SEST-6577

Geographic Information Systems for Security Studies

Lab 10 (+ Walk Through 2)

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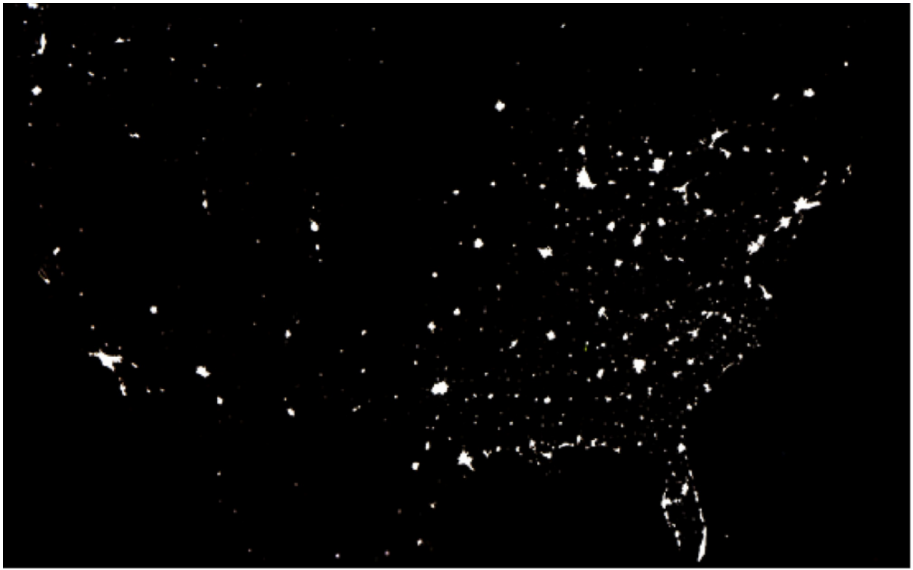


Figure 1: US nighttime lights data, 1994 (DMSP, composite from 29 orbits)

Figure 2: US nighttime lights data, 1995 (DMSP, composite from 236 orbits)

Overview

Nearly all production and consumption after sundown requires (and emits) light

1. Household appliances
2. Office equipment
3. Transportation
4. Sporting events
5. Street markets
6. Restaurants
7. Factory operations
8. Roadworks
9. Construction
10. Studying and homework

Remote sensing of nighttime lights allows us to observe human activity from space

Figure 3: Emitting light

Applications of Luminosity Data

Economic activity, income, growth

1. Persistent economic data challenges
   a) in most countries, GDP stats not available at the sub-national level
   b) national accounts & surveys are sometimes unreliable
   c) some locations too costly, dangerous for field & survey work
2. Luminosity has some advantages
   a) more spatially fine-grained than standard income accounts
   b) regular, frequent time intervals
   c) recorded homogeneously across national borders
   d) available in hard-to-reach areas
3. Not a bad proxy measure
   a) nighttime lights found to be positively correlated with GDP, GRP at multiple spatial scales

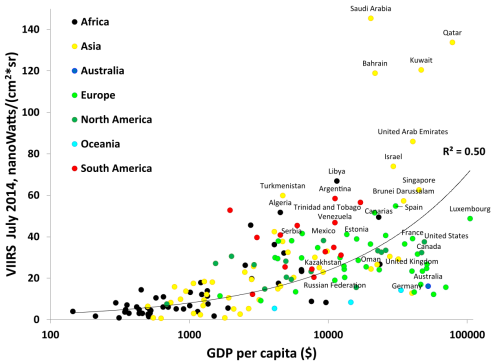


Figure 4: Luminosity and GDP/capita

Urbanization

1. First applications of luminosity data:
   a) delineate urban extents
   b) track electrification, street lighting
2. Luminosity captures things surveys, census can't
   a) growth of informal, illegal settlements
   b) communities with inadequate infrastructure
   c) emergence of new local urban centers
   d) characterize urban growth over time

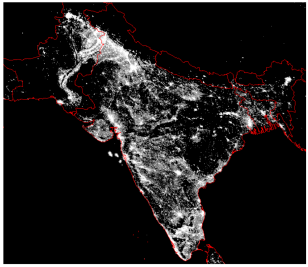


Figure 5: South Asia, 1994

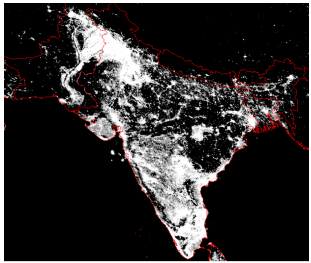


Figure 6: South Asia, 2010

Emergency management, recovery

1. Luminosity captures impact of emergencies
   a) disasters cause damage to power lines, disrupt electric utility services
   b) luminosity data can detect power outages, also fires, flares, other sudden increases in light
2. But not everything is visible from space
   a) cloud cover prevents real-time storm damage tracking and assessment
   b) luminosity better suited for monitoring non-meteorological events (e.g. earthquakes, accidents), long-term tracking of recovery efforts

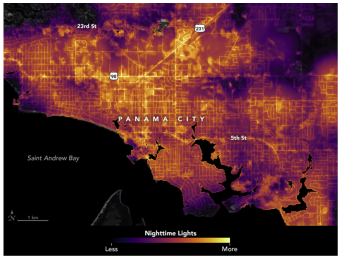


Figure 7: Before landfall

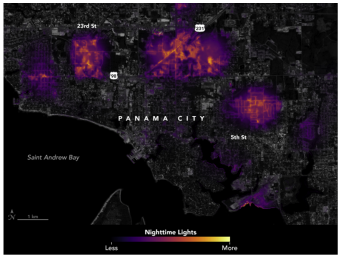


Figure 8: After landfall

Armed conflict

1. War creates darkness
   a) direct: power grid damage
   b) indirect: population displacement, curfews, intentional dimming to avoid detection
2. Danger lurks in darkness
   a) power disruptions constrain economic development, harm public health
   b) fall in light emissions is warning that civilians, hospitals lack stable electricity supply
3. Data can illuminate the physical impact of war
   a) luminosity data allow us to track impact of war on public services, utilities, urban economic activity
   b) this analysis can be near-real time

Figure 9: October 2021

Figure 10: October 2022

Technological change

1. Outdoor lighting technology evolves
   a) wood, dung $\rightarrow$ oil
   b) oil $\rightarrow$ gas
   c) gas $\rightarrow$ incandescent
   d) incandescent $\rightarrow$ LED, HID
2. Ecological and social impacts
   a) each change increases emissions, changes spectrum of visible light
   b) spectral change affects perception of artificial lights by animals
   c) LEDs are more easily dimmed, lighting becomes more temporally dynamic
3. This is also a measurement challenge
   a) change in spectrum can be mistaken for change in light intensity

Figure 11: Alles ist erleuchtet

Varieties of Luminosity Data

Space-based sensors for night-lights (partial list)

Sensor	**Spatial resolution**	**Temporal resolution**	**Availability**	**Free?**	**On-board calibration**
DMSP/OLS	3km	Monthly	1992-2013	✓	
Landsat 8	30m	Irregular	2013-	✓	
VIIRS/DNB	740m	Daily	2012-	✓	✓
EROS-B	<1m	Daily	2013-		✓
Jilin-1	<1m	Daily	2017-		✓

Defense Meteorological Satellite Program (DMSP)

1. History
   a) 1960s: starts as DoD's meteorological program
      - goal: prevent spy satellites from wasting resources when targets are cloud-covered
   b) 1992: images available in digital form
   c) 1994: NOAA launches global nightlights program
2. Limitations
   a) data from different years not directly comparable due to different atmospheric conditions, sensor settings and degradation
   b) temporal analysis requires intercalibration
      - use invariant pixels as training data
      - calibrate raw images to same radiometric level as base image
   c) images blurred due to scattering, saturation

Link: `eogdata.mines.edu/products/dmsp/`

Figure 12: DMSP-5D2

Visible Infrared Imaging Radiometer Suite (VIIRS)

1. History
   a) 2011: sensor launches onboard Suomi NPP satellite
   b) quickly becomes industry standard
   c) main product: Day and Night Band (DNB)
2. Advantages over DMSP
   - ☒ on-board calibration enables temporal comparisons
   - ☒ higher spatial precision
   - ☒ sensitive to lower light levels
   - ☒ no saturation in urban areas
   - ☒ cloud-free, stray light corrections
   - ☒ free daily images + monthly, annual composites

Link: `eogdata.mines.edu/products/vnl/`

Figure 13: Suomi NPP

Not all orbits make good data

Requirements for nighttime light observation:

1. Center half of orbital swath
   - (i.e. area being imaged by satellite)
2. No sunlight
   - (no high-latitude zones in summer)
3. No moonlight
   - (within-month variation)
4. No solar glare
   - (e.g. from solar panels)
5. Cloud-free
   - (sorry, Seattle. hello, Dubai)
6. No auroral emissions
   - (why Santa has evaded detection)
7. No forest fires
   - (no intense sources of natural light)

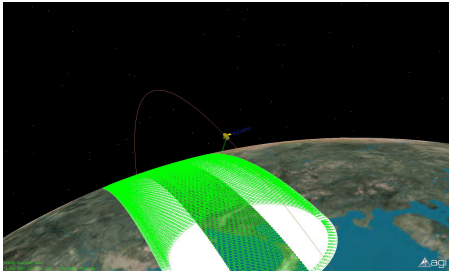


Figure 14: Swath path

Vignettes

Overview of lab exercise

1. Vignettes on differences in luminosity across borders
    a) Korean peninsula
    b) Island of Hispaniola
2. Vignette on differences in luminosity over time
    a) Syrian Civil War

