@sence_exercice_1

October 23, 2024

[1]:
```python
import numpy as np
from pathlib import Path
import matplotlib.pyplot as plt
import pandas as pd
from IPython.display import display
```

bash script to reproduce the results

#!/bin/bash

1 Get experiment name from first argument

EXPERIMENT_NAME="1"

2 Create experiment directory structure

EXPERIMENT_DIR="task$EXPERIMENT_NAME"INPUT_DIR$ = "{EXPERIMENT_DIR}/input" OUTPUT_DIR="${EXPERIMENT_DIR}/output"

3 Create directories

mkdir -p "$INPUT_DIR"mkdir - p$"{OUTPUT_DIR}"

echo "Created experiment directory: ${EXPERIMENT_DIR}" echo "Input files will be stored in: ${INPUT_DIR}" echo "Output files will be stored in: ${OUTPUT_DIR}"

index=1 for mol_modify_H2O in $(seq 1 3 40); do sza=40 mol_modify_O3=200 # mol_modify_H2O=10 day_of_year=170 albedo=0.2 wavelength_start=300.0 wavelength_end=2000.0

```
# Create input file in the input directory
cat << EOF > "${INPUT_DIR}/input${index}.inp"
```

data_files_path /opt/libRadtran/data/ atmosphere_file /opt/libRadtran/data/atmmod/afglus.dat # Location of the extraterrestrial spectrum # source solar /opt/libRadtran/data/solar_flux/atlas_plus_modtran source solar /opt/libRadtran/data/solar_flux/kurudz_0.1nm.dat mol_modify O3 ${mol_modify_O3}. DU # Set ozone column mol_modify H2O ${mol_modify_H2O} MM aerosol_default aerosol_modify tau set 0.1 aerosol_modify ssa set 0.85 #aerosol_angstrom 1.5 0.1 day_of_year ${day_of_year} # Correct for Earth-Sun distance albedo ${albedo} # Surface albedo sza ${sza} # Solar zenith angle rte_solver disort # Radiative transfer equation solver number_of_streams 6 # Number of streams wavelength ${wavelength_start} ${wavelength_end} # Wavelength range [nm] output_user lambda eglo edir edn EOF

```
echo "File '${INPUT_DIR}/input${index}.inp' created successfully."

# Run Docker command with input and output in their respective directories
docker_command="docker run -i siarhei/libradtran uvspec < ${INPUT_DIR}/input${index}.inp >${OU
echo "$docker_command"

# Run the Docker command
if eval "$docker_command"; then
    echo "Docker command executed successfully."
else
    echo "Error running Docker command"
fi

# Increment the index for the next iteration
((index++))
```

done

Mathis

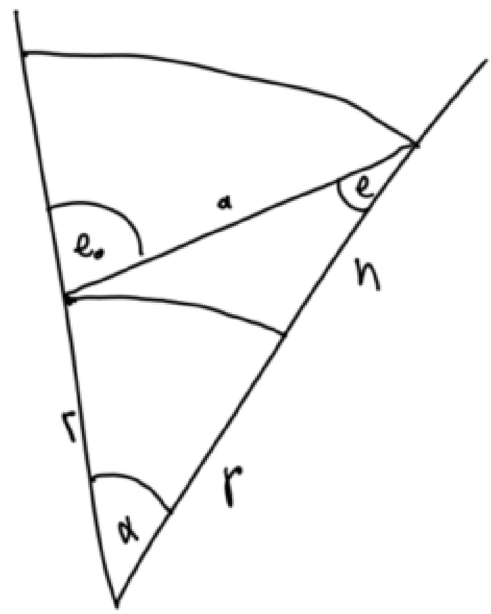
4 Atmospheric remote sensing Exercise 1

4.1 Task 0 Impact of airmass in various altitudes under different incident angels.

The airmass under a incident angle θ_0 is still $m = \frac{1}{cos(\theta)}$. To find θ we use the sin theorem: $\frac{r+h}{sin(180-\theta_0)} = \frac{r}{sin(\theta)}$

