GOES-16 In The Classroom Using Python

There are any number of ways to utilize the new GOES-16 (and GOES-17) in the classroom from Synoptic meteorology to radiation. This lecture will use Jupyter notebooks with Python to read, calculate, and visualize GOES-16 GOES Rebroadcast (GRB) feed data that is accessed from a THREDDS data server. The data from the GRB are radiance values for a particular channel (1-16), which need to be modified to plot the typical variables that are plotted and used by meteorologists.

Importing Needed Libraries

There are a number of different libraries that are needed to read, calculate, and plot satellite data. The following is a list of the libraries used in this lecture.

- datetime (https://docs.python.org/3/library/datetime.html (https://docs.python.org/3/library/datetime.html))
- cartopy (https://scitools.org.uk/cartopy/docs/latest/ (https://scitools.org.uk/cartopy/docs/latest/))
- matplotlib (https://matplotlib.org (https://matplotlib.org))
- metpy (https://unidata.github.io/MetPy/latest/index.html (https://unidata.github.io/MetPy/latest/index.html))
- netCDF4 (http://unidata.github.io/netcdf4-python/ (http://unidata.github.io/netcdf4-python/))
- numpy (https://docs.scipy.org/doc/numpy-1.14.0/reference/ (https://docs.scipy.org/doc/numpy-1.14.0/reference/))
- siphon (https://unidata.github.io/siphon/latest/index.html (https://unidata.github.io/siphon/latest/index.html))
- scipy (https://docs.scipy.org/doc/scipy/reference/ (https://docs.scipy.org/doc/scipy/reference/))
- xarray (http://xarray.pydata.org/en/stable/ (http://xarray.pydata.org/en/stable/))

In [1]:
```
import warnings
warnings.filterwarnings('ignore')

from datetime import datetime

import cartopy.crs as ccrs
import cartopy.feature as cfeature
import matplotlib.pyplot as plt
import metpy.calc as mpcalc
from metpy.plots import ctables
from metpy.units import units
from netCDF4 import num2date
import numpy as np
from scipy.ndimage import gaussian_filter
from siphon.catalog import TDSCatalog
import xarray as xr
```

GOES-16 Data - Access from Python

As seen in previous presentations, there are a number of different ways to access GOES-16 data. Here we will use the Siphon (https://unidata.github.io/siphon/latest/index.html (https://unidata.github.io/siphon/latest/index.html)) library to find the most recent file and obtain the URL for the OPeNDAP access method.

Recent GOES-16 Data available at: http://thredds-test.unidata.ucar.edu/thredds/catalog/satellite/goes16/catalog.html (http://thredds-test.unidata.ucar.edu/thredds/catalog/satellite/goes16/catalog.html)

Note: When using Siphon, switch from using ".html" to ".xml" - if you don't, Siphon will make the change for you and give you a warning message.

```
In [17]: # Set channel number (1-16)
         # Channels 1-6 (Visible)
         # Channel 7 (daylight/nighttime band)
         # Channels 8-10 (Water Vapor)
         # Channels 11-16 (IR)

         channel = 13
         catalog_url = 'http://thredds-test.unidata.ucar.edu/thredds/catalog/sa
         tellite/'\
                       'goes16/GRB16/ABI/CONUS/Channel{:02d}/current/'.format(c
         hannel)
         current_goes16 = TDSCatalog(catalog_url+'catalog.xml')

         latest_file = current_goes16.datasets[-1]
         latest_file_url = latest_file.access_urls['OPENDAP']
         print(latest_file_url)
```

```
http://thredds-test.unidata.ucar.edu/thredds/dodsC/satellite/goes16/
GRB16/ABI/CONUS/Channel13/current/OR_ABI-L1b-RadC-M3C13_G16_s2018178
2102189_e20181782104574_c20181782105014.nc
```

Remote data read

We will use the Xarray library to remotely read the data from the THREDDS server using the URL we found (and is printed above).

By using Xarray we will have access to a data handle that we can couple that with the metpy library to allow us easier access to the appropriate map projection information needed for plotting.

Note: Xarray is "lazy" meaning that it is not going to actually download the data until it need to access it. This is great in the case of needing to subset data prior to using it in a calculation because it will only bring back the data that you need and not the whole dataset.

```
In [18]: # Access the remote file on the THREDDS server
         ds = xr.open_dataset(latest_file_url)
         ds
```

```
Out[18]: <xarray.Dataset>
         Dimensions:                                        (band: 1, num_star_looks
         : 24, number_of_image_bounds: 2, number_of_time_bounds: 2, x: 2500,
         y: 1500)
         Coordinates:
           * y                                              (y) float32 0.128212 0.1
         28156 ...
           * x                                              (x) float32 -0.101332 -0
         .101276 ...
             t                                              datetime64[ns] ...
             y_image                                        float32 ...
             x_image                                        float32 ...
             band_id                                        (band) uint8 ...
```

```
    band_wavelength                          (band) float32 ...
    t_star_look                              (num_star_looks) datetim
e64[ns] ...
    band_wavelength_star_look                (num_star_looks) float32
...
Dimensions without coordinates: band, num_star_looks, number_of_imag
e_bounds, number_of_time_bounds
Data variables:
    time_bounds                              (number_of_time_bounds)
float64 ...
    goes_imager_projection                   int32 ...
    y_image_bounds                           (number_of_image_bounds)
float32 ...
    x_image_bounds                           (number_of_image_bounds)
float32 ...
    nominal_satellite_subpoint_lat           float32 ...
    nominal_satellite_subpoint_lon           float32 ...
    nominal_satellite_height                 float32 ...
    geospatial_lat_lon_extent                float32 ...
    yaw_flip_flag                            float32 ...
    esun                                     float32 ...
    kappa0                                   float32 ...
    planck_fk1                               float32 ...
    planck_fk2                               float32 ...
    planck_bc1                               float32 ...
    planck_bc2                               float32 ...
    valid_pixel_count                        float64 ...
    missing_pixel_count                      float64 ...
    saturated_pixel_count                    float64 ...
    undersaturated_pixel_count               float64 ...
    min_radiance_value_of_valid_pixels       float32 ...
    max_radiance_value_of_valid_pixels       float32 ...
    mean_radiance_value_of_valid_pixels      float32 ...
    std_dev_radiance_value_of_valid_pixels   float32 ...
    percent_uncorrectable_L0_errors          float32 ...
    earth_sun_distance_anomaly_in_AU         float32 ...
    algorithm_dynamic_input_data_container   int32 ...
    processing_parm_version_container        int32 ...
    algorithm_product_version_container      int32 ...
    star_id                                  (num_star_looks) float32
...
    Rad                                      (y, x) float32 ...
    DQF                                      (y, x) float32 ...
Attributes:
    naming_authority:          gov.nesdis.noaa
    Conventions:               CF-1.7
    Metadata_Conventions:      Unidata Dataset Discovery v1.0
    standard_name_vocabulary:  CF Standard Name Table (v25, 05 July
2013)
    institution:               DOC/NOAA/NESDIS > U.S. Department of
Commerce,...
    project:                   GOES
    production_site:           RBU
```

```
    production_environment:    OE
    spatial_resolution:        2km at nadir
    orbital_slot:              GOES-East
    platform_ID:               G16
    instrument_type:           GOES R Series Advanced Baseline Image
r
    scene_id:                  CONUS
    instrument_ID:             FM1
    title:                     ABI L1b Radiances
    summary:                   Single emissive band ABI L1b Radiance
Products...
    keywords:                  SPECTRAL/ENGINEERING > INFRARED WAVEL
ENGTHS > ...
    keywords_vocabulary:       NASA Global Change Master Directory (
GCMD) Ear...
    iso_series_metadata_id:    a70be540-c38b-11e0-962b-0800200c9a66
    license:                   Unclassified data.  Access is restric
ted to ap...
    processing_level:          L1b
    cdm_data_type:             Image
    dataset_name:              OR_ABI-L1b-RadC-M3C13_G16_s2018178210
2189_e201...
    production_data_source:    Realtime
    timeline_id:               ABI Mode 3
    date_created:              2018-06-27T21:05:01.4Z
    time_coverage_start:       2018-06-27T21:02:18.9Z
    time_coverage_end:         2018-06-27T21:04:57.4Z
    created_by:                CSPP Geo GRB-R v0.4.7
```