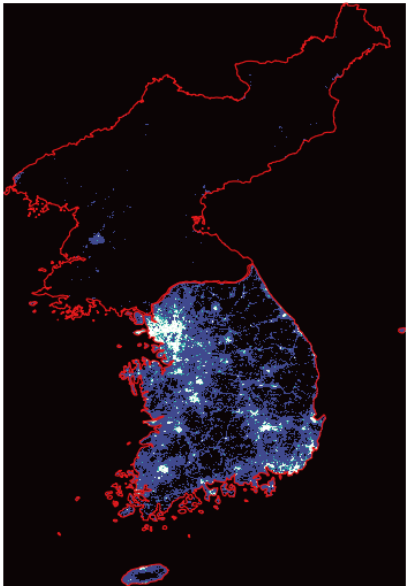


Figure 15: Vignette 1 / Korea

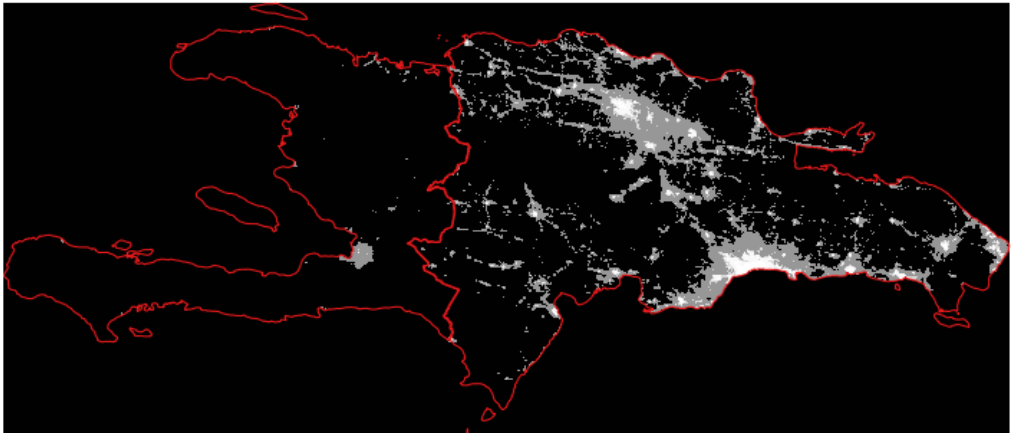


Figure 16: Vignette 2 / Hispaniola

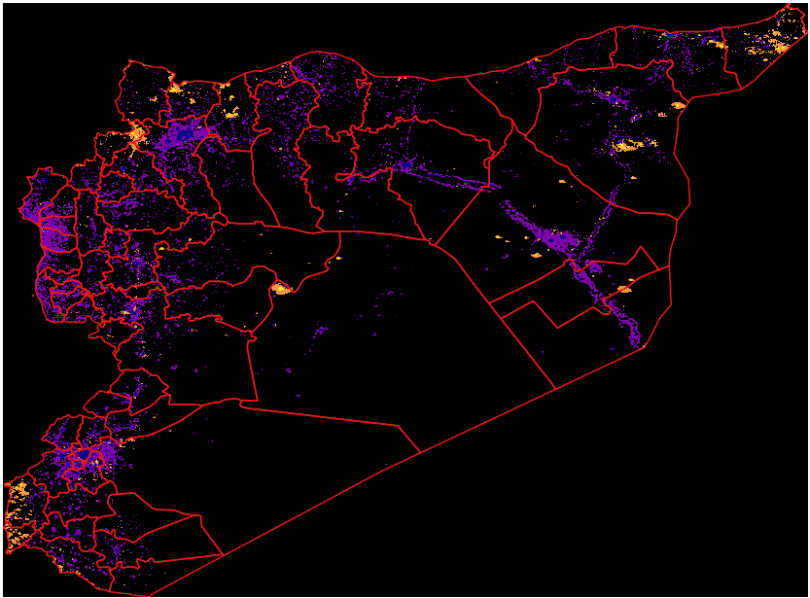
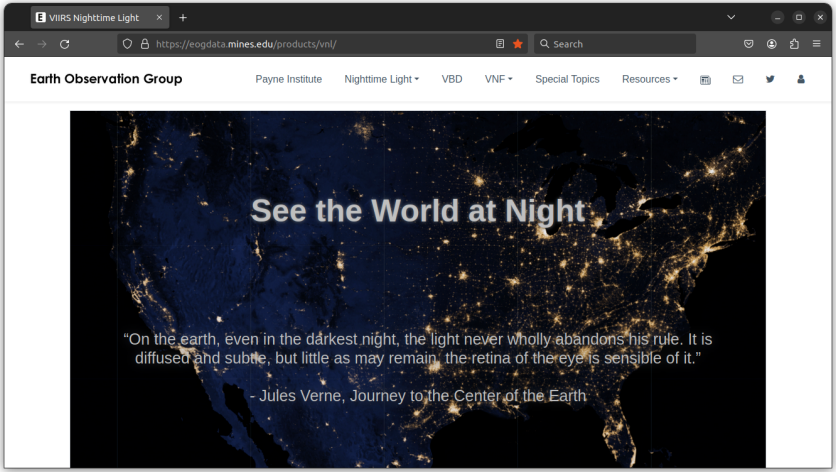
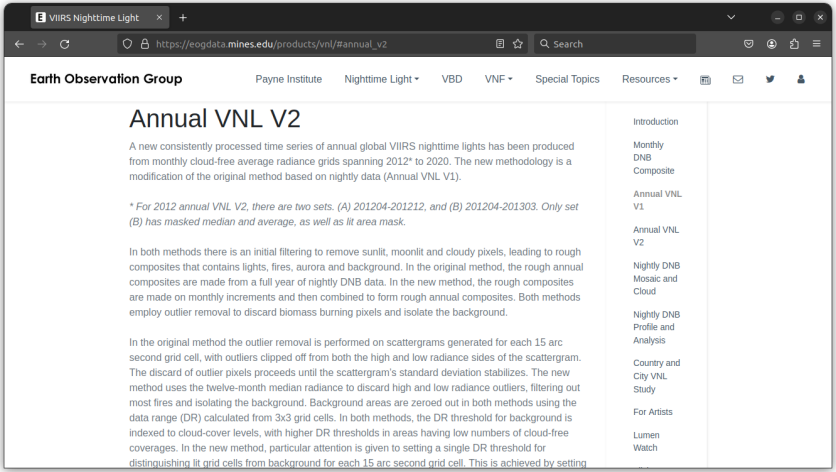


Figure 17: Vignette 3 / Syria

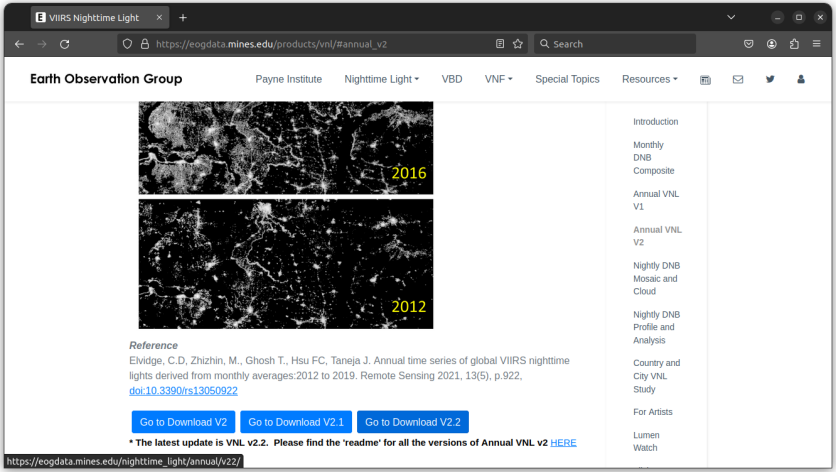
We can obtain **VIIRS nighttime luminosity (vnl) data** from `eogdata.mines.edu/products/vnl/`



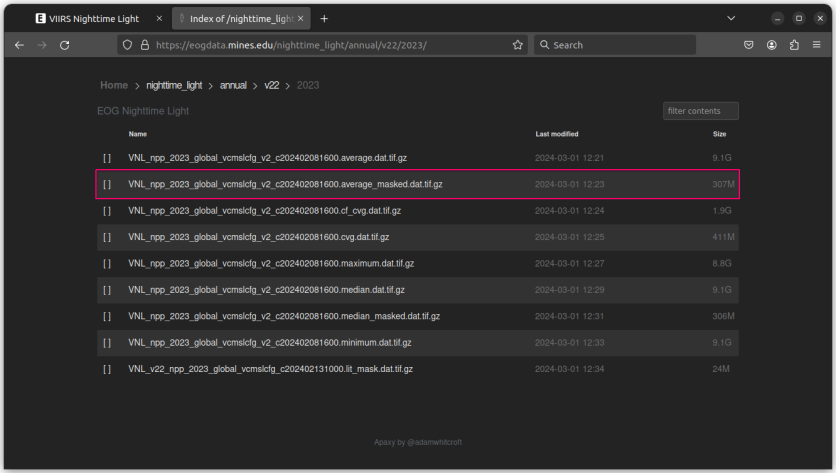
Scroll down to the “Annual VNL V2” section



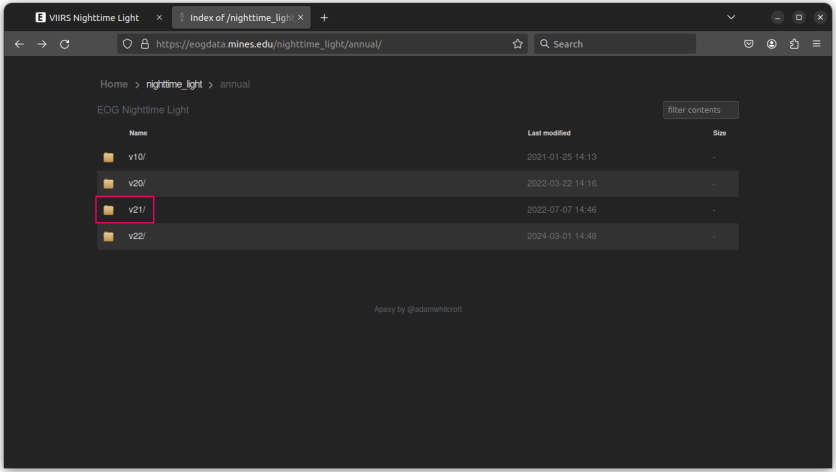
Click on the “Go to Download V2.2” button for the most recent year’s data



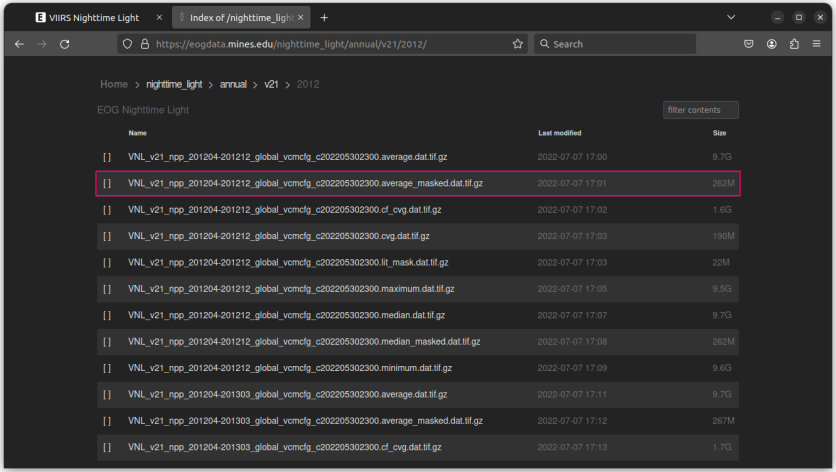
Download the file ending with `.average_masked.dat.tif.gz`



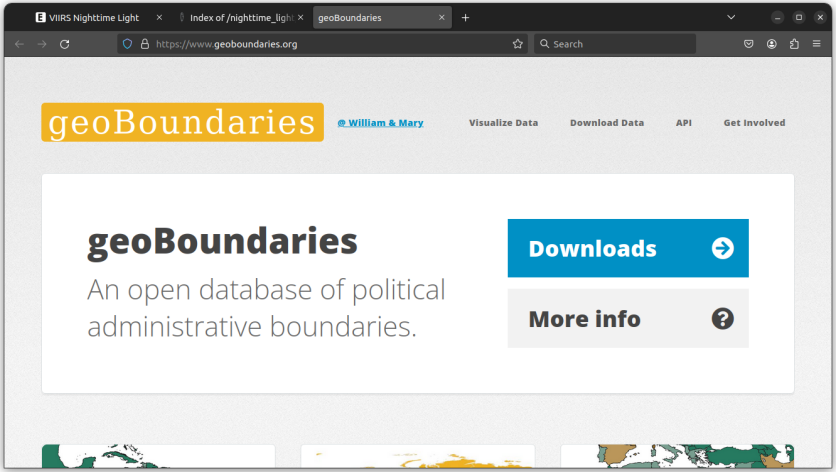
Let's also grab data for the "oldest" year available.
Navigate to the parent directory and find the annual data in the `v21/` folder