[2]:
```
h = np.array([1,5,20])
theta_0 = np.array([45, 80, 85])
```

[3]:
```
image = plt.imread('skizze.png')
plt.imshow(image)
plt.axis('off')
plt.show()
```



[4]:
```
r = 6300
def get_airmass(h, theta_0):
    theta_0 = np.radians(theta_0)
    theta = np.arcsin(r * np.sin(np.pi-theta_0)/(r+h))
    airmass = 1/np.cos(theta)
    return airmass
```

[5]:
```
results = []

# Calculate airmass for each combination of elevation and angle
for elevation in h:
    for angle in theta_0:
        airmass = get_airmass(elevation, angle)
        results.append({
            'Elevation (km)': elevation,
            'Solar Zenith Angle (°)': angle,
            'Airmass (m)': round(airmass, 2)  # Round to 2 decimal places
        })

# Create a DataFrame
pd.set_option('display.float_format', '{:.2f}'.format)

df = pd.DataFrame(results)
```

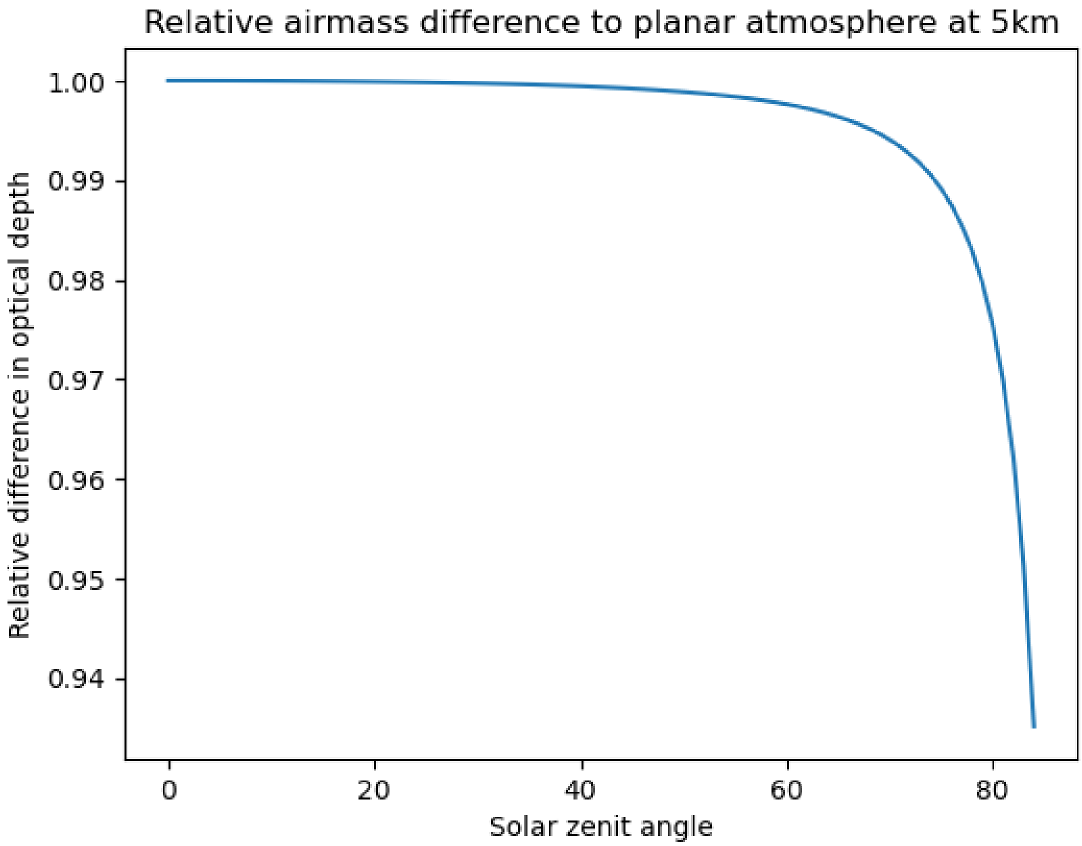
```python
# Pivot the DataFrame to have elevations as rows and angles as columns
pivot_df = df.pivot(columns='Elevation (km)', index='Solar Zenith Angle (°)',␣
 ↪values='Airmass (m)')

# Display the pivot DataFrame
print('Air mass at different elevations under different zenit angles:')
display(pivot_df)
```

```
Air mass at different elevations under different zenit angles:
```