In [19]:

```
# Get projection information from the file
rad = ds.metpy.parse_cf('Rad')
dataproj = rad.metpy.cartopy_crs

# Grab coordinate data
x = rad.x
y = rad.y

# Grab time from file and convert to a nice format
vtime = datetime.strptime(ds.time_coverage_end, '%Y-%m-%dT%H:%M:%S.%fZ
')
```

In [20]:

```
print(dataproj)
```

```
<cartopy.crs.Geostationary object at 0x1a1be49ca8>
```

In [21]:
```
# Isolate the radiance values from the dataset
# Note: the data isn't downloaded here, just metadata
ir_rad = ds.Rad
print(ir_rad)
```

```
<xarray.DataArray 'Rad' (y: 1500, x: 2500)>
[3750000 values with dtype=float32]
Coordinates:
  * y          (y) float32 0.128212 0.128156 0.12810001 0.12804401 0.1
2798801 ...
  * x          (x) float32 -0.101332 -0.101276 -0.101220004 -0.101164
...
    t          datetime64[ns] ...
    y_image    float32 ...
    x_image    float32 ...
Attributes:
    long_name:                ABI L1b Radiances
    standard_name:            toa_outgoing_radiance_per_unit_wavenumbe
r
    sensor_band_bit_depth:    12
    valid_range:              [    0 4094]
    units:                    mW m-2 sr-1 (cm-1)-1
    resolution:               y: 0.000056 rad x: 0.000056 rad
    cell_methods:             t: point area: point
    ancillary_variables:      DQF
```

Radiance to Brightness Temperature

The GRB feed has the top of the atmosphere radiance values with the units given above. The data that we are accessing is from Channel 14, which happens to be the 11 micron channel, which is an infrared channel. Typically we would want to plot the Brightness Temperature (BT). This can be accomplished by using our knowledge of radiation through Plank's Function.

Radiance based on Plank function

$$L_\lambda = \frac{fk_1}{e^{fk2/T} - 1}$$

Inverse Plank Function to get Brightness Temperature

$$T = \frac{fk_2}{ln\left[\frac{fk_1}{L_\lambda} + 1\right]}$$

$$BT = T * bc_2 + bc_1$$

Equation 3-5 from page 22 (NOAA 2018)

where

fk_1 is the 1st Plank Constant

fk_2 is the 2nd Plank Constant

bc_1 is a spectral bandpass offest for BT

bc_2 is a spectral bandpass scale factor for BT

Source: NOAA 2018, https://www.star.nesdis.noaa.gov/goesr/docs/ATBD/Imagery.pdf (https://www.star.nesdis.noaa.gov/goesr/docs/ATBD/Imagery.pdf)

The constants that are needed to complete the calculation are different depending on the exact channel used and are included im the the file as variables.

In [22]:
```
print(ds.planck_bc1)
print(ds.planck_bc2)
print(ds.planck_fk1)
print(ds.planck_fk2)
```

```
<xarray.DataArray 'planck_bc1' ()>
array(0.0755)
Coordinates:
    t        datetime64[ns] ...
    y_image  float32 ...
    x_image  float32 ...
Attributes:
    long_name:  spectral bandpass correction offset for brightness t
emperatur...
    units:      K
<xarray.DataArray 'planck_bc2' ()>
array(0.99975)
Coordinates:
    t        datetime64[ns] ...
    y_image  float32 ...
    x_image  float32 ...
Attributes:
    long_name:  spectral bandpass correction scale factor for bright
ness temp...
    units:      1
<xarray.DataArray 'planck_fk1' ()>
array(10803.299805)
Coordinates:
    t        datetime64[ns] ...
    y_image  float32 ...
    x_image  float32 ...
Attributes:
    long_name:  wavenumber-dependent coefficient (2 h c2/ nu3) used
in the AB...
    units:      W m-1
<xarray.DataArray 'planck_fk2' ()>
array(1392.74, dtype=float32)
Coordinates:
    t        datetime64[ns] ...
    y_image  float32 ...
    x_image  float32 ...
Attributes:
    long_name:  wavenumber-dependent coefficient (h c nu/b) used in
the ABI e...
    units:      K
```

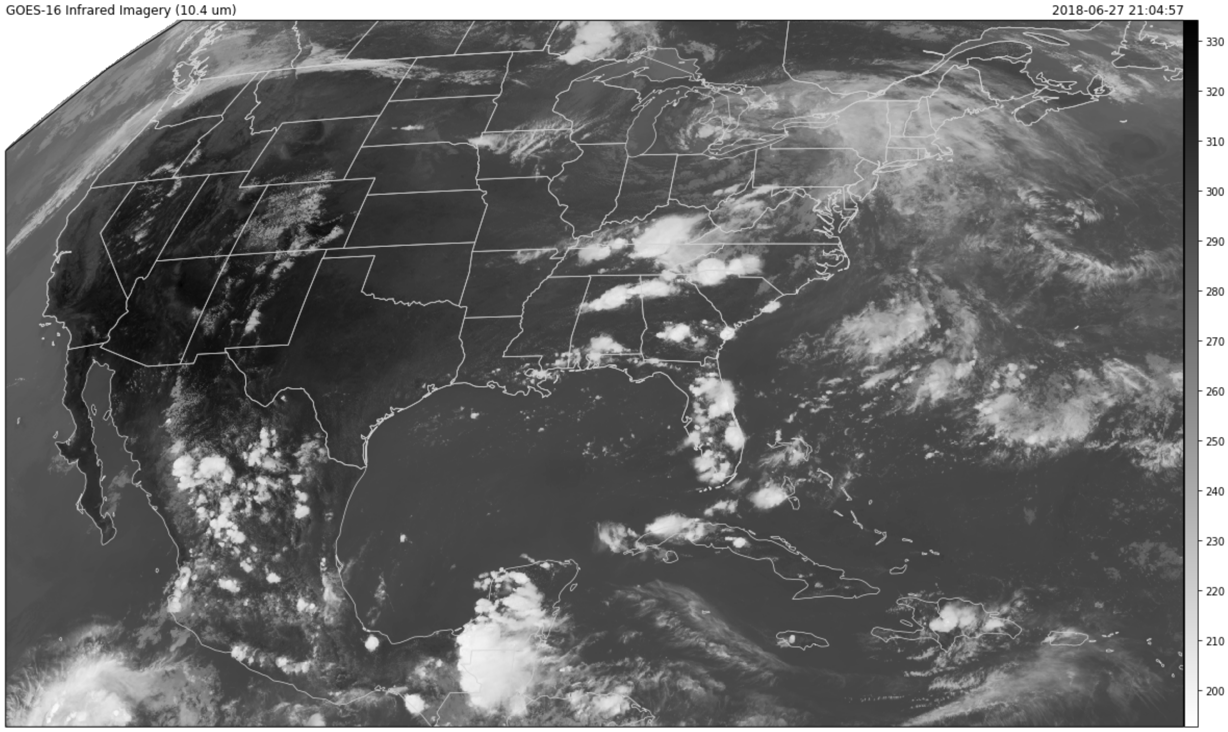
In [23]:
```
# Save values needed for conversion to variables
fk1 = ds.planck_fk1
fk2 = ds.planck_fk2
bc1 = ds.planck_bc1
bc2 = ds.planck_bc2

# Calculate the brightness temperature from inverse Plank
T = fk2 / (np.log((fk1 / ir_rad) + 1))

# Add scale and offest correction to obtain final BT for particular ch
annel
ir_BT = bc2*T + bc1
```

