CNN

November 26, 2024

[2]:
```python
import xarray as xr
import pandas as pd
import numpy as np
import cartopy.crs as ccrs
import matplotlib.pyplot as plt
```

[3]:
```python
names = ['ssp585',
         'ssp370-lowNTCF',
         "ssp370",
         'ssp126',
         'hist-aer',
         'hist-GHG',
         'historical',
         #'abrupt-4xCO2',
         #'1pctCO2'
        ]
```

[4]:
```python
outputs={}
inputs={}
for name in names:
    inputs[f"{name}"] = xr.open_dataset(f"./train_val/inputs_{name}.nc")

    outputs_temp = xr.open_dataset(f"./train_val/outputs_{name}.nc").
 ↪mean(dim='member')
    outputs_temp = outputs_temp.assign({"pr": outputs_temp.pr * 86400, "pr90":␣
 ↪outputs_temp.pr90 * 86400})
    outputs_temp = outputs_temp.rename({'lon':'longitude', 'lat': 'latitude'})
    outputs[f"{name}"] = outputs_temp
```

[61]:
```python
def get_rmse(truth, pred):
    weights = np.cos(np.deg2rad(truth.lat))
    return np.sqrt(((truth-pred)**2).weighted(weights).mean(['lat', 'lon'])).
 ↪data.mean()
```

[6]:
```python
slider=10
```

[7]:
```
def training_input(X_train):
    X_train_np = X_train.to_array().transpose('time', 'latitude', 'longitude',␣
↪'variable').data

    time_length = X_train_np.shape[0]
    X_train_mod = np.array([X_train_np[i:i+slider] for i in range(0,␣
↪time_length - slider+1)])

    return X_train_mod

def training_output(Y_train, var):
    Y_train_np = Y_train[var].data

    time_length = Y_train_np.shape[0]
    Y_train_mod = np.array([Y_train_np[i+slider-1] for i in range(0,␣
↪time_length-slider+1)])

    return Y_train_mod
```

[8]:
```
X = [inputs['ssp370'], inputs['ssp126']]
```

[9]:
```
Y = [outputs['ssp370'], outputs['ssp126']]
```

[10]:
```
mean={}
std={}
input_vars = ['CO2', 'SO2', 'CH4', 'BC']
for var in input_vars:

    array = np.array(X[0][var].data + X[1][var].data)
    mean[var] = array.mean()
    std[var] = array.std()
```

[11]:
```
print("Means ", mean)
print("Standard Deviation ", std)
```

```
Means  {'CO2': 6405.910174326076, 'SO2': 5.717767908934675e-12, 'CH4':
0.7688742321323471, 'BC': 5.054034441801042e-13}
Standard Deviation  {'CO2': 1906.325135441283, 'SO2': 3.772588788161702e-11,
'CH4': 0.04038698254177525, 'BC': 2.7361256290235744e-12}
```

[12]:
```
def normalize(data, mean, std):
    return (data-mean)/std

def unnormalize(data, mean, std):
    return data * std + mean
```

[13]:
```
X_norm = []
for i, training in enumerate(X):
    for var in input_vars:
        dims = X[i][var].dims
        training = training.assign({var: (dims, normalize(training[var].data,␣
↪mean[var], std[var]))})
    X_norm.append(training)
```

[14]:
```
X_norm
```

[14]:
```
[<xarray.Dataset> Size: 19MB
 Dimensions:    (time: 86, longitude: 144, latitude: 96)
 Coordinates:
   * longitude  (longitude) float64 1kB 0.0 2.5 5.0 7.5 … 352.5 355.0 357.5
   * latitude   (latitude) float64 768B -90.0 -88.11 -86.21 … 86.21 88.11 90.0
   * time       (time) int64 688B 2015 2016 2017 2018 … 2097 2098 2099 2100
 Data variables:
     CO2        (time) float64 688B -2.555 -2.535 -2.516 … 0.104 0.1458 0.1878
     SO2        (time, latitude, longitude) float64 10MB -0.1516 … -0.146
     CH4        (time) float64 688B -9.784 -9.638 -9.492 … -0.5787 -0.4771
     BC         (time, latitude, longitude) float64 10MB -0.1847 … -0.1826,
 <xarray.Dataset> Size: 19MB
 Dimensions:    (time: 86, longitude: 144, latitude: 96)
 Coordinates:
   * longitude  (longitude) float64 1kB 0.0 2.5 5.0 7.5 … 352.5 355.0 357.5
   * latitude   (latitude) float64 768B -90.0 -88.11 -86.21 … 86.21 88.11 90.0
   * time       (time) int64 688B 2015 2016 2017 2018 … 2097 2098 2099 2100
 Data variables:
     CO2        (time) float64 688B -2.555 -2.536 -2.517 … -1.889 -1.892
-1.895
     SO2        (time, latitude, longitude) float64 10MB -0.1516 … -0.1506
     CH4        (time) float64 688B -9.784 -9.983 -10.18 … -16.19 -16.21
-16.22
     BC         (time, latitude, longitude) float64 10MB -0.1847 … -0.1831]
```

