opt = {
          'n_estimators': 300,
          'min_samples_split': 10,
          'min_samples_leaf': 12,
          'max depth': 20
      }
[21]: # Used log2 instead of sqrt for max_features
      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()
[22]: ## 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"]
[23]: # 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)
[24]: 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 +
```

⇒2014)

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

0.0.6 Testing out predictions with test set

```
[25]: 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: 0.6602302805441683

RMSE: 0.16537489851670092

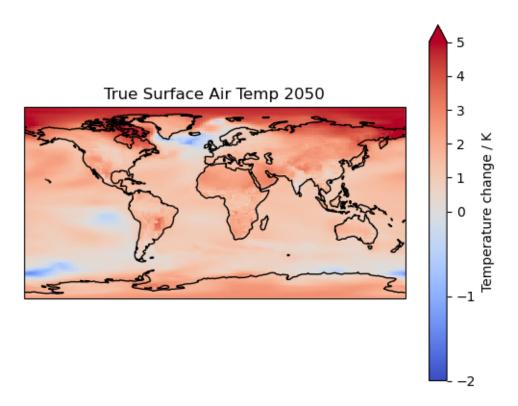
RMSE: 0.5494657322063173

RMSE: 1.5880423328622344

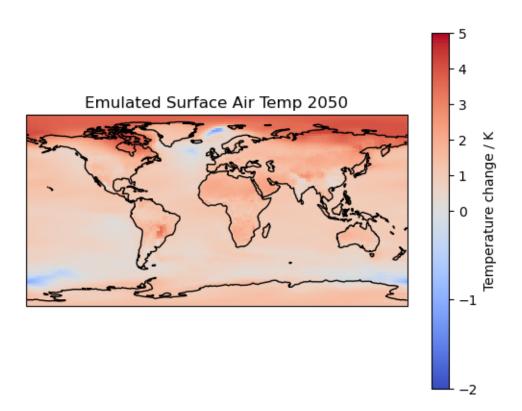
0.0.7 Comparing emulated results of New RF model to True Results Graphically (Year 2050)

True vs Emulated Surface Air Temperature

[26]: <cartopy.mpl.feature_artist.FeatureArtist at 0x15396cf13970>

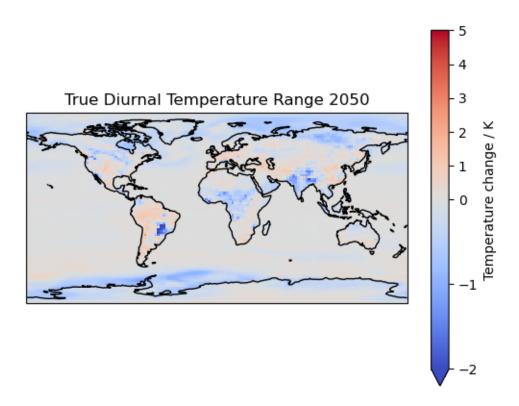


[27]: <cartopy.mpl.feature_artist.FeatureArtist at 0x15396c0b54b0>

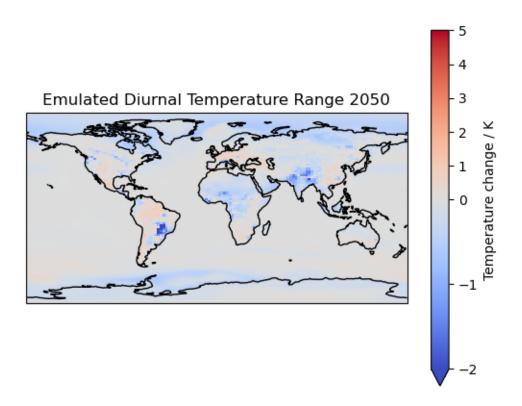


True vs Emulated Diurnal Temperature Range

[28]: <cartopy.mpl.feature_artist.FeatureArtist at 0x15396c3761a0>

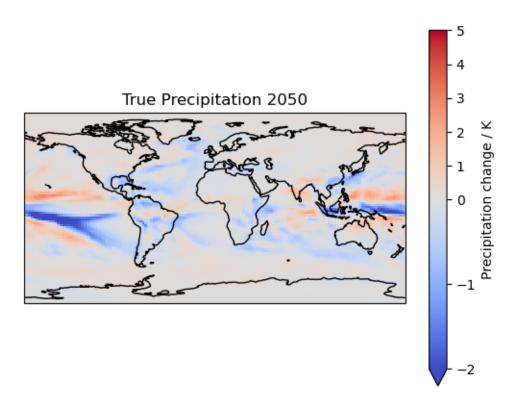


[29]: <cartopy.mpl.feature_artist.FeatureArtist at 0x15396cf3e170>

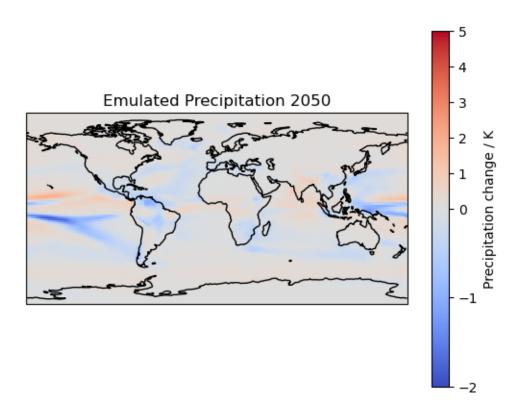


True vs Emulated Precipitation

[30]: <cartopy.mpl.feature_artist.FeatureArtist at 0x15396cf6c760>

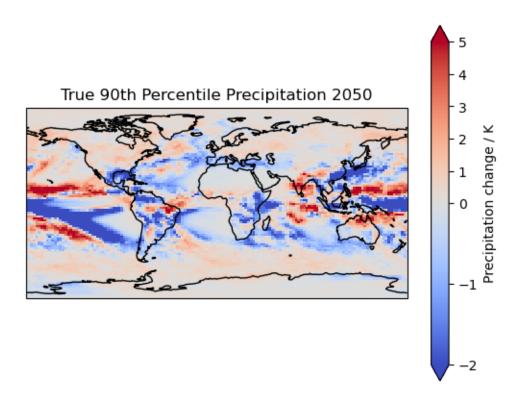


[31]: <cartopy.mpl.feature_artist.FeatureArtist at 0x153965c05360>



True vs Emulated 90th Percentile Precipitation

[32]: <cartopy.mpl.feature_artist.FeatureArtist at 0x15396597ea10>



[33]: <cartopy.mpl.feature_artist.FeatureArtist at 0x1539659a0460>