Create a plot of our Brightness Temperature data

The following code uses a combination of matplotlib, cartopy, and metpy to plot our BT data on a map in the correct projection wth an appropriate colormap.

In [24]:

```
# Start figure and set up projected axis for plotting
fig = plt.figure(1, figsize=(20,10))
ax = plt.subplot(111, projection=dataproj)

# Use cartopy feature module to add coastlines, country borders, and s
tate lines
ax.add_feature(cfeature.COASTLINE.with_scale('50m'), edgecolor='lightg
rey', linewidths=0.75)
ax.add_feature(cfeature.BORDERS.with_scale('50m'), edgecolor='lightgre
y', linewidths=0.75)
ax.add_feature(cfeature.STATES.with_scale('50m'), edgecolor='lightgrey
', linewidths=0.75)

# Get a colormap from metpy with a range of brightness values
ir_norm, ir_cmap = ctables.registry.get_with_range('ir_drgb_r', 190, 3
50)

# Plot the BT data with a colorbar describing the colors by temperatur
e
#img = ax.imshow(ir_BT, extent=(x.min(), x.max(), y.min(), y.max()), o
rigin='upper', cmap=ir_cmap, norm=ir_norm)
img = ax.imshow(ir_BT, extent=(x.min(), x.max(), y.min(), y.max()), or
igin='upper', cmap=plt.cm.gray_r)
plt.colorbar(img, orientation='vertical', pad=0, aspect=50, ticks=rang
e(190,351,10))

# Add some titles
plt.title('GOES-16 Infrared Imagery ({:0.1f} um)'.format(ds.band_wavel
ength.data[0]), loc='left')
plt.title('{0:%Y-%m-%d %H:%M:%S}'.format(vtime), loc='right')

# Show the plot
plt.tight_layout()
plt.show()
# plt.savefig('IR_satellite.png')
```



Radiance to Emitted Energy

Now lets use a channel that is responsive to the amount of water vapor (Channel 9). Here we are going to use the same process that we used for the infrared channel above to get to the Brightness Temperature

In [25]:
```
channel = 9
catalog_url = 'http://thredds-test.unidata.ucar.edu/thredds/catalog/sa
tellite/'\
              'goes16/GRB16/ABI/CONUS/Channel{:02d}/current/'.format(c
hannel)
current_goes16 = TDSCatalog(catalog_url+'catalog.xml')

latest_file = current_goes16.datasets[-1]
latest_file_url = latest_file.access_urls['OPENDAP']
print(latest_file_url)

ds = xr.open_dataset(latest_file_url)
rad = ds.metpy.parse_cf('Rad')

dataproj = rad.metpy.cartopy_crs

x = rad.x
y = rad.y

vtime = datetime.strptime(ds.time_coverage_end, '%Y-%m-%dT%H:%M:%S.%fZ
')

wv_rad = ds.Rad

fk1 = ds.planck_fk1
fk2 = ds.planck_fk2
bc1 = ds.planck_bc1
bc2 = ds.planck_bc2

wv_BT = (fk2 / (np.log((fk1/wv_rad)+1)) - bc1)/bc2
```

```
http://thredds-test.unidata.ucar.edu/thredds/dodsC/satellite/goes16/
GRB16/ABI/CONUS/Channel09/current/OR_ABI-L1b-RadC-M3C09_G16_s2018178
2107189_e20181782109568_c20181782110014.nc
```