[20]:
```
predict='tas'
```

[21]:
```
X_trained = np.concatenate([training_input(X_norm[i]) for i in range(len(X))],␣
↪axis = 0)
Y_trained = np.concatenate([training_output(Y[i], predict) for i in␣
↪range(len(Y))], axis=0)
print(X_trained.shape)
print(Y_trained.shape)
```

```
(154, 10, 96, 144, 4)
(154, 96, 144)
```

[22]:
```
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense, Activation, Conv2D, Flatten, Input,␣
 ↪Reshape, AveragePooling2D, MaxPooling2D, Conv2DTranspose, TimeDistributed,␣
 ↪LSTM, GlobalAveragePooling2D, BatchNormalization
from tensorflow.keras.regularizers import l2

import random
seed = 6
random.seed(seed)
np.random.seed(seed)
tf.random.set_seed(seed)
```

[19]:
```
cnn_model = Sequential()
cnn_model.add(Input(shape=(slider, 96, 144, 4)))
cnn_model.add(TimeDistributed(Conv2D(20, (3, 3), padding='same',␣
 ↪activation='relu'), input_shape=(slider, 96, 144, 4)))
cnn_model.add(TimeDistributed(AveragePooling2D(2)))
cnn_model.add(TimeDistributed(GlobalAveragePooling2D()))
cnn_model.add(LSTM(25, activation='relu'))
cnn_model.add(Dense(1*96*144))
cnn_model.add(Activation('linear'))
cnn_model.add(Reshape((1, 96, 144)))
```

```
/glade/u/home/czwang/.local/lib/python3.10/site-
packages/keras/src/layers/core/wrapper.py:27: UserWarning: Do not pass an
`input_shape`/`input_dim` argument to a layer. When using Sequential models,
prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(**kwargs)
2024-11-20 14:49:56.293811: 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
```

[23]:
```
cnn_model.compile(optimizer='rmsprop', loss='mse', metrics=['mse'])
```