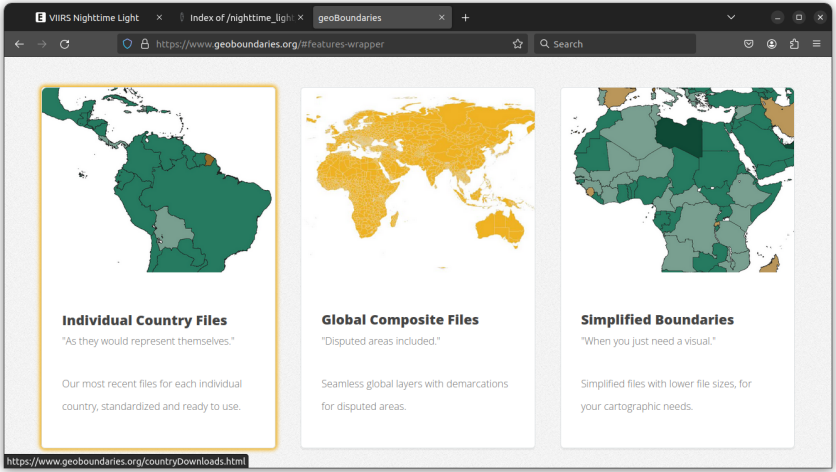
There are two files ending in `.average_masked.dat.tif.gz` here.
Download the first one (April through December)



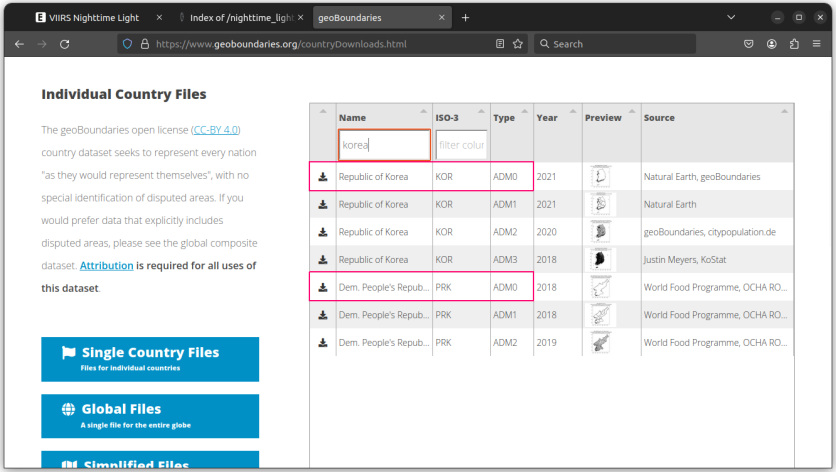
Let's get some **country and administrative boundaries** from `geoboundaries.org`



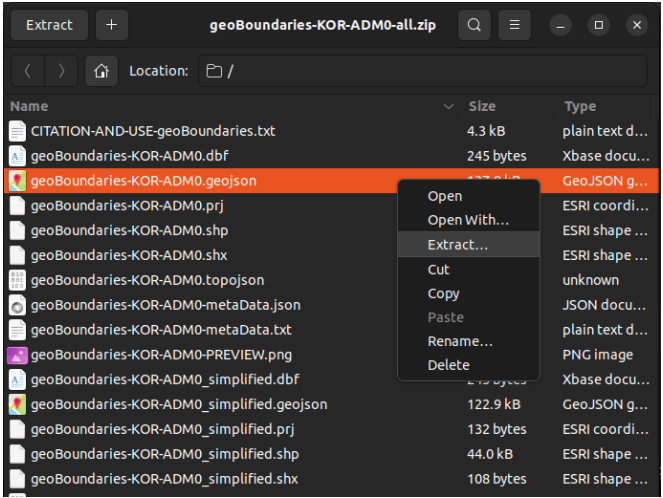
Navigate to the “Individual Country Files” section



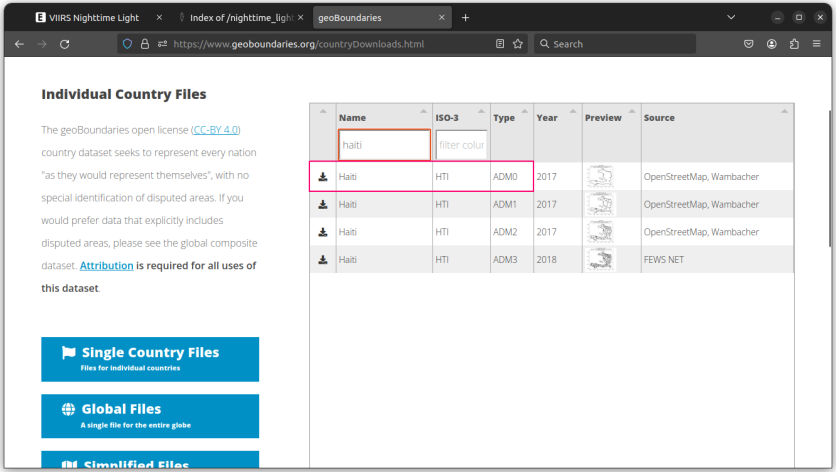
Download country-level (`ADM0`) data for South and North Korea (`KOR`, `PRK`)



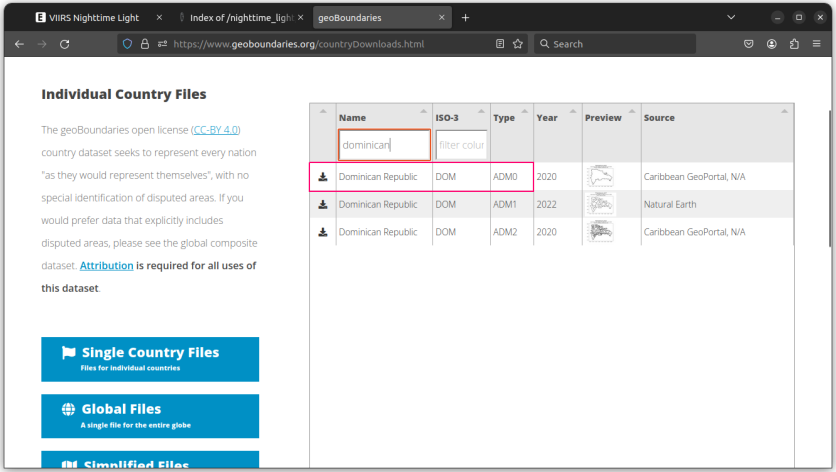
When you unzip, the only file you need to extract is one ending in `ADM0.geojson`



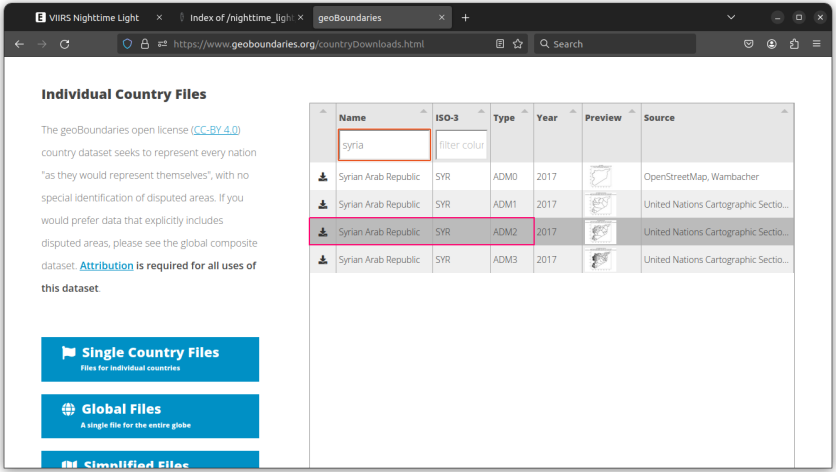
Repeat this process for country-level (`ADM0`) data for Haiti (`HTI`)...



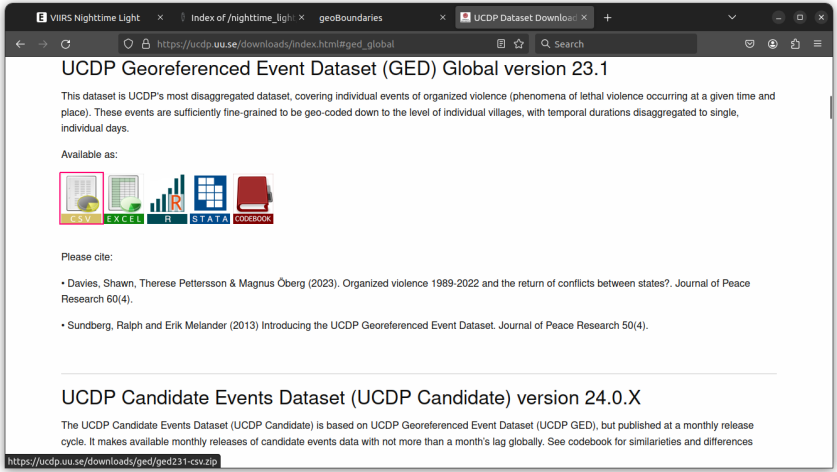
and country-level (`ADM0`) data for Dominican Republic (`DOM`)...



and district-level (ADM2) data for Syria (SYR)



We will be using the same event **data on violence** as in the last lab: UCDP GED version 23.1, in csv format



Here is the full list of data sources and links:

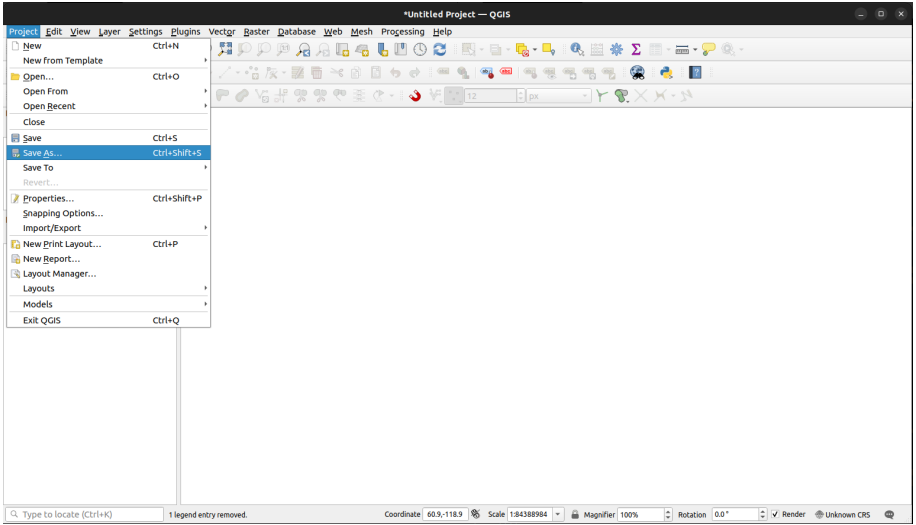
Category	Type	Format	Data source
Nighttime luminosity	Raster	`.tif`	VIIRS
Administrative units	Vector (polygons)	`.geojson`	geoBoundaries
Political violence	Table (non-geo)	`.csv`	UCDP GED

These are all in the `Lab10WT02.zip` file posted on Canvas.