In [26]:
```
print(ds.band_wavelength.data[0], ds.band_wavelength.units)
```

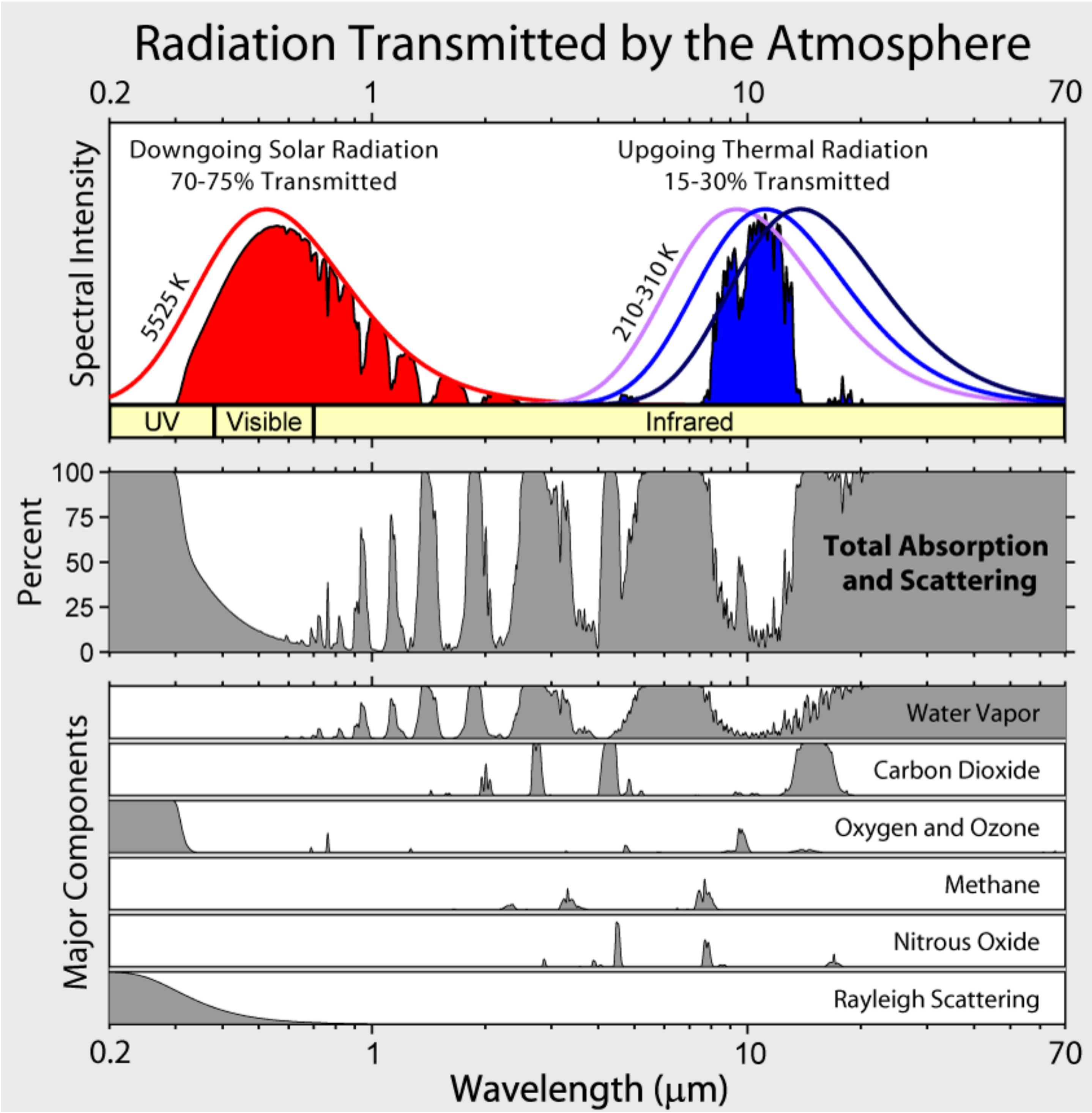
```
6.95 um
```

Stefan-Boltzman Law

Outgoing longwave radiation is absorbed by water vapor in the wavelength range of 5.2-7.2 microns, which means that less energy escapes to space. We can use the Stefan-Boltzman law to confirm that is the case.

$$E = \sigma T^4$$

where σ is the Stefan-Boltzman constant $5.67e^{-8}$

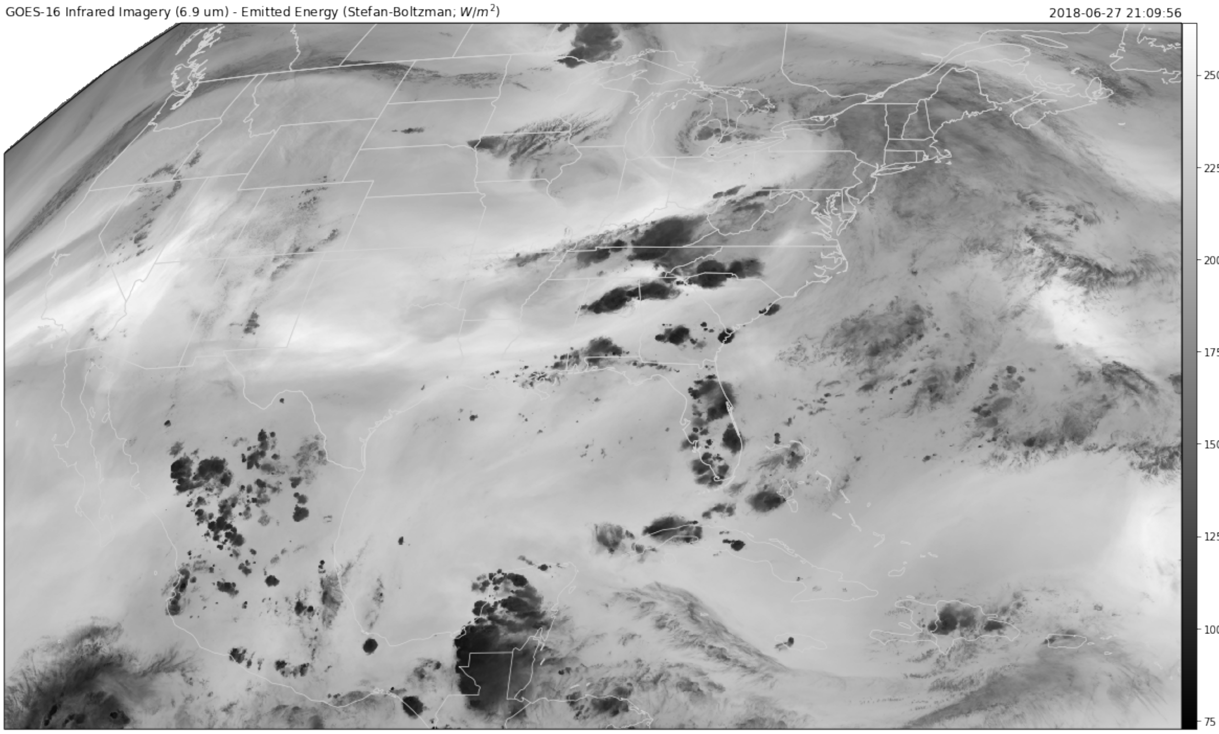


Source: https://cosmoscon.files.wordpress.com/2011/12/atmospheric_transmission.png (https://cosmoscon.files.wordpress.com/2011/12/atmospheric_transmission.png)

In [27]:
```
# Set Stefan-Boltzman Constant
sb_constant = 5.67e-8

# Calculate Emitted Energy based on Stefan-Boltzman relationship
E = sb_constant*wv_BT**4

print(E.min().data)
```

```
72.66214664547101
```

In [28]:
```
# Start figure and set up projected axis for plotting
fig = plt.figure(1, figsize=(20,10))
ax = plt.subplot(111, projection=dataproj)

# Add geopolitical lines
ax.add_feature(cfeature.COASTLINE.with_scale('50m'), edgecolor='lightg
rey', linewidths=0.75)
ax.add_feature(cfeature.BORDERS.with_scale('50m'), edgecolor='lightgre
y', linewidths=0.75)
ax.add_feature(cfeature.STATES.with_scale('50m'), edgecolor='lightgrey
', linewidths=0.75)

# Plot emitted energy based on Stefan-Boltzman
img = ax.imshow(E, extent=(x.min(), x.max(), y.min(), y.max()), origin
='upper', cmap=plt.cm.gray)
plt.colorbar(img, orientation='vertical', pad=0, aspect=50)

# Plot titles
plt.title('GOES-16 Infrared Imagery ({:0.1f} um) - Emitted Energy (Ste
fan-Boltzman; $W/m^2$)'.format(ds.band_wavelength.data[0]),
          loc='left')
plt.title('{0:%Y-%m-%d %H:%M:%S}'.format(vtime), loc='right')

plt.tight_layout()
plt.show()
# plt.savefig('WV_Stefan_Boltzman.png')
```