[20]:
```
hist = cnn_model.fit(X_trained,
                     Y_trained,
                     #workers=5,
                     batch_size=16,
                     epochs=30,
                     verbose=1)
```

```
Epoch 1/30
10/10              20s 2s/step - loss:
6.0657 - mse: 6.0657
```

```
Epoch 2/30
10/10              20s 2s/step - loss:
3.1280 - mse: 3.1280
Epoch 3/30
10/10              20s 2s/step - loss:
2.4630 - mse: 2.4630
Epoch 4/30
10/10              21s 2s/step - loss:
2.1525 - mse: 2.1525
Epoch 5/30
10/10              21s 2s/step - loss:
1.8860 - mse: 1.8860
Epoch 6/30
10/10              20s 2s/step - loss:
1.7504 - mse: 1.7504
Epoch 7/30
10/10              20s 2s/step - loss:
1.7476 - mse: 1.7476
Epoch 8/30
10/10              21s 2s/step - loss:
1.7007 - mse: 1.7007
Epoch 9/30
10/10              20s 2s/step - loss:
1.3869 - mse: 1.3869
Epoch 10/30
10/10              20s 2s/step - loss:
1.3828 - mse: 1.3828
Epoch 11/30
10/10              20s 2s/step - loss:
1.4029 - mse: 1.4029
Epoch 12/30
10/10              20s 2s/step - loss:
1.3384 - mse: 1.3384
Epoch 13/30
10/10              21s 2s/step - loss:
1.3610 - mse: 1.3610
Epoch 14/30
10/10              20s 2s/step - loss:
1.2664 - mse: 1.2664
Epoch 15/30
10/10              21s 2s/step - loss:
1.3157 - mse: 1.3157
Epoch 16/30
10/10              20s 2s/step - loss:
1.3741 - mse: 1.3741
Epoch 17/30
10/10              20s 2s/step - loss:
1.2905 - mse: 1.2905
```

```
Epoch 18/30
10/10              20s 2s/step - loss:
1.3088 - mse: 1.3088
Epoch 19/30
10/10              21s 2s/step - loss:
1.2928 - mse: 1.2928
Epoch 20/30
10/10              20s 2s/step - loss:
1.2880 - mse: 1.2880
Epoch 21/30
10/10              20s 2s/step - loss:
1.2815 - mse: 1.2815
Epoch 22/30
10/10              20s 2s/step - loss:
1.2763 - mse: 1.2763
Epoch 23/30
10/10              20s 2s/step - loss:
1.2704 - mse: 1.2704
Epoch 24/30
10/10              20s 2s/step - loss:
1.2661 - mse: 1.2661
Epoch 25/30
10/10              20s 2s/step - loss:
1.2631 - mse: 1.2631
Epoch 26/30
10/10              20s 2s/step - loss:
1.2606 - mse: 1.2606
Epoch 27/30
10/10              20s 2s/step - loss:
1.2574 - mse: 1.2574
Epoch 28/30
10/10              21s 2s/step - loss:
1.2544 - mse: 1.2544
Epoch 29/30
10/10              20s 2s/step - loss:
1.2521 - mse: 1.2521
Epoch 30/30
10/10              20s 2s/step - loss:
1.2480 - mse: 1.2480
```

[21]:
```
cnn_model.save('./models/cnn_2.keras')
```

[28]:
```
cnn_model = tf.keras.models.load_model('./models/cnn_2.keras')
```

[29]:
```
X_test = xr.open_dataset(f"./test/inputs_ssp245.nc")
Y_test = xr.open_dataset(f"./test/outputs_ssp245.nc")
```

[30]:
```
X_test_norm = xr.Dataset()
for var in input_vars:
    dims = X_test[var].dims
    X_test_norm = X_test_norm.assign({var: (dims, normalize(X_test[var].data,␣
↪mean[var], std[var]))} )
```

[31]:
```
X_test_new  = training_input(X_test_norm)
```

[32]:
```
m_pred = cnn_model.predict(X_test_new)
```

```
3/3            1s 267ms/step
```

[33]:
```
m_pred = m_pred.reshape(m_pred.shape[0], m_pred.shape[2], m_pred.shape[3])
```

[34]:
```
m_pred = xr.DataArray(m_pred, dims=['time', 'lat', 'lon'], coords=[X_test.time.
↪data[slider-1:], X_test.latitude.data, X_test.longitude.data])
m_pred = m_pred.transpose('lat', 'lon', 'time').sel(time=slice(2015, 2101)).
↪to_dataset(name=predict)
if ((predict == "pr90") | (predict == "pr")):
    m_pred = m_pred.assign({predict: m_pred[var_to_predict] / 86400})
m_pred
```