Elevation (km)	1	5	20
Solar Zenith Angle (°)			
45	1.41	1.41	1.41
80	5.73	5.62	5.25
85	11.24	10.44	8.49

From the Beer-Lambert law $I = I_o \exp(-\tau m)$ we find $\tau = \frac{\ln \frac{I_0}{I}}{m}$. The relative deviation only dependent on the airmass.

[6]:
```python
angels = np.arange(0,85)
plt.plot(angels, get_airmass(5,angels)* np.cos(np.radians(angels)))
plt.title('Relative airmass difference to planar atmosphere at 5km')
plt.xlabel('Solar zenit angle')
plt.ylabel('Relative difference in optical depth')
plt.show()
```



4.2 Task 1 Sensitivity to total column ozone

For this experiment we use the uvspec solver of libradtrans to simulate a atmosphere with different ozon amounts. All experiments were conducted with a solar zenit angel of 40°, 10mm of water, and a albedo of 0.2.

The spectral ranges that are affected the most are between 280 nm and 350 nm and between 500 nm and 700 nm.

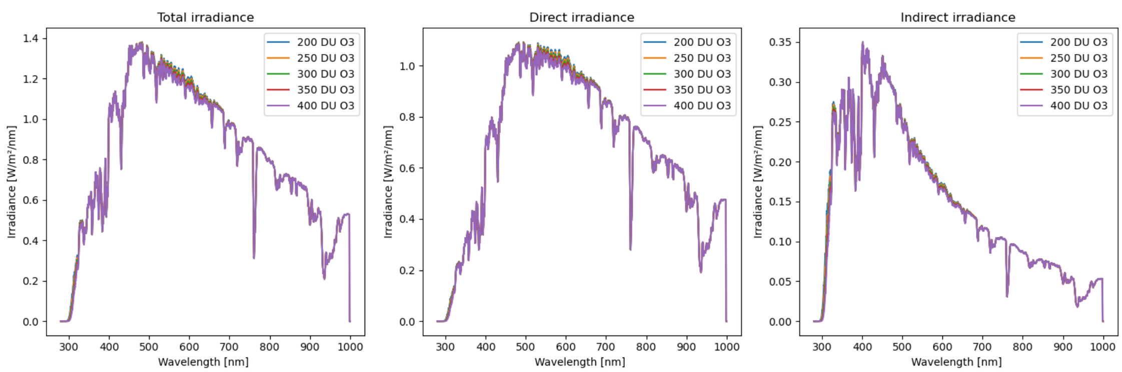
[7]:
```
def erythema_spectrum(wavelengths):
    """
    Calculate the CIE erythema action spectrum for given wavelengths.

    Args:
        wavelengths: numpy array of wavelengths in nanometers

    Returns:
        numpy array of corresponding action spectrum values
    """
    spectrum = np.zeros_like(wavelengths, dtype=float)
```

```
    # Define the conditions according to the CIE standard
    mask1 = (wavelengths >= 250) & (wavelengths <= 298)
    mask2 = (wavelengths > 298) & (wavelengths <= 328)
    mask3 = (wavelengths > 328) & (wavelengths <= 400)

    # Apply the different formulas for each wavelength range
    spectrum[mask1] = 1.0
    spectrum[mask2] = 10.0 ** (0.094 * (298 - wavelengths[mask2]))
    spectrum[mask3] = 10.0 ** (0.015 * (140 - wavelengths[mask3]))

    # Set values outside the defined ranges to 0
    # (wavelengths < 250 or wavelengths > 400)

    return spectrum

# Generate wavelength array from 99 to 1000 nm
```