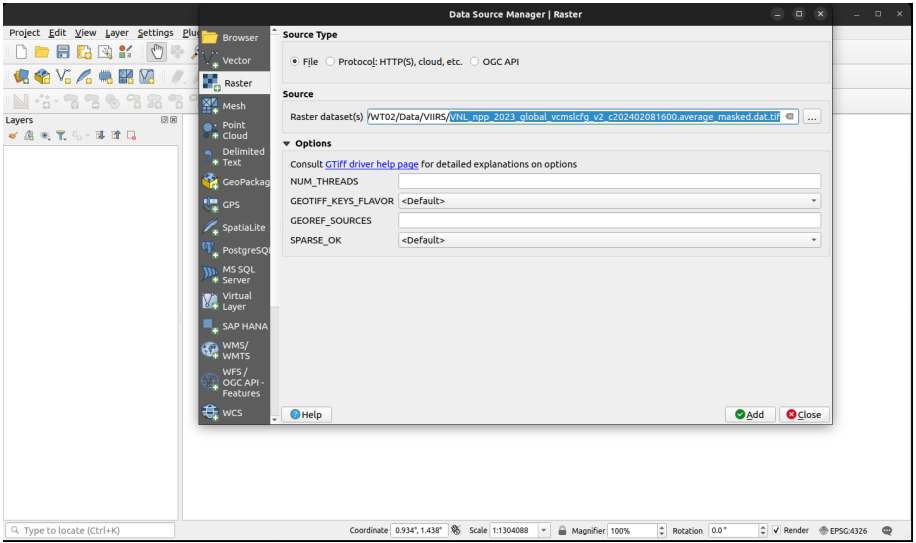
Differences in Luminosity Across Countries (Korea and Hispaniola)

Always save your progress!

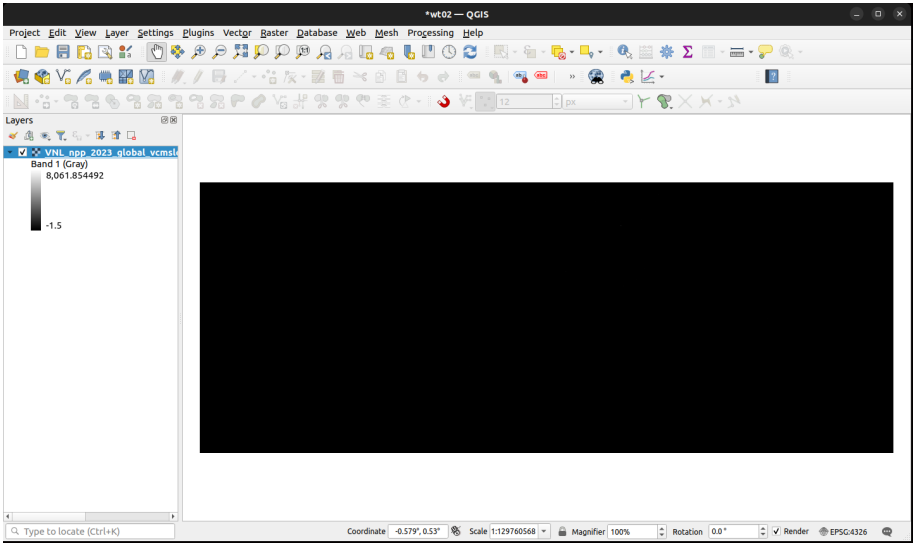
Go to `Project` → `Save As...`



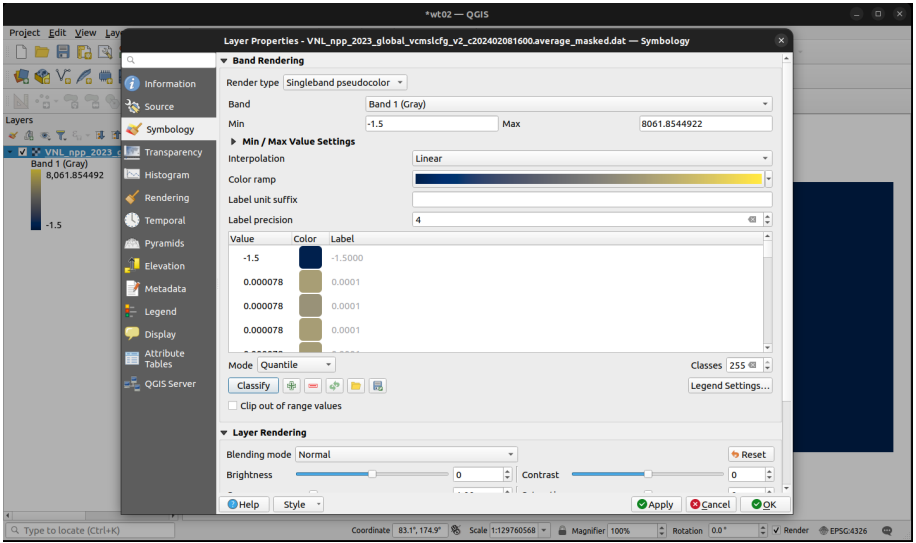
Vignette 1. Load the *2023 VNL data* (`Layer` → `Add Layer` → `Add Raster Layer`). `VNL_npp_2023_....tif` file in `Data/VIIRS` folder



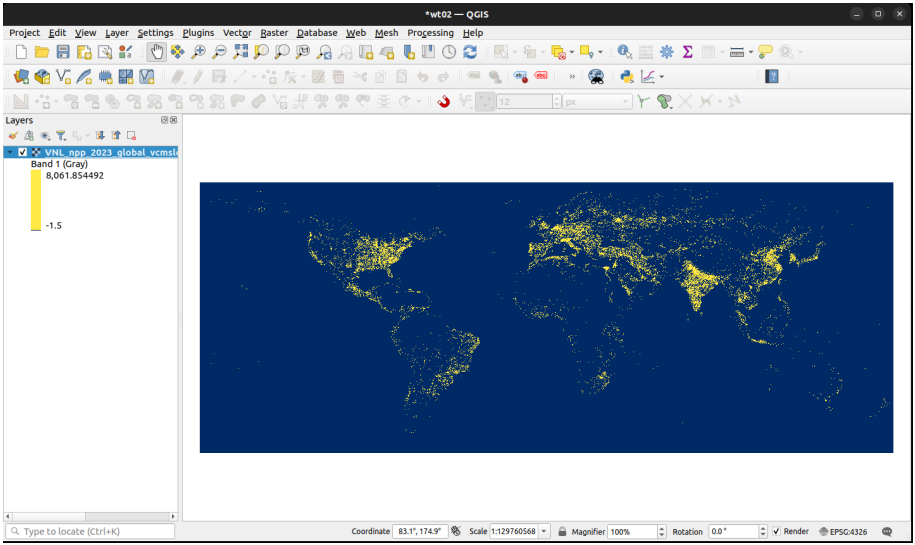
The default color scheme is too dark. Let's see if we can add some contrast



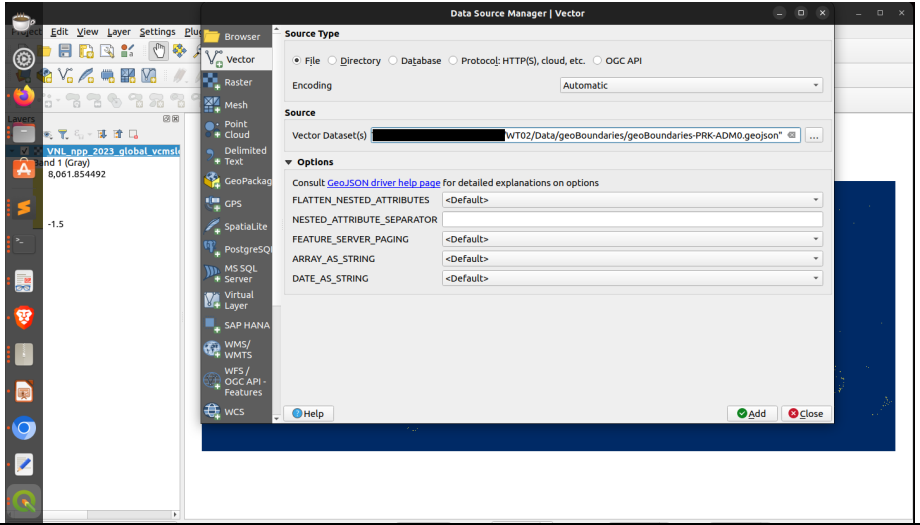
In the layer's `Properties`, change `Render type` to `Singleband pseudocolor` and set `Mode` to `Quantile`. Click `Classify` and `OK`



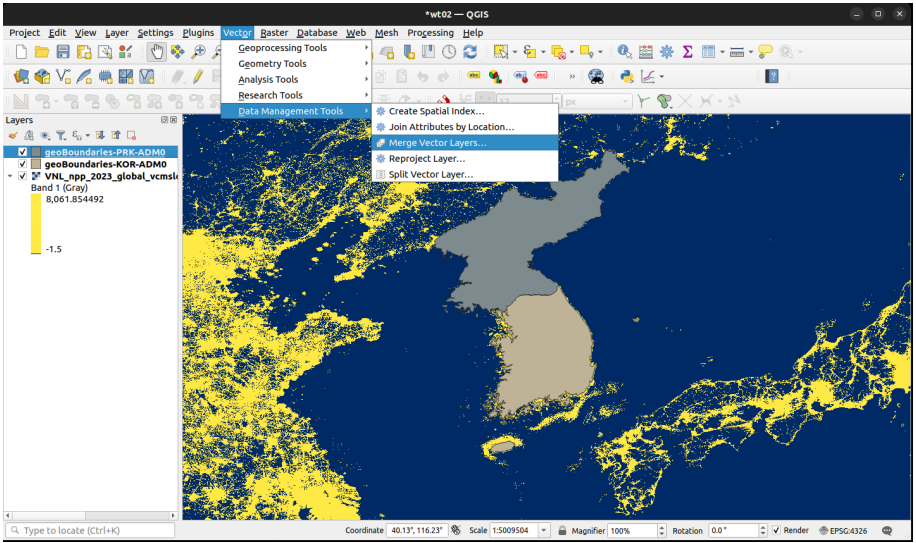
This is probably too much contrast, but at least we can see the distribution



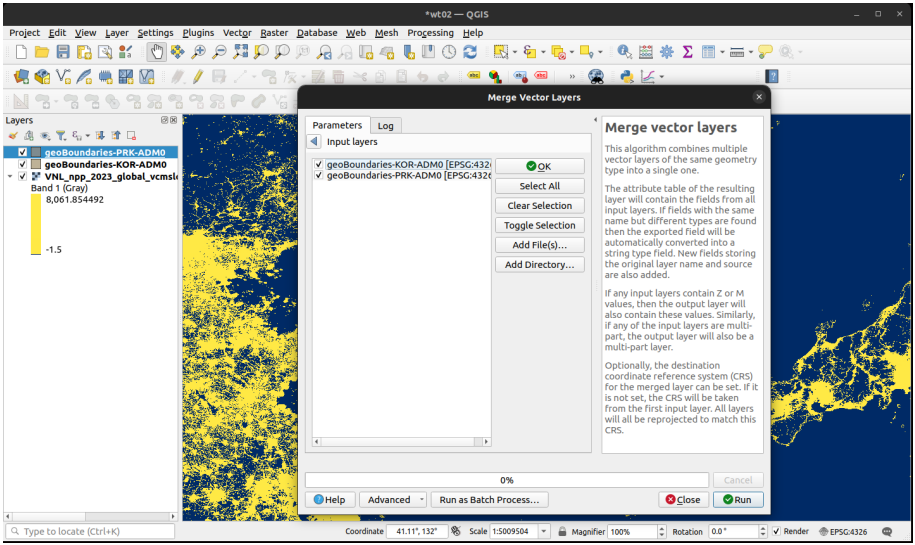
Load *country boundaries* for the two Koreas (`Layer` → `Add Layer` → `Add Vector Layer`). 2 files: `geoBoundaries-PRK-ADM0.geojson` and `geoBoundaries-KOR-ADM0.geojson` from `Data/geoBoundaries` folder.