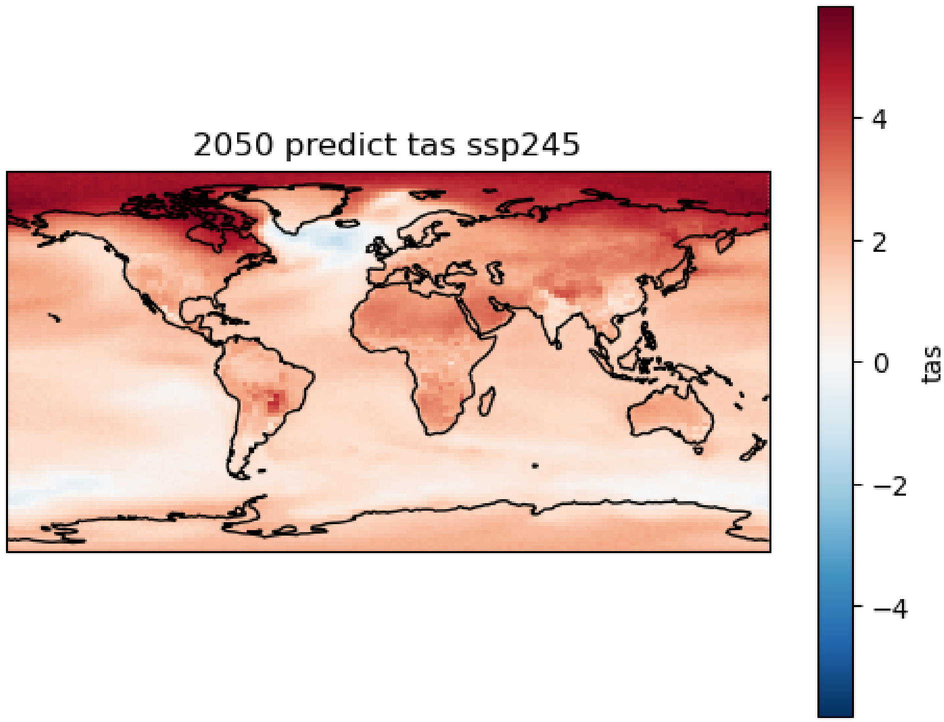
[34]:
```
<xarray.Dataset> Size: 4MB
Dimensions:  (time: 77, lat: 96, lon: 144)
Coordinates:
  * time     (time) int64 616B 2024 2025 2026 2027 2028 … 2097 2098 2099 2100
  * lat      (lat) float64 768B -90.0 -88.11 -86.21 -84.32 … 86.21 88.11 90.0
  * lon      (lon) float64 1kB 0.0 2.5 5.0 7.5 10.0 … 350.0 352.5 355.0 357.5
Data variables:
    tas      (lat, lon, time) float32 4MB 2.231 2.225 2.22 … 4.415 4.413 4.412
```

[62]:
```
get_rmse(Y_test['tas'].mean('member')[9:], m_pred['tas'])
```

[62]:
```
0.6349405982873716
```

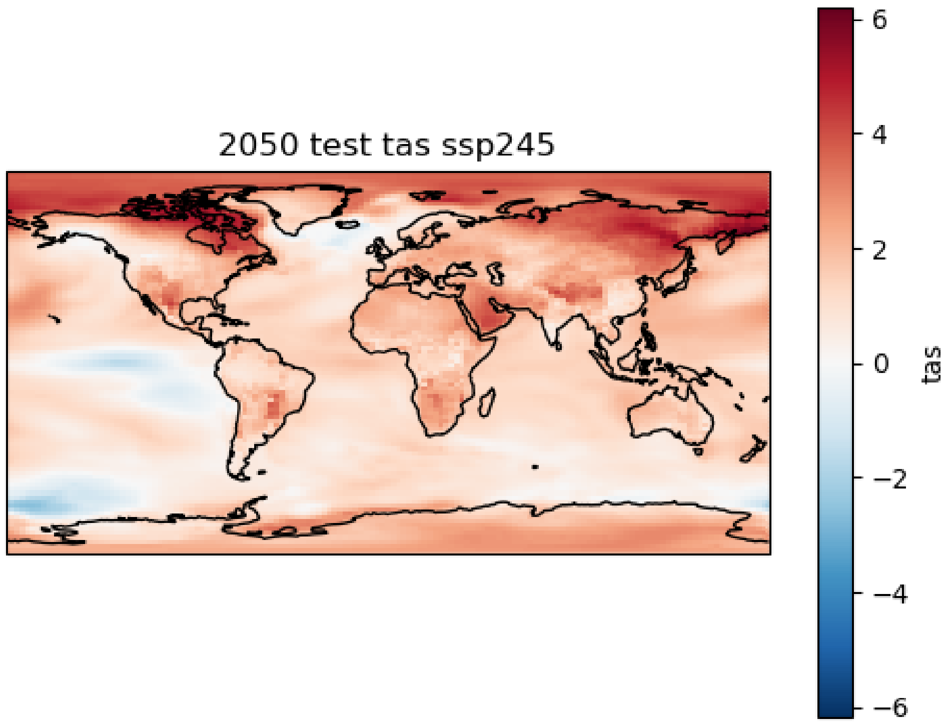
[43]:
```
alpha = m_pred['tas'].sel(time=2050).plot(transform=ccrs.PlateCarree(),
                                            subplot_kws={'projection':␣
↪ccrs.PlateCarree()})
plt.gca().set_title('2050 predict tas ssp245')
plt.gca().coastlines()
```