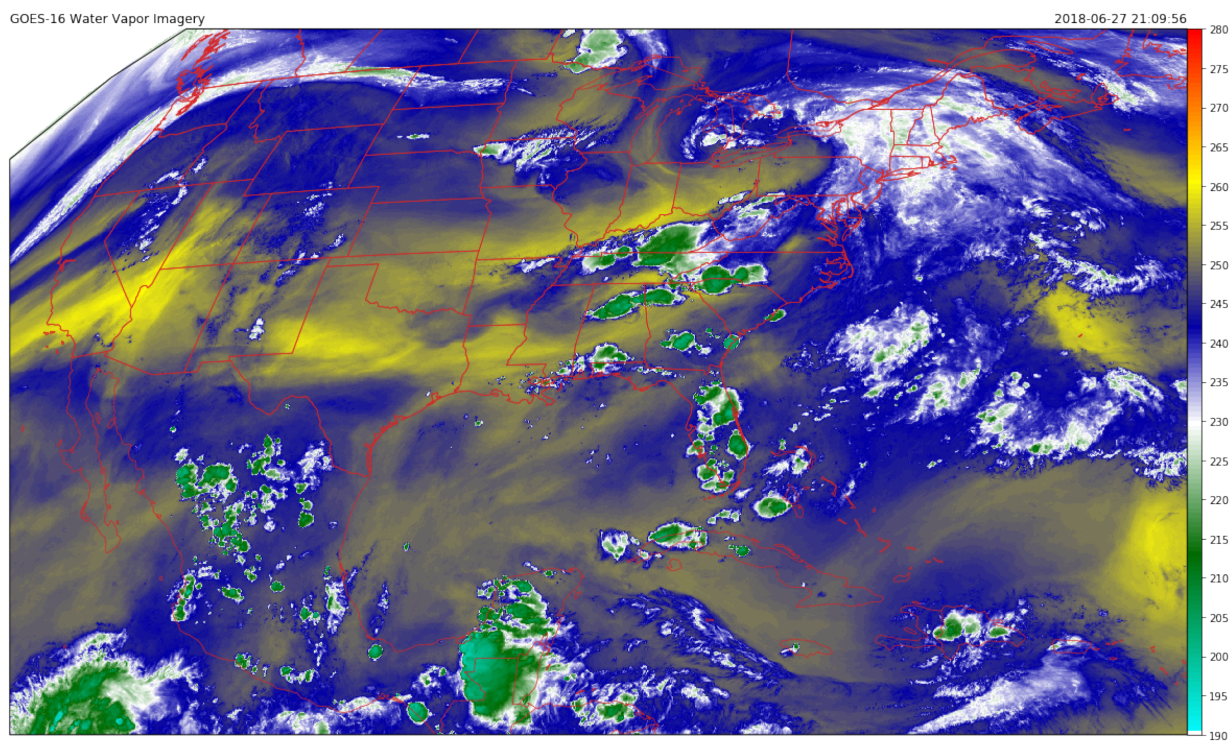


Notice that the dark areas on this plot are where there is a lot of water vapor in the atmospheric column, meaning the outgoing longwave radiation is being absorbed at this particular wavelength.

We can compare that to how we would normally view a water vapor image from a Geostationary satellite.

Plot regular Water Vapor Imagery

In [29]:
```
# Start figure and set up projected axis for plotting
fig = plt.figure(1, figsize=(20,10))
ax = plt.subplot(111, projection=dataproj)

# Add geopolitical lines
ax.add_feature(cfeature.COASTLINE.with_scale('50m'), edgecolor='tab:re
d', linewidths=0.75)
ax.add_feature(cfeature.BORDERS.with_scale('50m'), edgecolor='tab:red'
, linewidths=0.75)
ax.add_feature(cfeature.STATES.with_scale('50m'), edgecolor='tab:red',
linewidths=0.75)

# WV Colormap from MetPy
wv_norm, wv_cmap = ctables.registry.get_with_range('WVCIMSS_r', 190, 2
80)

# Plot BT WV using the colormap
img = ax.imshow(wv_BT, extent=(x.min(), x.max(), y.min(), y.max()), or
igin='upper', cmap=wv_cmap, norm=wv_norm)
plt.colorbar(img, orientation='vertical', pad=0, aspect=50, ticks=rang
e(180,290,5))

# Plot titles
plt.title('GOES-16 Water Vapor Imagery', loc='left')
plt.title('{0:%Y-%m-%d %H:%M:%S}'.format(vtime), loc='right')

plt.tight_layout()
plt.show()
# plt.savefig('WV_satellite.png')
```



Overlay Isentropic and Satellite Imagery

Another great way to use satellite data is to use it in combination with another data source, such as a model analysis. Here we will use the BEST GFS to plot visible satellite data imagery with an isentropic surface. We'll need to use MetPy to calalculate atmospheric values on an isentropic surface (e.g., 300 K), then an overlay will be relatively easy when we use Cartopy to do some transofmraiton from lat/lon coordinates to the Geostationary projection.

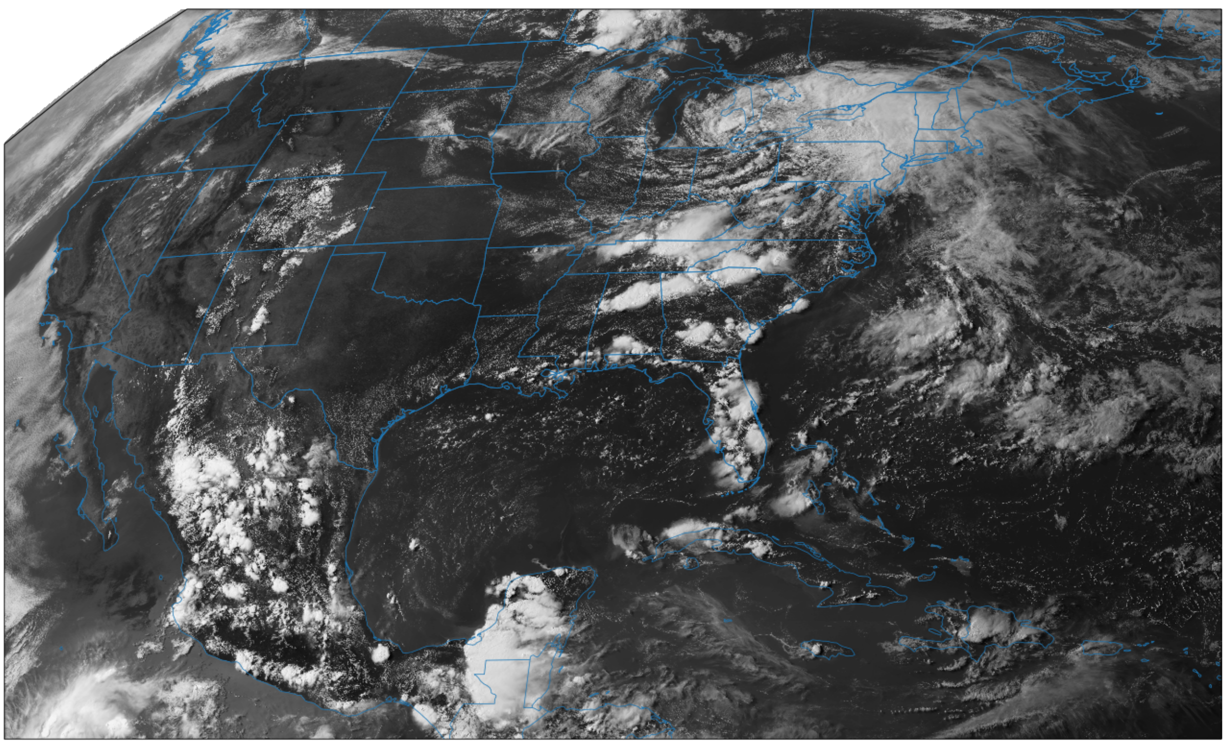
Visible Satellite Imagery

We'll continue to use the same source for the Visible statllite imagery (Channel 1), but here we won't need to convert to Brightness Temperature, we'll convert from radiance to reflectance factor (i.e., Albedo) and apply a gamma correction. This will take just a little longer than the IR data due to the finer spatial resolution of the visible data.