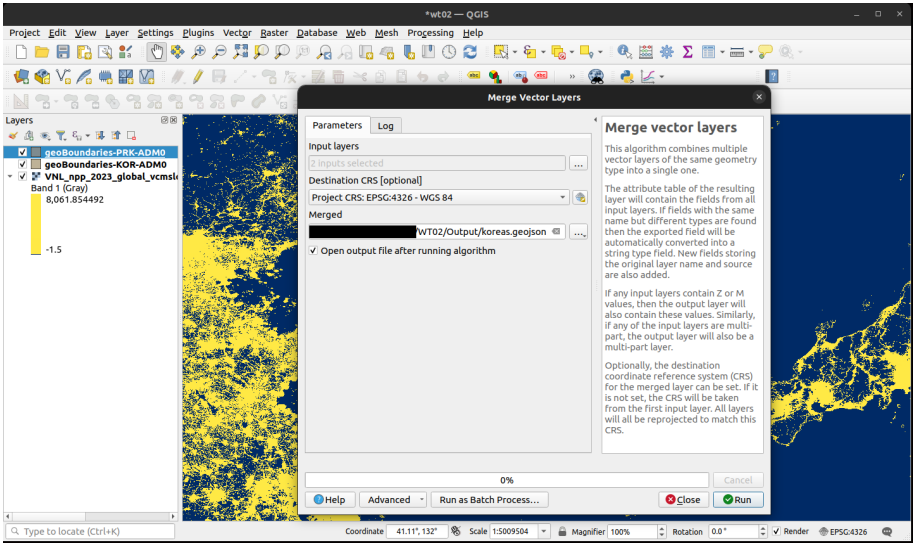
Let's merge the two Koreas into a single layer (`Vector` menu → `Data Management Tools` → `Merge Vector Layers...`)



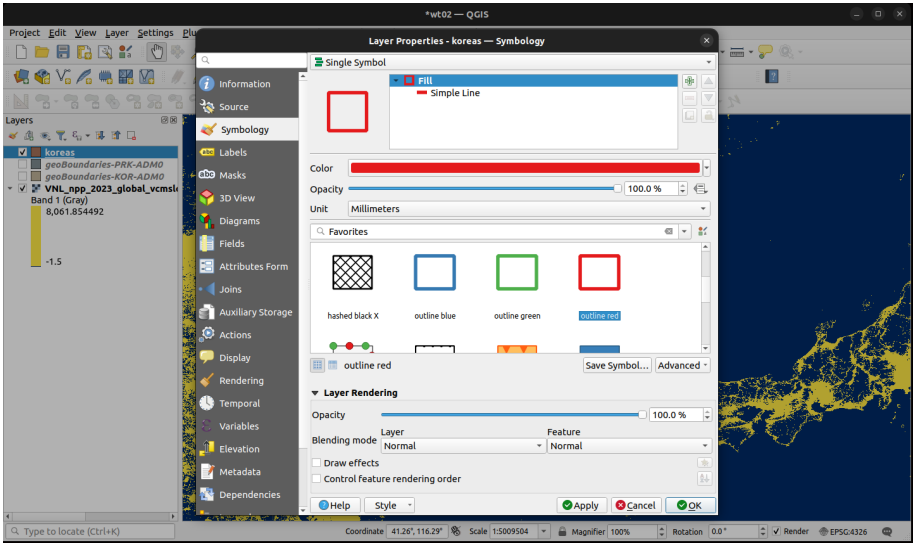
Input layers = geoBoundaries-KOR-ADM0 and geoBoundaries-PRK-ADM0



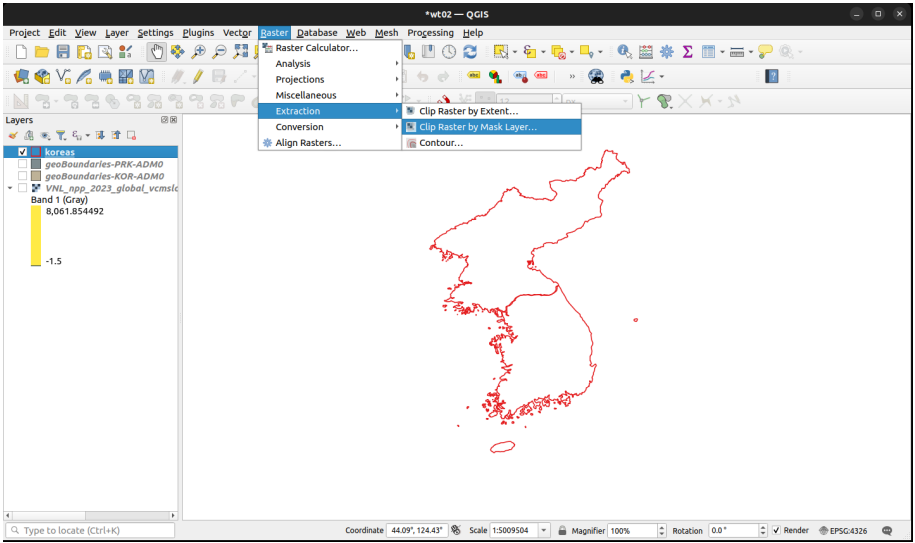
Save the merged file as `koreas.geojson`



Change the symbology of the new layer, to make all but the borders transparent

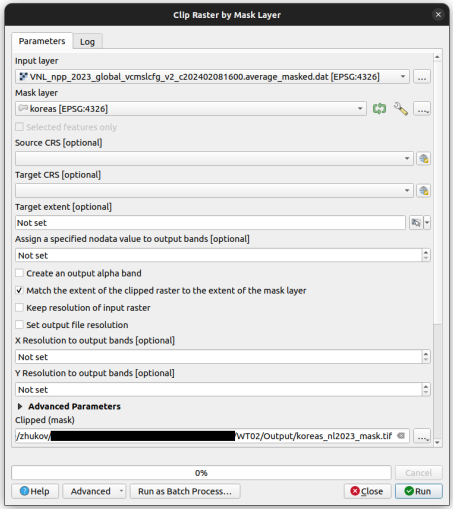


Let's extract the part of the global VNL raster that overlaps with the Koreas.
Go to `Raster` menu → `Extraction` → `Clip Raster by Mask Layer...`

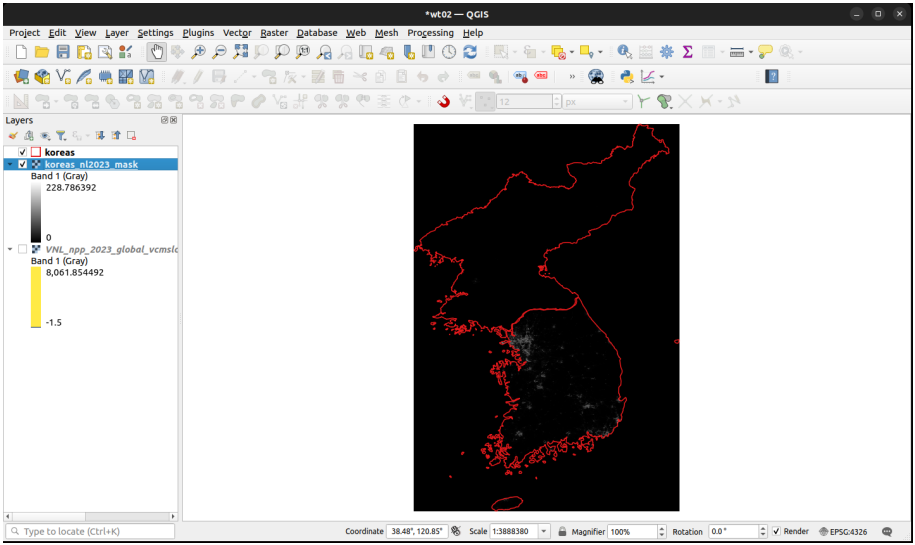


Set parameters

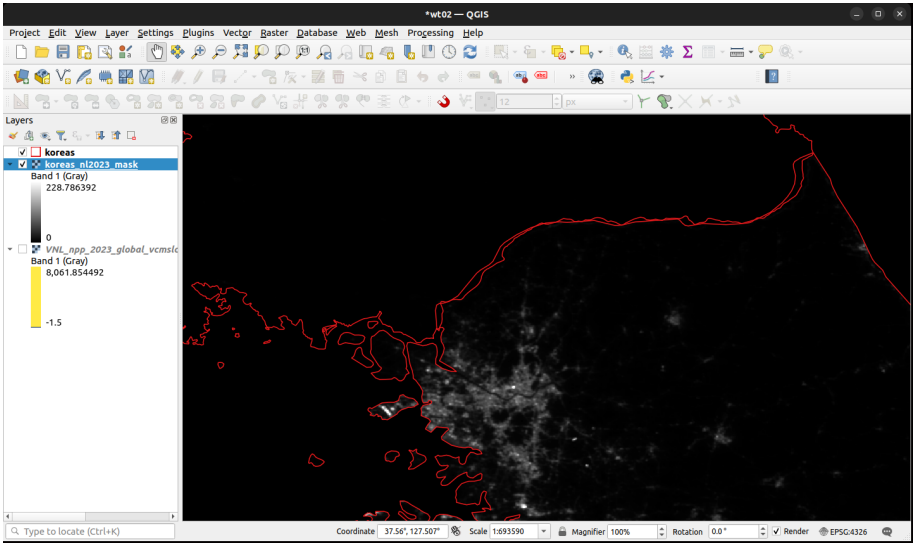
- `Input layer` = `VNL_npp_2023...`
- `Mask layer` = `koreas`
- ✓`Match the extent of the clipped raster to the extent of the mask layer`
- Save file as `koreas_nl2023_mask.tif`



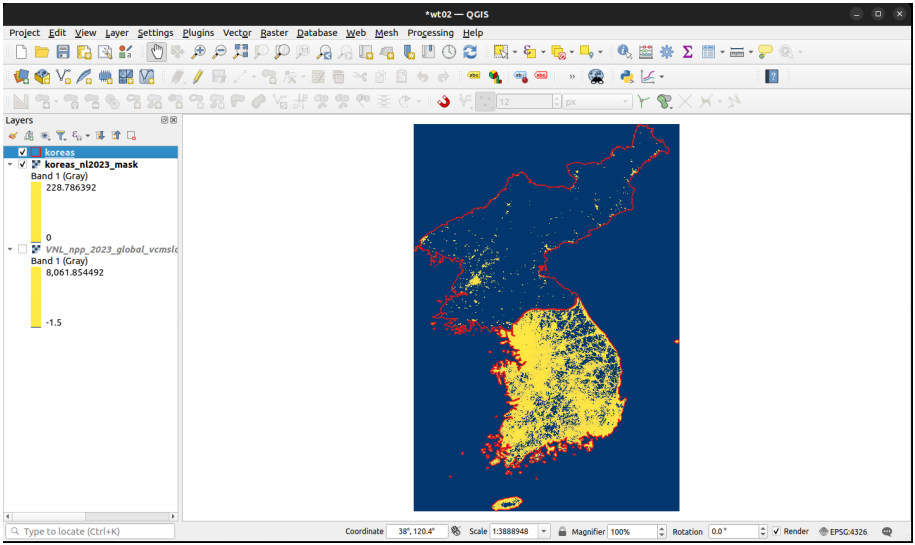
The clipped raster should look something like this