[43]:
```
<cartopy.mpl.feature_artist.FeatureArtist at 0x14964865a4a0>
```



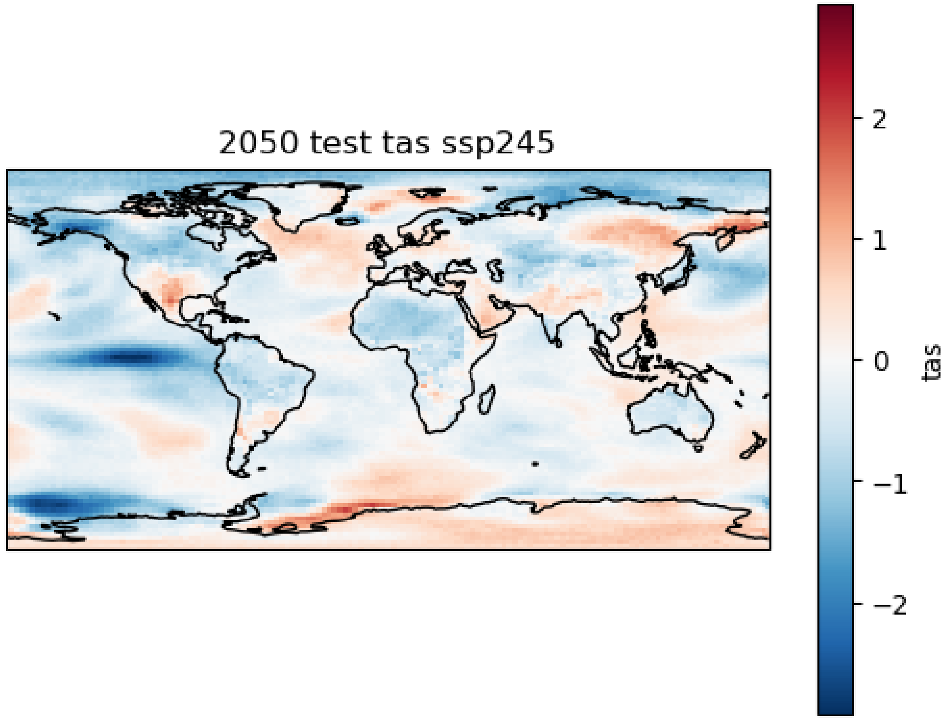

```
[44]: beta = Y_test['tas'].sel(time=2050, member=1).plot(transform=ccrs.PlateCarree(),
                                                         subplot_kws={'projection':␣
       ↪ccrs.PlateCarree()})
      plt.gca().set_title('2050 test tas ssp245')
      plt.gca().coastlines()
```

```
[44]: <cartopy.mpl.feature_artist.FeatureArtist at 0x1495d6f83d00>
```



[45]:
```
(Y_test['tas'].sel(member=1)-m_pred['tas']).sel(time=2050).plot(transform=ccrs.
 ↪PlateCarree(),
                                                         subplot_kws={'projection':␣
 ↪ccrs.PlateCarree()})
plt.gca().set_title('2050 test tas ssp245')
plt.gca().coastlines()
```

[45]: <cartopy.mpl.feature_artist.FeatureArtist at 0x149635869570>



[62]:
```
X = [inputs['ssp126'], inputs['ssp370']]
Y = [inputs['ssp126'], inputs['ssp370']]
```

[63]:
```
X_2 = [xr.concat([inputs['historical'], inputs['ssp126']], dim='time'), xr.
 ↪concat([inputs['historical'], inputs['ssp126']], dim='time')]
Y = [xr.concat([outputs['historical'], outputs['ssp126']], dim='time'), xr.
 ↪concat([outputs['historical'], outputs['ssp126']], dim='time')]
```

[65]:
```
mean={}
std={}
input_vars = ['CO2', 'SO2', 'CH4', 'BC']
for var in input_vars:

    array = np.array(X_2[0][var].data + X_2[1][var].data)
    mean[var] = array.mean()
    std[var] = array.std()
```

[66]:
```
X_norm_2 = []
for i, training in enumerate(X_2):
    for var in input_vars:
        dims = X_2[i][var].dims
        training = training.assign({var: (dims, normalize(training[var].data,␣
 ↪mean[var], std[var]))})
```

```
    X_norm_2.append(training)
```