In [30]:
```
channel = 1
catalog_url = 'http://thredds-test.unidata.ucar.edu/thredds/catalog/sa
tellite/'\
              'goes16/GRB16/ABI/CONUS/Channel{:02d}/current/'.format(c
hannel)
current_goes16 = TDSCatalog(catalog_url+'catalog.xml')

latest_file = current_goes16.datasets[-1]
latest_file_url = latest_file.access_urls['OPENDAP']
print(latest_file_url)

ds = xr.open_dataset(latest_file_url)

# Get projection from satellite data
rad = ds.metpy.parse_cf('Rad')
dataproj = rad.metpy.cartopy_crs

# Grab coordinate data
x = rad.x
y = rad.y

# Grab time from file and convert to a nice format
vtime = datetime.strptime(ds.time_coverage_end, '%Y-%m-%dT%H:%M:%S.%fZ
')

# Get Visible data, convert to reflectance factor and apply gamma corr
ection
vis = np.sqrt(ds.Rad*ds.kappa0)
```

```
http://thredds-test.unidata.ucar.edu/thredds/dodsC/satellite/goes16/
GRB16/ABI/CONUS/Channel01/current/OR_ABI-L1b-RadC-M3C01_G16_s2018178
2127189_e20181782129563_c20181782130007.nc
```

In [31]:
```
# Start figure and set up projection on axes for plotting
fig = plt.figure(1, figsize=(18,12))
ax = plt.subplot(111, projection=dataproj)

# Plot geopolitical lines
ax.add_feature(cfeature.COASTLINE.with_scale('50m'), edgecolor='tab:bl
ue', linewidths=0.75)
ax.add_feature(cfeature.BORDERS.with_scale('50m'), edgecolor='tab:blue
', linewidths=0.75)
ax.add_feature(cfeature.STATES.with_scale('50m'), edgecolor='tab:blue'
, linewidths=0.75)

# Plot gamma correction visible reflectance values
ax.imshow(vis, extent=(x.min(), x.max(), y.min(), y.max()), origin='up
per', cmap=plt.cm.Greys_r)

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



GFS Data

The GFS provides a nice global dataset that can be used to obtain the most recent (nearset 6 hour analysis) to overlay on top of satellite imagery. We can use the same functionality from Siphon and Xarray to read the remote dataset.

In [32]:
```
catalog_url = 'https://thredds.ucar.edu/thredds/catalog/grib/NCEP/GFS/
Global_0p5deg_ana/latest.xml'
latest_gfs = TDSCatalog(catalog_url).datasets[0].access_urls['OPENDAP'
]

ds = xr.open_dataset(latest_gfs)
ds
```

Out[32]:
```
<xarray.Dataset>
Dimensions:
(altitude_above_msl: 3, height_above_ground: 2, isobaric: 31, isobar
ic1: 1, isobaric2: 21, isobaric3: 26, isobaric4: 17, isobaric5: 25,
lat: 361, lon: 720, potential_vorticity_surface: 2, pressure_differe
nce_layer: 1, pressure_difference_layer1: 1, pressure_difference_lay
er1_bounds_1: 2, pressure_difference_layer_bounds_1: 2, sigma: 1, si
gma_layer: 4, sigma_layer_bounds_1: 2, time: 1)
Coordinates:
  * lat
(lat) float32 90.0 ...
  * lon
(lon) float32 0.0 ...
    reftime
datetime64[ns] ...
  * time
(time) datetime64[ns] 2018-06-27T12:00:00 ...
  * isobaric
(isobaric) float32 100.0 ...
  * sigma
(sigma) float32 0.995 ...
  * pressure_difference_layer
(pressure_difference_layer) float32 1500.0 ...
  * isobaric1
(isobaric1) float32 50000.0 ...
  * isobaric2
(isobaric2) float32 10000.0 ...
  * pressure_difference_layer1
(pressure_difference_layer1) float32 9000.0 ...
  * altitude_above_msl
(altitude_above_msl) float32 1829.0 ...
  * height_above_ground
(height_above_ground) float32 80.0 ...
  * isobaric3
(isobaric3) float32 1000.0 ...
  * sigma_layer
(sigma_layer) float32 0.58000004 ...
  * isobaric4
(isobaric4) float32 100.0 ...
  * potential_vorticity_surface
(potential_vorticity_surface) float32 -2e-06 ...
  * isobaric5
(isobaric5) float32 1000.0 ...
Dimensions without coordinates: pressure_difference_layer1_bounds_1,
```

```
pressure_difference_layer_bounds_1, sigma_layer_bounds_1
Data variables:
    LatLon_Projection
int32 ...
    pressure_difference_layer_bounds
(pressure_difference_layer, pressure_difference_layer_bounds_1) floa
t32 ...
    pressure_difference_layer1_bounds
(pressure_difference_layer1, pressure_difference_layer1_bounds_1) fl
oat32 ...
    sigma_layer_bounds
(sigma_layer, sigma_layer_bounds_1) float32 ...
    Absolute_vorticity_isobaric
(time, isobaric3, lat, lon) float32 ...
    Cloud_mixing_ratio_isobaric
(time, isobaric2, lat, lon) float32 ...
    Cloud_water_entire_atmosphere_single_layer
(time, lat, lon) float32 ...
    Convective_available_potential_energy_pressure_difference_layer
(time, pressure_difference_layer1, lat, lon) float32 ...
    Convective_available_potential_energy_surface
(time, lat, lon) float32 ...
    Convective_inhibition_surface
(time, lat, lon) float32 ...
    Convective_inhibition_pressure_difference_layer
(time, pressure_difference_layer1, lat, lon) float32 ...
    Geopotential_height_surface
(time, lat, lon) float32 ...
    Geopotential_height_isobaric
(time, isobaric, lat, lon) float32 ...
    Geopotential_height_zeroDegC_isotherm
(time, lat, lon) float32 ...
    Geopotential_height_potential_vorticity_surface
(time, potential_vorticity_surface, lat, lon) float32 ...
    Geopotential_height_maximum_wind
(time, lat, lon) float32 ...
    Geopotential_height_tropopause
(time, lat, lon) float32 ...
    Geopotential_height_highest_tropospheric_freezing
(time, lat, lon) float32 ...
    ICAO_Standard_Atmosphere_Reference_Height_maximum_wind
(time, lat, lon) float32 ...
    ICAO_Standard_Atmosphere_Reference_Height_tropopause
(time, lat, lon) float32 ...
    Potential_temperature_sigma
(time, sigma, lat, lon) float32 ...
    Precipitable_water_entire_atmosphere_single_layer
(time, lat, lon) float32 ...
    Pressure_surface
(time, lat, lon) float32 ...
    Pressure_potential_vorticity_surface
(time, potential_vorticity_surface, lat, lon) float32 ...
    Pressure_maximum_wind
```