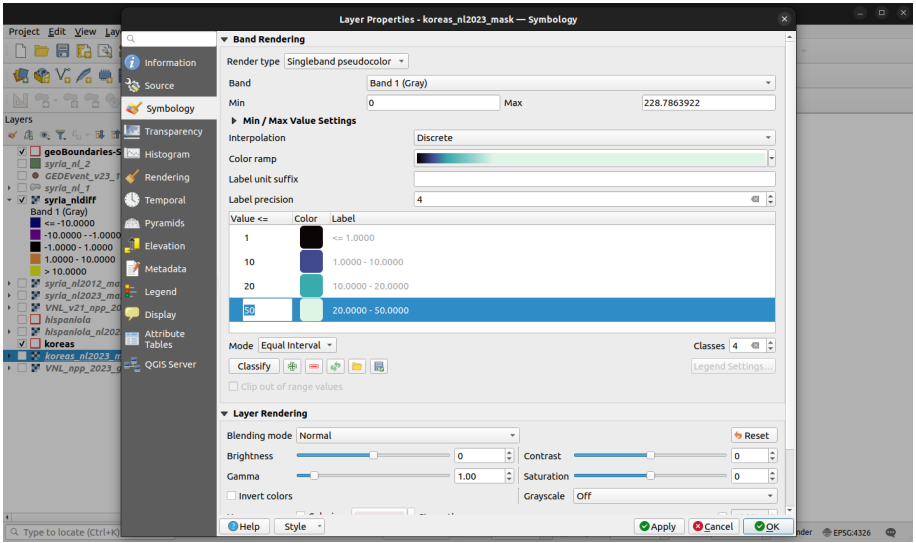
You can zoom in to see Seoul in greater detail



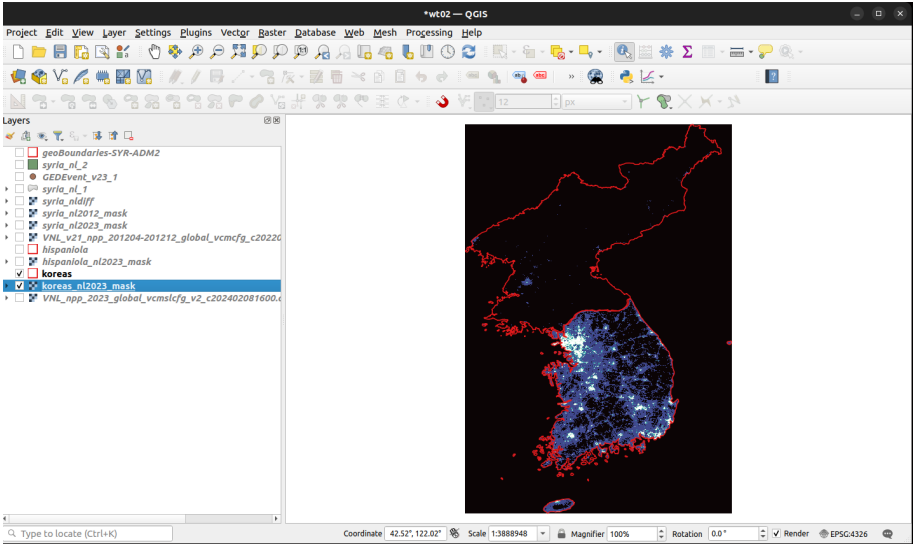
Change color scheme to `Singleband pseudocolor`, `Quantile` again for contrast



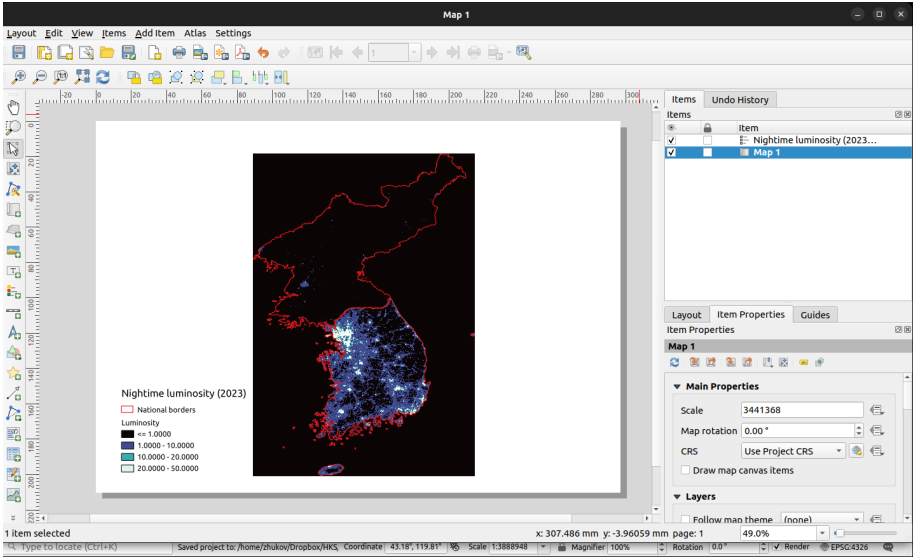
General tip: set `Interpolation` = `Discrete`, `Mode` = `Equal interval` and *manually edit the cutpoints* like this



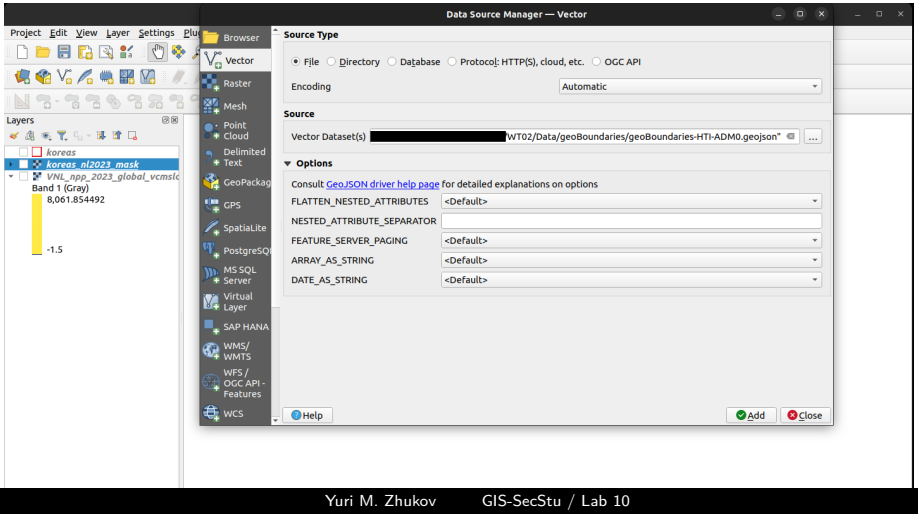
This way, you can customize the appearance of the map for your needs



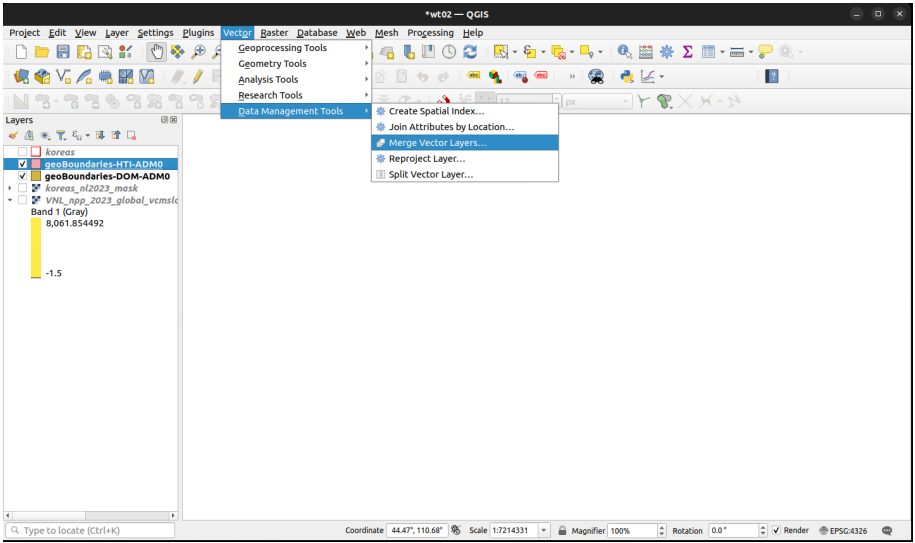
This map is ready to be exported (you know how to do this)



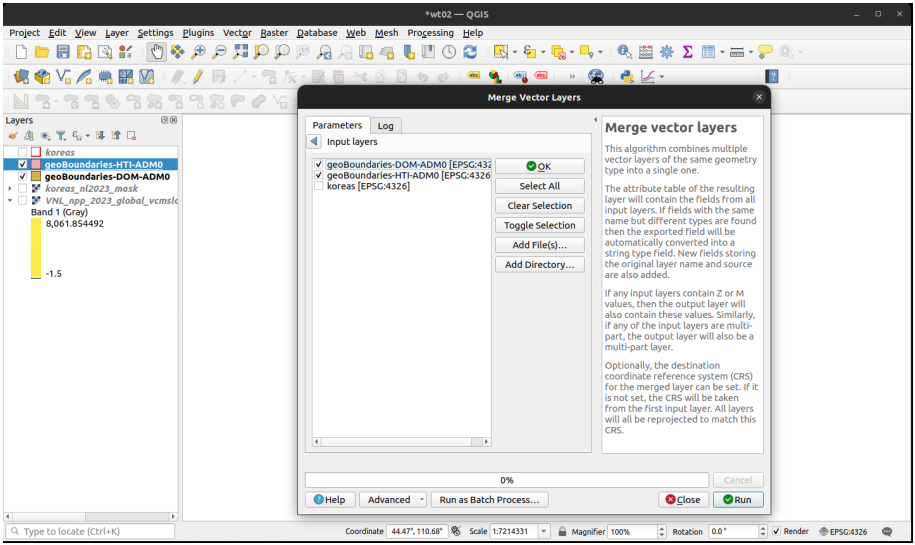
Now for **Vignette 2**, let's repeat this process for the island of Hispaniola.
Load *country boundaries* for Haiti and the Dominican Republic (2 files: `geoBoundaries-HTI-ADM0.geojson` and `geoBoundaries-DOM-ADM0.geojson` from `Data/geoBoundaries`).