[67]:
```
X_trained = np.concatenate([training_input(X_norm_2[i]) for i in␣
 ↪range(len(X_2))], axis = 0)
Y_trained = np.concatenate([training_output(Y[i], predict) for i in␣
 ↪range(len(Y))], axis=0)
print(X_trained.shape)
print(Y_trained.shape)
```

```
(484, 10, 96, 144, 4)
(484, 96, 144)
```

[71]:
```
hist_2 = cnn_model.fit(X_trained,
                     Y_trained,
                     #workers=5,
                     batch_size=16,
                     epochs=10,
                     verbose=1)
```

```
Epoch 1/10
31/31              63s 2s/step - loss:
0.7949 - mse: 0.7949
Epoch 2/10
31/31              74s 2s/step - loss:
0.7946 - mse: 0.7946
Epoch 3/10
31/31              82s 2s/step - loss:
0.7944 - mse: 0.7944
Epoch 4/10
31/31              82s 2s/step - loss:
0.7942 - mse: 0.7942
Epoch 5/10
31/31              81s 2s/step - loss:
0.7940 - mse: 0.7940
Epoch 6/10
31/31              81s 2s/step - loss:
0.7938 - mse: 0.7938
Epoch 7/10
31/31              83s 2s/step - loss:
0.7937 - mse: 0.7937
Epoch 8/10
31/31              81s 2s/step - loss:
0.7935 - mse: 0.7935
Epoch 9/10
31/31              83s 2s/step - loss:
0.7933 - mse: 0.7933
Epoch 10/10
```

```
31/31              82s 2s/step - loss:
0.7932 - mse: 0.7932
```

[72]:
```
cnn_model.save('./models/cnn_3.keras')
```

[70]:
```
cnn_model = tf.keras.models.load_model('./models/cnn_3.keras')
```

[71]:
```
X_test_new  = training_input(X_test_norm)
```

[72]:
```
m_pred = cnn_model.predict(X_test_new)
```

```
WARNING:tensorflow:5 out of the last 7 calls to <function
TensorFlowTrainer.make_predict_function.<locals>.one_step_on_data_distributed at
0x155129ba3520> triggered tf.function retracing. Tracing is expensive and the
excessive number of tracings could be due to (1) creating @tf.function
repeatedly in a loop, (2) passing tensors with different shapes, (3) passing
Python objects instead of tensors. For (1), please define your @tf.function
outside of the loop. For (2), @tf.function has reduce_retracing=True option that
can avoid unnecessary retracing. For (3), please refer to
https://www.tensorflow.org/guide/function#controlling_retracing and
https://www.tensorflow.org/api_docs/python/tf/function for  more details.
2/3             0s
155ms/stepWARNING:tensorflow:6 out of the last 9 calls to <function
TensorFlowTrainer.make_predict_function.<locals>.one_step_on_data_distributed at
0x155129ba3520> triggered tf.function retracing. Tracing is expensive and the
excessive number of tracings could be due to (1) creating @tf.function
repeatedly in a loop, (2) passing tensors with different shapes, (3) passing
Python objects instead of tensors. For (1), please define your @tf.function
outside of the loop. For (2), @tf.function has reduce_retracing=True option that
can avoid unnecessary retracing. For (3), please refer to
https://www.tensorflow.org/guide/function#controlling_retracing and
https://www.tensorflow.org/api_docs/python/tf/function for  more details.
3/3             1s 264ms/step
```

[73]:
```
m_pred = m_pred.reshape(m_pred.shape[0], m_pred.shape[2], m_pred.shape[3])
```

[74]:
```
m_pred = xr.DataArray(m_pred, dims=['time', 'lat', 'lon'], coords=[X_test.time.
  ↪data[slider-1:], X_test.latitude.data, X_test.longitude.data])
m_pred = m_pred.transpose('lat', 'lon', 'time').sel(time=slice(2015, 2101)).
  ↪to_dataset(name=predict)
if ((predict == "pr90") | (predict == "pr")):
    m_pred = m_pred.assign({predict: m_pred[var_to_predict] / 86400})
m_pred
```

[74]:
```
<xarray.Dataset> Size: 4MB
Dimensions:  (time: 77, lat: 96, lon: 144)
Coordinates:
```