[8]:

```
# Read all files
data_list = []
output_path = Path('task1/output')

for file_path in sorted(output_path.glob('*')):
    if file_path.is_file():
        # Load data from file
        data = np.loadtxt(file_path)
        data_list.append(data)

# Stack into 3D array (batch, row, column)
data = np.stack(data_list)
# adjust the unit of the values to [W/m²/nm]
data[:,:,1:4]*= 1E-3
# Now data_array.shape will be (n_files, n_rows, n_columns)

data_trans = np.zeros_like(data)

# window size that is used to smooth the curves for better readibility.
window = 31

# Parameters for the legend and title of the plots
ozon_values = [200, 250, 300, 350,400]
channel_titles = ['','Total irradiance', 'Direct irradiance', 'Indirect␣
 ↪irradiance']
plt.figure(figsize=(15, 5))

# Loop through channels
for c in range(3):
```

```
    # Create subplot in position c+1
    plt.subplot(1, 3, c+1)
    c = c+1
    for i in range(data.shape[0]):
        # smooth the data
        data_trans[i,:,c] = np.pad(np.convolve(data[i,:,c], np.ones(window)/
 ↪window, mode='valid'),
            pad_width=int(np.floor(window/2))
        )
        plt.plot(data[i,:,0], data_trans[i,:,c],
                label=f'{ozon_values[i]} DU O3')

    plt.title(f'{channel_titles[c]}')
    plt.xlabel('Wavelength [nm] ')
    plt.ylabel('Irradiance [W/m²/nm]')
    plt.legend()

# Adjust layout to prevent overlap
plt.tight_layout()
plt.show()
```



In both cases the indirect irradiance is the main contributor to the reduced irradiance. For the wavelength range between 280 nm and 380 nm we find that an increse of Ozon higher then 300 du does not lead to lower irradiance. This result does not align with what we expect and contradicts the findings of the erythemal analysis.

[9]:
```
pd.set_option('display.float_format', '{:.3}'.format)

print('Table of integrated irradiance differences between 280nm and 380 nm')
res = np.sum(data[:,0:100,1:4]-data[0,0:100,1:4], axis=1)
df_300 = pd.DataFrame(res, columns=['Total Irradiance difference [w/m²]',␣
 ↪'Direct', 'Indirect'], index= ozon_values)
df_300.index.name = 'Ozone content [du]'
display(df_300)
```

```
print('Table of integrated irradiance differences between 500 nm and 700 nm')
res = np.sum(data[:,220:420,1:4]-data[0,220:420,1:4], axis=1)
df_600 = pd.DataFrame(res, columns=['Total Irradiance difference [w/m²]',␣
↪'Direct', 'Indirect'], index= ozon_values)
df_600.index.name = 'Ozone content [du]'
display(df_600)
```

Table of integrated irradiance differences between 280nm and 380 nm

Ozone content [du]	Total Irradiance difference [w/m²]	Direct	Indirect
200	0.0	0.0	0.0
250	-7.48e-05	-2.83e-05	-4.66e-05
300	-7.95e-05	-3.01e-05	-4.95e-05
350	-7.95e-05	-3.01e-05	-4.95e-05
400	-7.95e-05	-3.01e-05	-4.95e-05