```
(time, lat, lon) float32 ...
    Pressure_tropopause
(time, lat, lon) float32 ...
    Pressure_reduced_to_MSL_msl
(time, lat, lon) float32 ...
    Relative_humidity_pressure_difference_layer
(time, pressure_difference_layer, lat, lon) float32 ...
    Relative_humidity_sigma_layer
(time, sigma_layer, lat, lon) float32 ...
    Relative_humidity_isobaric
(time, isobaric5, lat, lon) float32 ...
    Relative_humidity_zeroDegC_isotherm
(time, lat, lon) float32 ...
    Relative_humidity_entire_atmosphere_single_layer
(time, lat, lon) float32 ...
    Relative_humidity_highest_tropospheric_freezing
(time, lat, lon) float32 ...
    Relative_humidity_sigma
(time, sigma, lat, lon) float32 ...
    Specific_humidity_pressure_difference_layer
(time, pressure_difference_layer, lat, lon) float32 ...
    Temperature_pressure_difference_layer
(time, pressure_difference_layer, lat, lon) float32 ...
    Temperature_isobaric
(time, isobaric, lat, lon) float32 ...
    Temperature_potential_vorticity_surface
(time, potential_vorticity_surface, lat, lon) float32 ...
    Temperature_altitude_above_msl
(time, altitude_above_msl, lat, lon) float32 ...
    Temperature_maximum_wind
(time, lat, lon) float32 ...
    Temperature_tropopause
(time, lat, lon) float32 ...
    Temperature_height_above_ground
(time, height_above_ground, lat, lon) float32 ...
    Temperature_sigma
(time, sigma, lat, lon) float32 ...
    Total_ozone_entire_atmosphere_single_layer
(time, lat, lon) float32 ...
    Ozone_Mixing_Ratio_isobaric
(time, isobaric4, lat, lon) float32 ...
    Vertical_Speed_Shear_potential_vorticity_surface
(time, potential_vorticity_surface, lat, lon) float32 ...
    Vertical_Speed_Shear_tropopause
(time, lat, lon) float32 ...
    MSLP_Eta_model_reduction_msl
(time, lat, lon) float32 ...
    5-Wave_Geopotential_Height_isobaric
(time, isobaric1, lat, lon) float32 ...
    Surface_Lifted_Index_surface
(time, lat, lon) float32 ...
    Best_4_layer_Lifted_Index_surface
(time, lat, lon) float32 ...
```

```
    Vertical_velocity_pressure_isobaric
(time, isobaric2, lat, lon) float32 ...
    Vertical_velocity_pressure_sigma
(time, sigma, lat, lon) float32 ...
    u-component_of_wind_pressure_difference_layer
(time, pressure_difference_layer, lat, lon) float32 ...
    u-component_of_wind_isobaric
(time, isobaric, lat, lon) float32 ...
    u-component_of_wind_potential_vorticity_surface
(time, potential_vorticity_surface, lat, lon) float32 ...
    u-component_of_wind_altitude_above_msl
(time, altitude_above_msl, lat, lon) float32 ...
    u-component_of_wind_maximum_wind
(time, lat, lon) float32 ...
    u-component_of_wind_height_above_ground
(time, height_above_ground, lat, lon) float32 ...
    u-component_of_wind_tropopause
(time, lat, lon) float32 ...
    u-component_of_wind_sigma
(time, sigma, lat, lon) float32 ...
    v-component_of_wind_pressure_difference_layer
(time, pressure_difference_layer, lat, lon) float32 ...
    v-component_of_wind_isobaric
(time, isobaric, lat, lon) float32 ...
    v-component_of_wind_potential_vorticity_surface
(time, potential_vorticity_surface, lat, lon) float32 ...
    v-component_of_wind_altitude_above_msl
(time, altitude_above_msl, lat, lon) float32 ...
    v-component_of_wind_maximum_wind
(time, lat, lon) float32 ...
    v-component_of_wind_height_above_ground
(time, height_above_ground, lat, lon) float32 ...
    v-component_of_wind_tropopause
(time, lat, lon) float32 ...
    v-component_of_wind_sigma
(time, sigma, lat, lon) float32 ...
Attributes:
    Originating_or_generating_Center:
...
    Originating_or_generating_Subcenter:
...
    GRIB_table_version:
...
    Type_of_generating_process:
...

Analysis_or_forecast_generating_process_identifier_defined_by_origin
ating...
    file_format:
...
    Conventions:
...
    history:
```

```
...
    featureType:
...
    _CoordSysBuilder:
...
```

Extracting the necessary variables is completed below. Since we do not desire to have the full global data and only need the values that surround the CONUS, we'll set up a slice variable so that we only download the data that we desire.

In [33]:

```
# Get the coordinate data
lats = ds.lat.data
lons = ds.lon.data

# Set subset slice for the geographic extent of data to limit download
lon_slice = slice(400,601)
lat_slice = slice(10,160)

# Subset lat/lon values
slons = lons[lon_slice]
slats = lats[lat_slice]
print(360-slons)
print(slats)

# Get the values needed to compute isentropic coordinates and subset o
n read
pres = ds[ds.Temperature_isobaric.dims[1]].data[:] * units('Pa')
tmpk = gaussian_filter(ds['Temperature_isobaric'].data[0,:,lat_slice,l
on_slice], sigma=1.0) * units.K
uwnd = gaussian_filter(ds['u-component_of_wind_isobaric'].data[0,:,lat
_slice,lon_slice], sigma=1.0) * units('m/s')
vwnd = gaussian_filter(ds['v-component_of_wind_isobaric'].data[0,:,lat
_slice,lon_slice], sigma=1.0) * units('m/s')

# Calculate the Potential Temperature from TMPK and PRES using MetPy
thta = mpcalc.potential_temperature(pres[:, None, None], tmpk)

# Get time value and put into a better format
vtime = datetime.strptime(str(ds.Geopotential_height_isobaric.time.dat
a[0].astype('datetime64[ms]')),
                          '%Y-%m-%dT%H:%M:%S.%f')
```