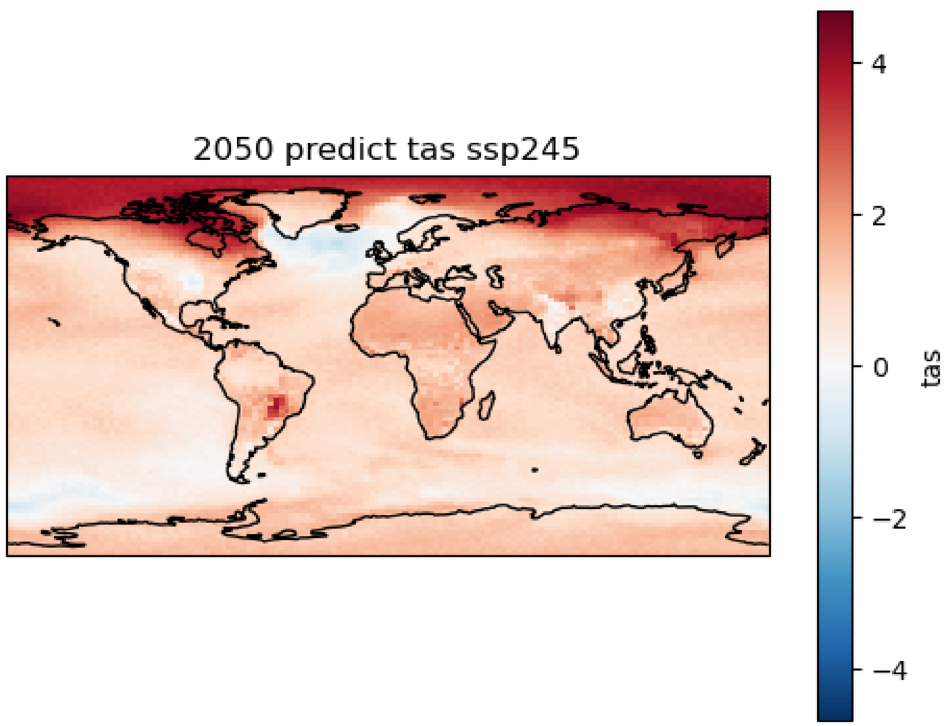
```
  * time      (time) int64 616B 2024 2025 2026 2027 2028 … 2097 2098 2099 2100
  * lat       (lat) float64 768B -90.0 -88.11 -86.21 -84.32 … 86.21 88.11 90.0
  * lon       (lon) float64 1kB 0.0 2.5 5.0 7.5 10.0 … 350.0 352.5 355.0 357.5
Data variables:
    tas       (lat, lon, time) float32 4MB 1.435 1.431 1.427 … 3.675 3.672
```

[75]:
```
get_rmse(Y_test['tas'].mean('member')[9:], m_pred['tas'])
```

[75]:
```
0.8059855650010936
```

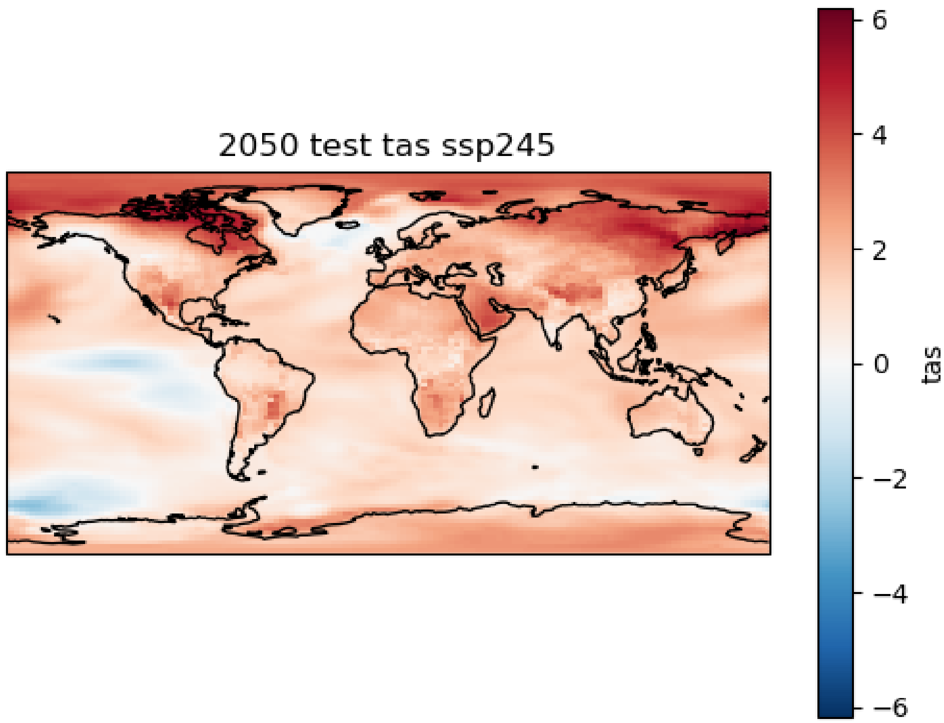
[78]:
```
alpha = m_pred['tas'].sel(time=2050).plot(transform=ccrs.PlateCarree(),
                                                    subplot_kws={'projection':␣
 ↪ccrs.PlateCarree()})
plt.gca().set_title('2050 predict tas ssp245')
plt.gca().coastlines()
```