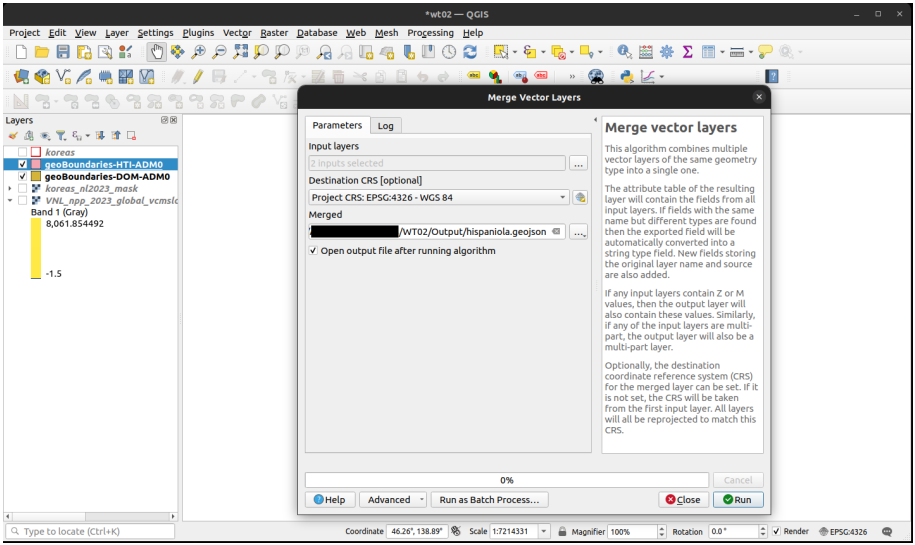
Once loaded, let's merge the two countries into a single layer again (`Vector` menu → `Data Management Tools` → `Merge Vector Layers...`)



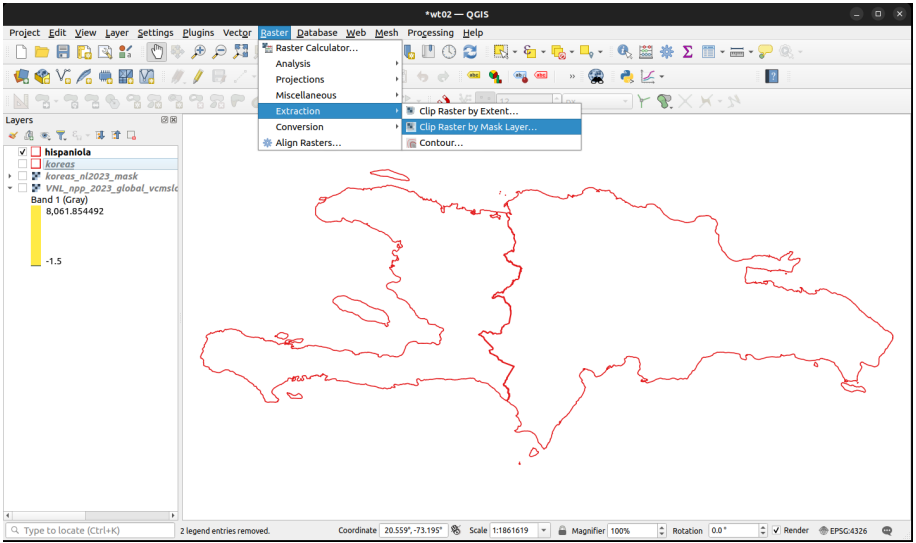
Input layers = geoBoundaries-DOM-ADM0 and geoBoundaries-HTI-ADM0



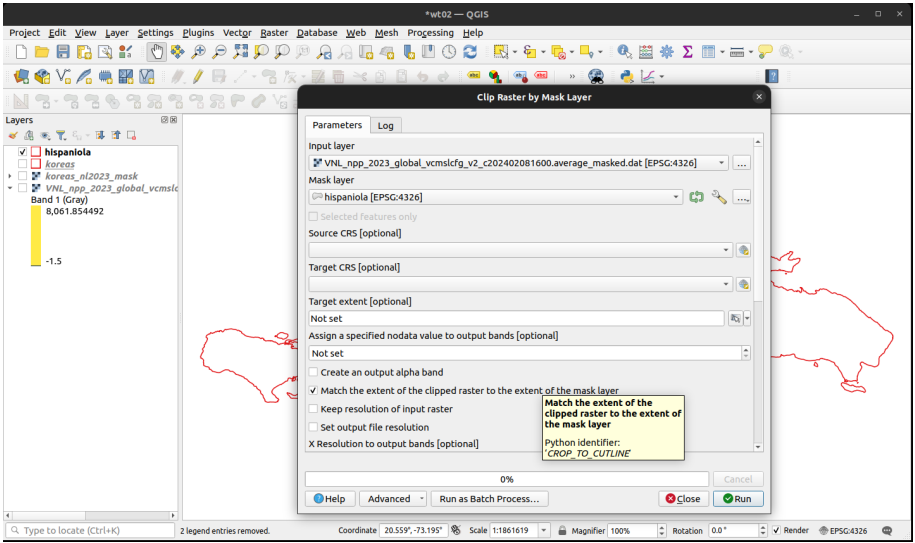
Save the merged file as `hispaniola.geojson`



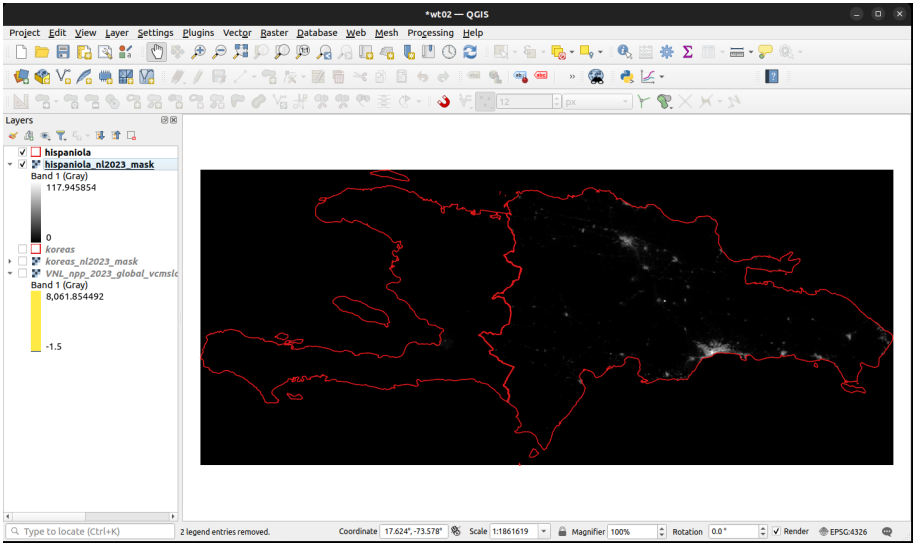
Let's extract the part of the global VNL raster that overlaps with the island.
Go to `Raster` menu → `Extraction` → `Clip Raster by Mask Layer...`



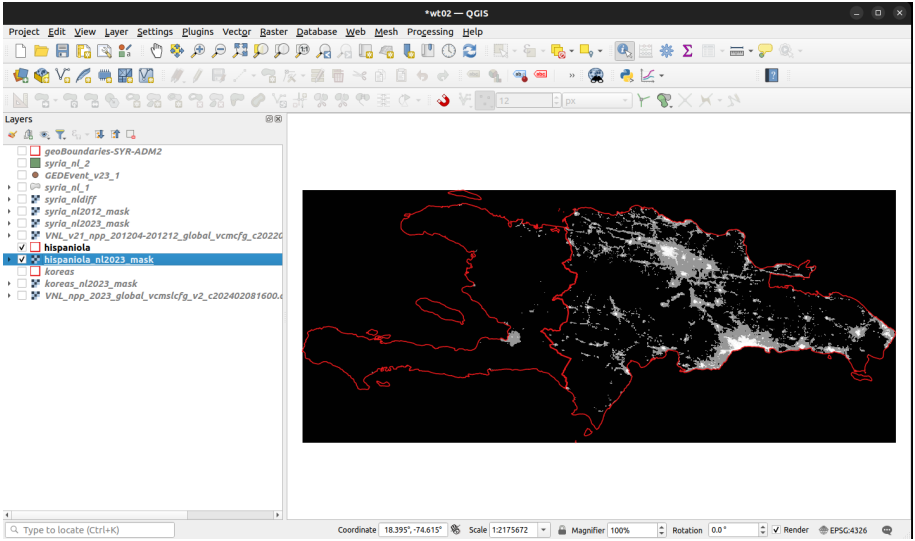
Set `Input layer` = `VNL_npp_2023...`, `Mask layer` = `hispaniola`. Save file as `hispaniola_nl2023_mask.tif`



The clipped raster should look something like this

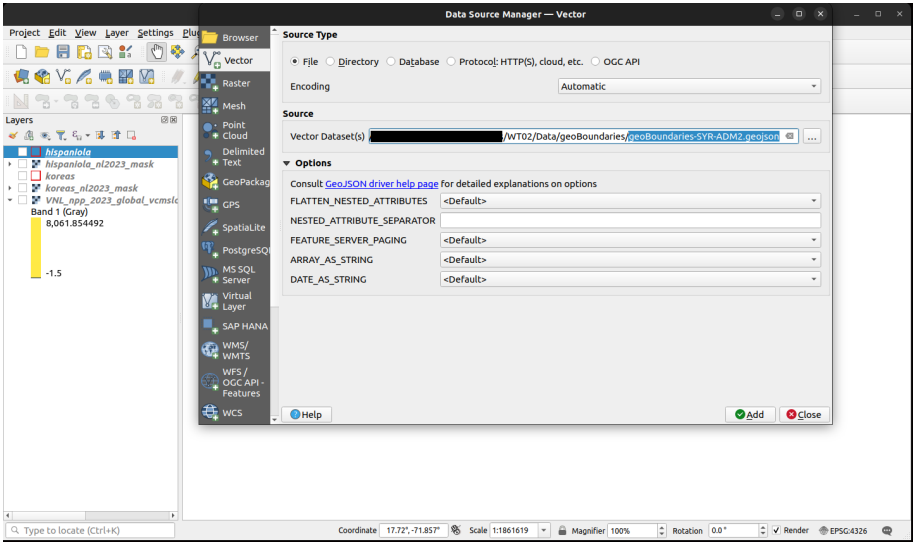


Customize the color ramp and export the map (just like last time)

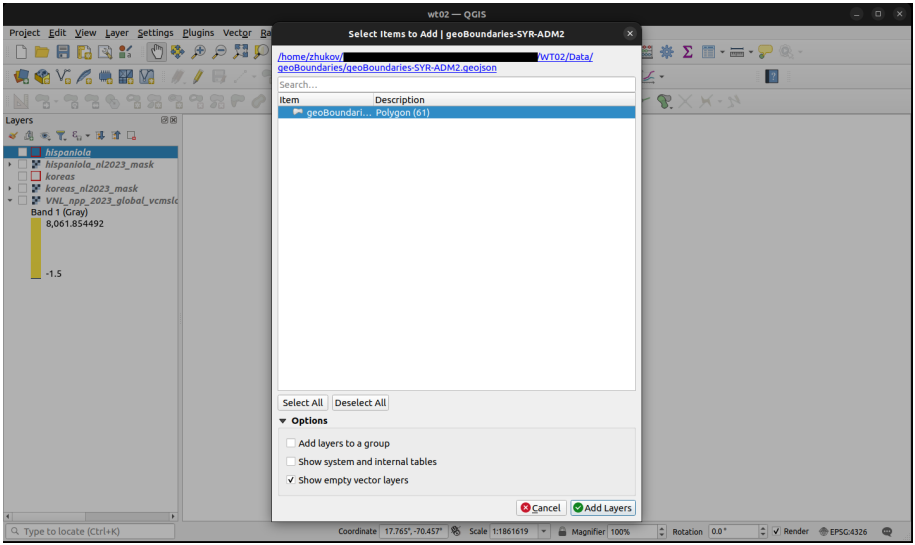


Differences in Luminosity Over Time (Syrian Civil War)

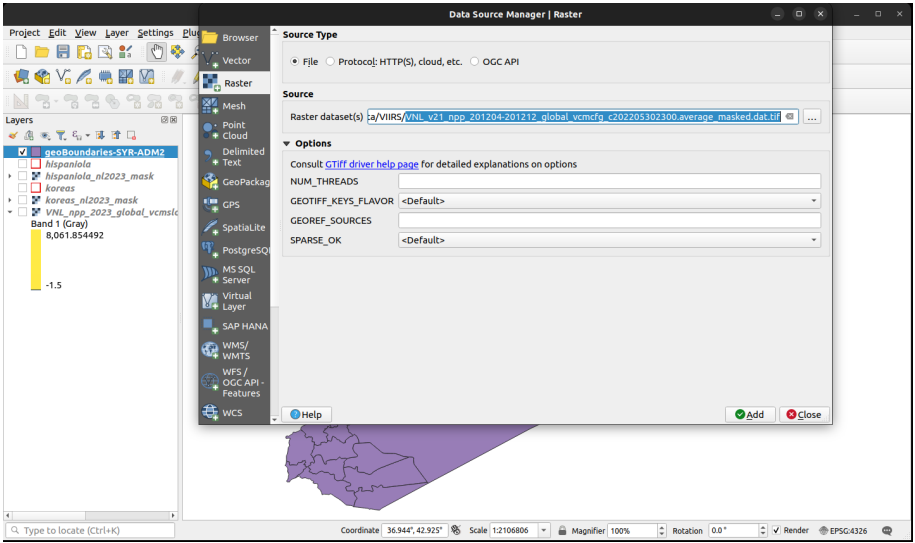
Vignette 3! Load *administrative boundaries* for Syria. File is `geoBoundaries-SYR-ADM2.geojson` from `Data/geoBoundaries` folder.