Table of integrated irradiance differences between 500 nm and 700 nm

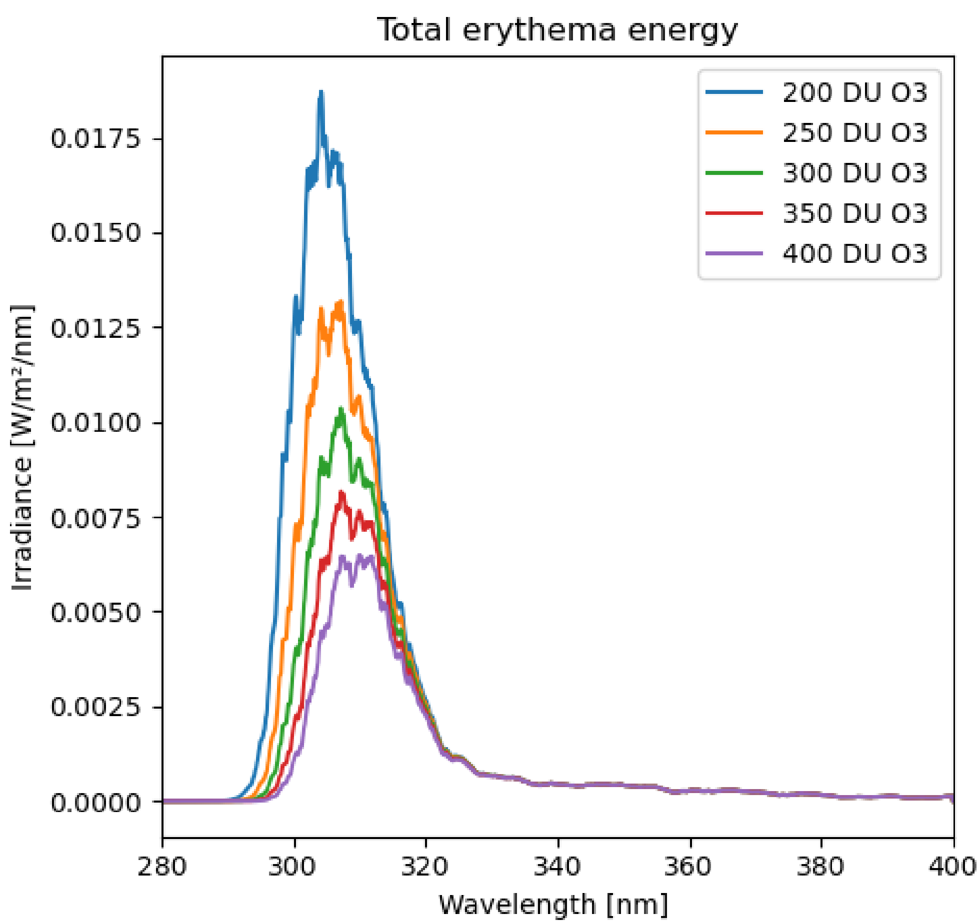
Ozone content [du]	Total Irradiance difference [w/m²]	Direct	Indirect
200	0.0	0.0	0.0
250	-4.07	-1.48	-2.59
300	-7.47	-2.73	-4.74
350	-10.3	-3.81	-6.53
400	-12.8	-4.74	-8.06

4.3 For the next subtask we analyse the erythemal impact of uv radiation.

[10]:

```
# Generate wavelength array from 99 to 1000 nm
wavelengths = np.arange(280, 1000.1, 0.1)

# Calculate the spectrum
spectrum = erythema_spectrum(wavelengths)

ozon_values = [200, 250, 300, 350,400]
channel_titles = ['','Total erythema energy', 'Direct irradiance', 'Diffuse␣
↪irradiance']

erythem_irradiance = np.zeros_like(data)

plt.figure(figsize=(14, 5))
for c in range(1):

    plt.subplot(1, 3, c+1)
    c = c+1
    for i in range(data.shape[0]):
        erythem_irradiance[i,:,c] = spectrum * data_trans[i,:,c]
```

```
        plt.plot(data[i,:,0],erythem_irradiance[i,:,c] ,
                 label=f'{ozon_values[i]} DU O3')


    plt.title(f'{channel_titles[c]}')
    plt.xlim(280,400)
    plt.xlabel('Wavelength [nm] ')
    plt.ylabel('Irradiance [W/m²/nm]')
    plt.legend()

plt.tight_layout()
plt.show()
```



We can integrate these curves and find the average irradiance difference per additional percent ozon in the atmosphere.