```
[160.  159.5 159.  158.5 158.  157.5 157.  156.5 156.  155.5 155.  1
54.5
 154.  153.5 153.  152.5 152.  151.5 151.  150.5 150.  149.5 149.  1
48.5
 148.  147.5 147.  146.5 146.  145.5 145.  144.5 144.  143.5 143.  1
42.5
 142.  141.5 141.  140.5 140.  139.5 139.  138.5 138.  137.5 137.  1
36.5
 136.  135.5 135.  134.5 134.  133.5 133.  132.5 132.  131.5 131.  1
30.5
```

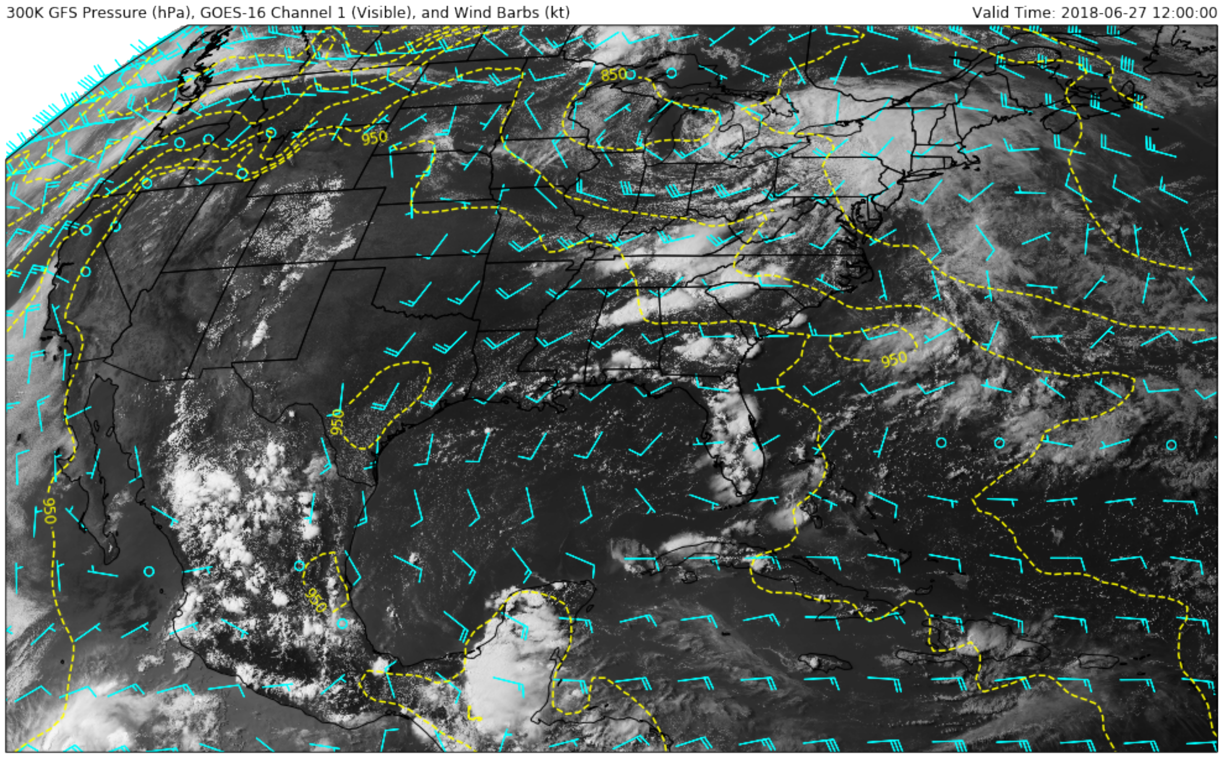
```
 130.  129.5 129.  128.5 128.  127.5 127.  126.5 126.  125.5 125.  1
24.5
 124.  123.5 123.  122.5 122.  121.5 121.  120.5 120.  119.5 119.  1
18.5
 118.  117.5 117.  116.5 116.  115.5 115.  114.5 114.  113.5 113.  1
12.5
 112.  111.5 111.  110.5 110.  109.5 109.  108.5 108.  107.5 107.  1
06.5
 106.  105.5 105.  104.5 104.  103.5 103.  102.5 102.  101.5 101.  1
00.5
 100.   99.5  99.   98.5  98.   97.5  97.   96.5  96.   95.5  95.
94.5
  94.   93.5  93.   92.5  92.   91.5  91.   90.5  90.   89.5  89.
88.5
  88.   87.5  87.   86.5  86.   85.5  85.   84.5  84.   83.5  83.
82.5
  82.   81.5  81.   80.5  80.   79.5  79.   78.5  78.   77.5  77.
76.5
  76.   75.5  75.   74.5  74.   73.5  73.   72.5  72.   71.5  71.
70.5
  70.   69.5  69.   68.5  68.   67.5  67.   66.5  66.   65.5  65.
64.5
  64.   63.5  63.   62.5  62.   61.5  61.   60.5  60. ]
[85.  84.5 84.  83.5 83.  82.5 82.  81.5 81.  80.5 80.  79.5 79.  78
.5
 78.  77.5 77.  76.5 76.  75.5 75.  74.5 74.  73.5 73.  72.5 72.  71
.5
 71.  70.5 70.  69.5 69.  68.5 68.  67.5 67.  66.5 66.  65.5 65.  64
.5
 64.  63.5 63.  62.5 62.  61.5 61.  60.5 60.  59.5 59.  58.5 58.  57
.5
 57.  56.5 56.  55.5 55.  54.5 54.  53.5 53.  52.5 52.  51.5 51.  50
.5
 50.  49.5 49.  48.5 48.  47.5 47.  46.5 46.  45.5 45.  44.5 44.  43
.5
 43.  42.5 42.  41.5 41.  40.5 40.  39.5 39.  38.5 38.  37.5 37.  36
.5
 36.  35.5 35.  34.5 34.  33.5 33.  32.5 32.  31.5 31.  30.5 30.  29
.5
 29.  28.5 28.  27.5 27.  26.5 26.  25.5 25.  24.5 24.  23.5 23.  22
.5
 22.  21.5 21.  20.5 20.  19.5 19.  18.5 18.  17.5 17.  16.5 16.  15
.5
 15.  14.5 14.  13.5 13.  12.5 12.  11.5 11.  10.5]
```

In [34]:
```
# Set levels to compute isentropic surfaces
isentlevs = list(range(280,331,2)) * units.K
print(isentlevs)

# Use MetPy functionality to computer isentropic levels
isent_anal = mpcalc.isentropic_interpolation(isentlevs,
                                             pres,
                                             tmpk,
                                             uwnd,
                                             vwnd)

isentprs, isentu, isentv = isent_anal

# Convert U and V to units of knots
isentu.ito('kt')
isentv.ito('kt')
```

```
[280 282 284 286 288 290 292 294 296 298 300 302 304 306 308 310 312
314 316 318 320 322 324 326 328 330] kelvin
```

In [37]:

```
# Set which isentropic level to plot from the above list
ilev = list(isentlevs.m).index(300)

# Set GFS data coordinate reference system,
# need to know this for transformation purposes
datacrs = ccrs.PlateCarree()

# Start figure and set up axes for plotting on the Geostationary proje
ction
fig = plt.figure(1, figsize=(14,12))
ax = plt.subplot(111, projection=dataproj)
ax.set_extent([x.min(), x.max(), y.min(), y.max()], dataproj)

# Add geopolitical lines for reference
ax.add_feature(cfeature.COASTLINE.with_scale('50m'))
ax.add_feature(cfeature.STATES.with_scale('50m'))

# Plot the visible satellite imagery
ax.imshow(vis, extent=(x.min(), x.max(), y.min(), y.max()), origin='up
per', cmap=plt.cm.Greys_r)

# Plot the pressure of the isentropic surface
clevs_pres = np.arange(0, 1100, 50)
cs1 = ax.contour(slons, slats, isentprs[ilev], clevs_pres, colors='yel
low',
                 linestyles='dashed', transform=datacrs)
plt.clabel(cs1, fmt='%d', fontsize='large')

# Plot the every fifth wind barb in knots on the isentropic surface
ax.barbs(slons[::5], slats[::5], isentu[ilev,::5,::5].m, isentv[ilev,:
:5,::5].m, pivot='middle',
         color='cyan', transform=datacrs)

# Plot some titles
plt.title('{}K GFS Pressure (hPa), GOES-16 Channel 1 (Visible), and Wi
nd Barbs (kt)'.format(isentlevs[ilev].m), loc='left')
plt.title('Valid Time: {}'.format(vtime), loc='right')

plt.tight_layout()
plt.show()
# plt.savefig('overlay_isent_visible_satellite.png')
```



Create your own Overlay Map with Satellite Imagery

In the cell below, create your own map that uses Satellite Imagery (any channel) with some GFS data (e.g., 300-hPa wind speed). Use code from various cells above to help - don't feel like you need to start over at the beginning.