[78]:
```
<cartopy.mpl.feature_artist.FeatureArtist at 0x1496341d3d90>
```



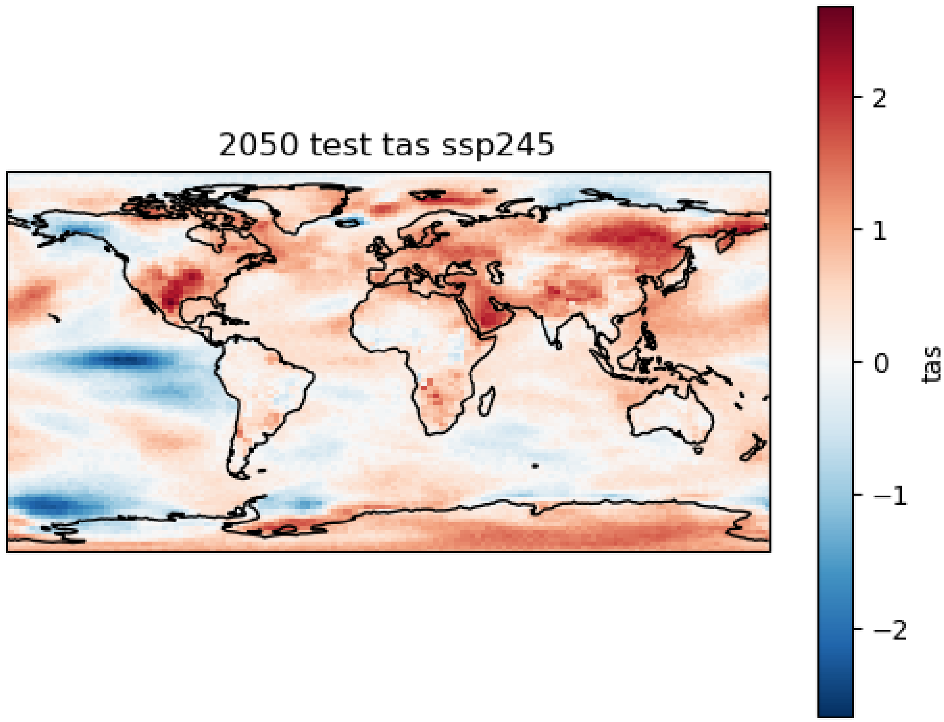
[79]:
```
beta = Y_test['tas'].sel(time=2050, member=1).plot(transform=ccrs.PlateCarree(),
                                                    subplot_kws={'projection':␣
 ↪ccrs.PlateCarree()})
plt.gca().set_title('2050 test tas ssp245')
plt.gca().coastlines()
```

[79]: <cartopy.mpl.feature_artist.FeatureArtist at 0x149626fb7c40>



[80]:
```
(Y_test['tas'].sel(member=1)-m_pred['tas']).sel(time=2050).plot(transform=ccrs.
 ↪PlateCarree(),
                                                       subplot_kws={'projection':␣
 ↪ccrs.PlateCarree()})
plt.gca().set_title('2050 test tas ssp245')
plt.gca().coastlines()
```

[80]: <cartopy.mpl.feature_artist.FeatureArtist at 0x149626e581f0>


2050 test tas ssp245
2
1
0
−1
−2
tas

```
[ ]:
```