[11]:
```
total_erythemal_irradiance = np.sum(erythem_irradiance, axis=1)[:,1]
```

```
uv_index = total_erythemal_irradiance *4

pd.set_option('display.float_format', '{:.2f}'.format)
df = pd.DataFrame(columns=['Ozone content [du]', 'Average irradiance increase␣
 ↪%'])

for i in range(4):
    avg_ozon = np.mean(ozon_values[i:i+2])
    irradiance_diff =␣
 ↪total_erythemal_irradiance[i]-total_erythemal_irradiance[i+1]
    diff_per_percent = irradiance_diff /(50/avg_ozon)
    df.loc[len(df)] = [avg_ozon, diff_per_percent]

display(df)

print('\n These findings lead to a uv index shown in the table below:')
pd.set_option('display.float_format', '{:.0f}'.format)
df_300 = pd.DataFrame(uv_index, columns=['UV index'], index= ozon_values)
df_300.index.name = 'Ozone content[du]'
display(df_300)
```

```
   Ozone content [du]  Average irradiance increase %
0              225.00                           3.17
1              275.00                           2.45
2              325.00                           1.96
3              375.00                           1.61
```

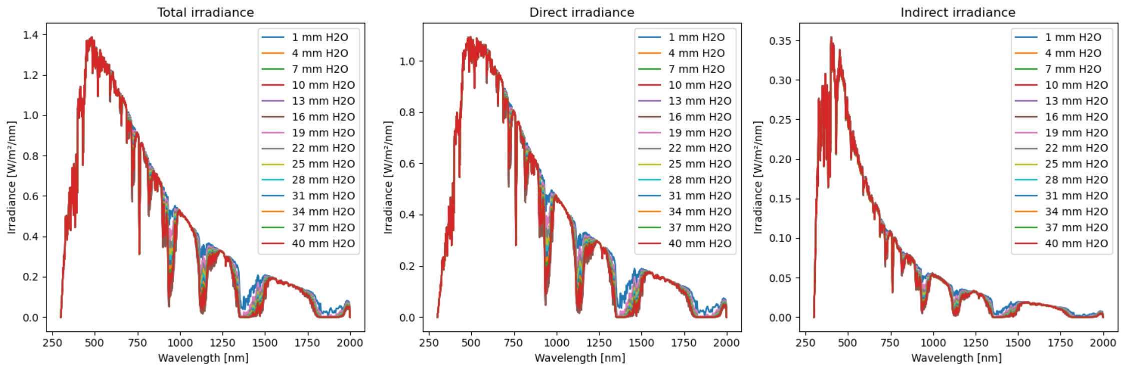
```
 These findings lead to a uv index shown in the table below:

                   UV index
Ozone content[du]
200                      11
250                       9
300                       7
350                       6
400                       5
```

4.4 Task 3 Sensitivity to precipitable water vapour

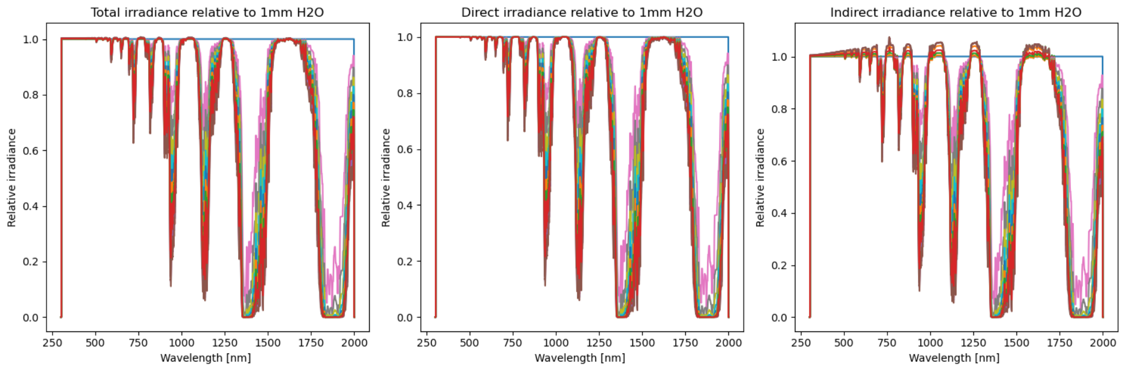
As in the last task we use the uvspec solver of libradtrans to solve for different atmospheres. In this experiment we vary the water content between 1mm and 40mm of precitable water vapor. For the solar zenit angle we use 40°, for the ozon content we use 200 du, and a surface albedo of 0.2.

[12]:
```
# Read all files
data_list = []
output_path = Path('task3/output')

for file_path in sorted(output_path.glob('*')):
```

```python
    if file_path.is_file():
        # Load data from file
        data = np.loadtxt(file_path)
        data_list.append(data)

# Stack into 3D array (batch, row, column)
data = np.stack(data_list)
# adjust the unit of the values to [W/m²/nm]
data[:,:,1:4]*= 1E-3


data_trans = np.zeros_like(data)

# window size that is used to smooth the curves for better readibility.
window = 31

# Parameters for the legend and title of the plots
ozon_values = np.linspace(1,40,14)
channel_titles = ['','Total irradiance', 'Direct irradiance', 'Indirect␣
 ↪irradiance']
plt.figure(figsize=(15, 5))

# Loop through channels
for c in range(3):

    plt.subplot(1, 3, c+1)
    c = c+1
    for i in range(data.shape[0]):
        # smooth the data
        data_trans[i,:,c] = np.pad(np.convolve(data[i,:,c], np.ones(window)/
 ↪window, mode='valid'),
            pad_width=int(np.floor(window/2))
        )
        plt.plot(data[i,:,0], data_trans[i,:,c],
                label=f'{ozon_values[i]:.0f} mm H2O')

    plt.title(f'{channel_titles[c]}')
    plt.xlabel('Wavelength [nm] ')
    plt.ylabel('Irradiance [W/m²/nm]')
    plt.legend()

# Adjust layout to prevent overlap
plt.tight_layout()
plt.show()
```



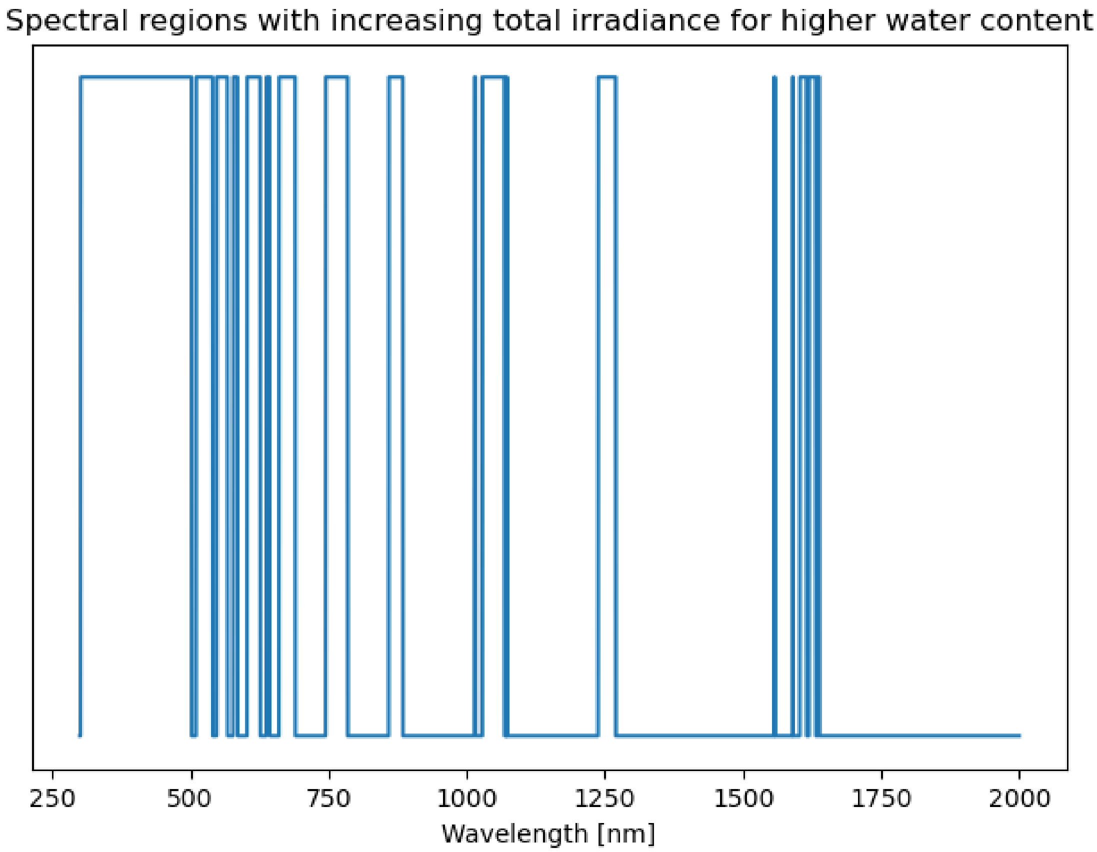
[13]:
```
plt.figure(figsize=(15, 5))
channel_titles = ['','Total irradiance relative to 1mm H2O', 'Direct irradiance␣
↪relative to 1mm H2O', 'Indirect irradiance relative to 1mm H2O']
for c in range(3):

    plt.subplot(1, 3, c+1)
    c = c+1
    for i in range(data.shape[0]):
        # smooth the data
        data_trans[i,:,c] = np.pad(np.convolve(data[i,:,c], np.ones(window)/
↪window, mode='valid'),
            pad_width=int(np.floor(window/2))
        )
        plt.plot(data[i,:,0], data_trans[i,:,c]/(data_trans[0,:,c]+ 0.
↪0000000000000001),
                label=f'{ozon_values[i]:.0f} mm H2O')

    plt.title(f'{channel_titles[c]}')
    plt.xlabel('Wavelength [nm] ')
    plt.ylabel('Relative irradiance')


plt.tight_layout()
plt.show()
```



We find several strong absorbtion bands from 550 nm until the end of our analysed range of 2000 nm. At 1400 nm and 1800 nm we see wide absorbtion bands at which already relatively small changes can fully absorb and lead to barely any incomming radiation. To retrive the percipitable water content we best use the absorbtion band at 900 nm or the one at 1100 nm, as they do not get desaturated and show a strong signal. Of the two the absorbtion band around 900 nm seems more usefull, as it yealds a stronger signal and has less overlap with absorbtion bands from other trance gases like methan.

An interresting finding is that the indirrect irradiance increases with an increasing Water content. This effect is so strong that the total irradiance increases in certain regions. This is an interresting effect, as it needs additional emission. This can be either a numerical error of uvspec of some of the absorbed light gets reemitted ad a different wavelength and thereby increases irradiance in certain wavelength regions.

[14]:
```
plt.plot(data[0,:,0], data_trans[1,:,1]/(data_trans[0,:,1]+ 0.0000000000000001)␣
 ↪> 1)
plt.title('Spectral regions with increasing total irradiance for higher water␣
 ↪content')
plt.tight_layout()
plt.gca().yaxis.set_visible(False)
plt.xlabel('Wavelength [nm]')
plt.show()
```


Spectral regions with increasing total irradiance for higher water content
250
500
750
1000
1250
1500
1750
2000
Wavelength [nm]