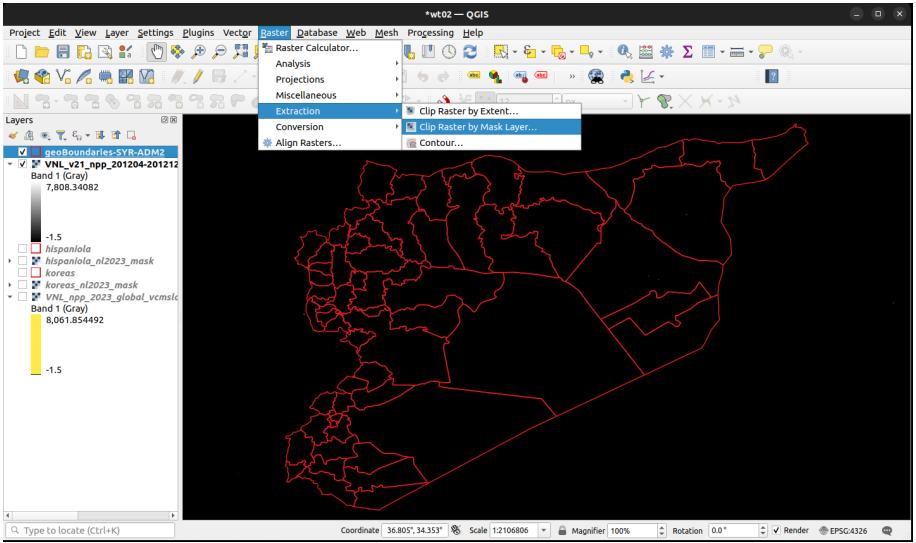
You may see a "Select Items to Add" screen after clicking `Add`. Click `Add Layers`



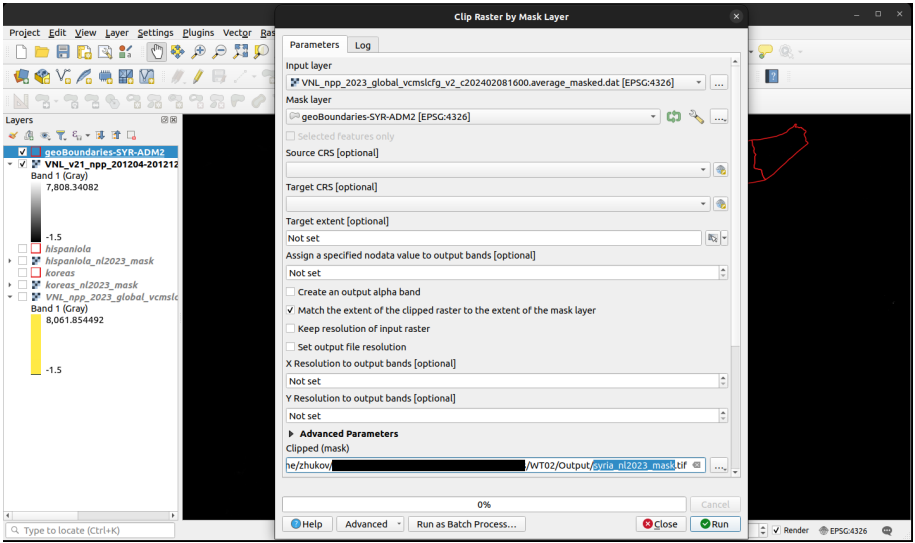
To compare current luminosity to a period earlier in the Syrian Civil War, load the *2012 VNL data* (`VNL_v21_npp_201204....tif` file in `Data/VIIRS` folder)



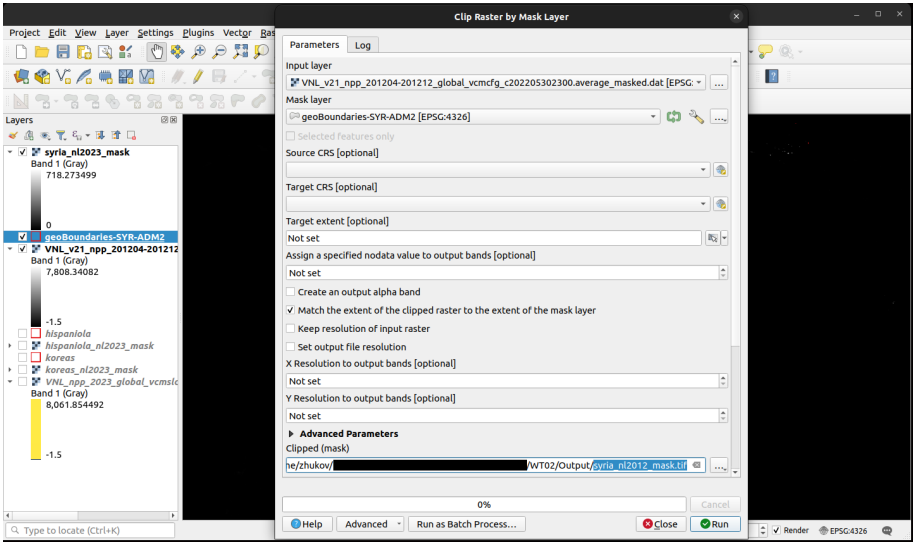
Let's extract the parts of both the 2023 and 2012 global VNL rasters that overlap with Syria. `Raster` menu → `Extraction` → `Clip Raster by Mask Layer...`



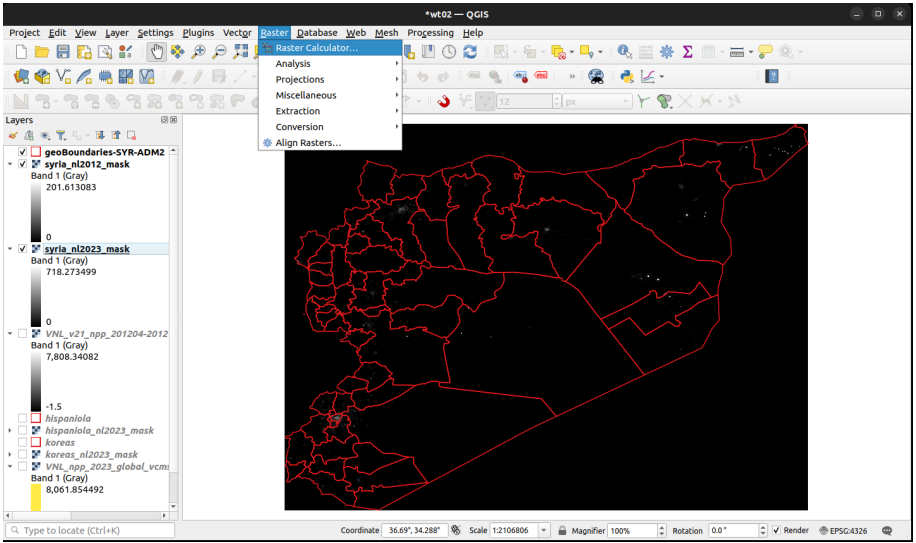
Set `Input layer` = `VNL_npp_2023...`, `Mask layer` = `geoBoundaries-SYR-ADM2`. Save file as `syria_nl2023_mask.tif`



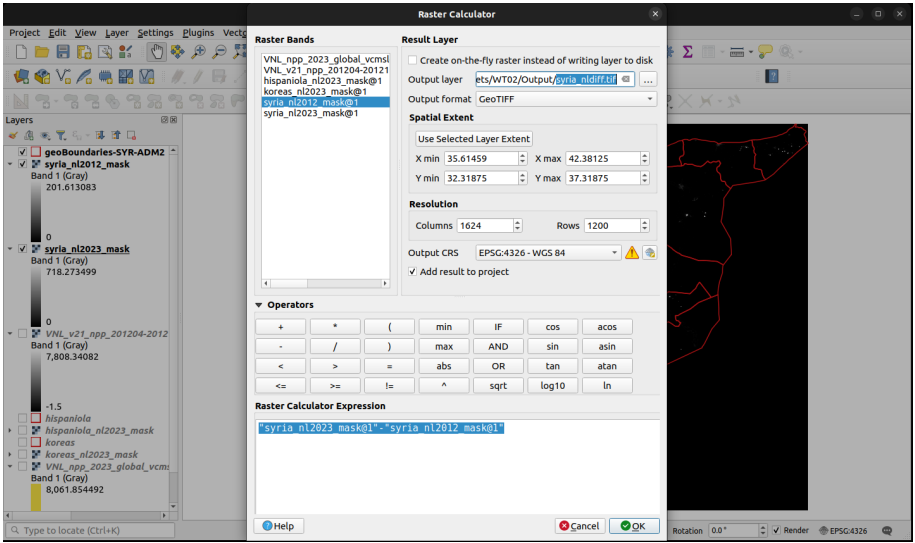
Repeat with `Input layer` = `VNL_v21_npp_2012...`, `Mask layer` = `geoBoundaries-SYR-ADM2`. Save file as `syria_nl2012_mask.tif`



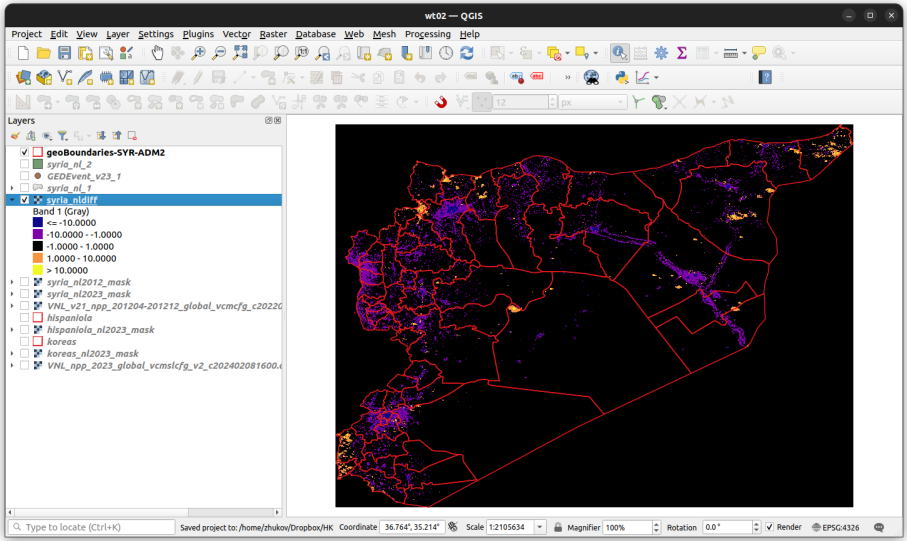
Let's now *calculate the difference between 2023 and 2012.* Go to `Raster` menu → `Raster Calculator...`



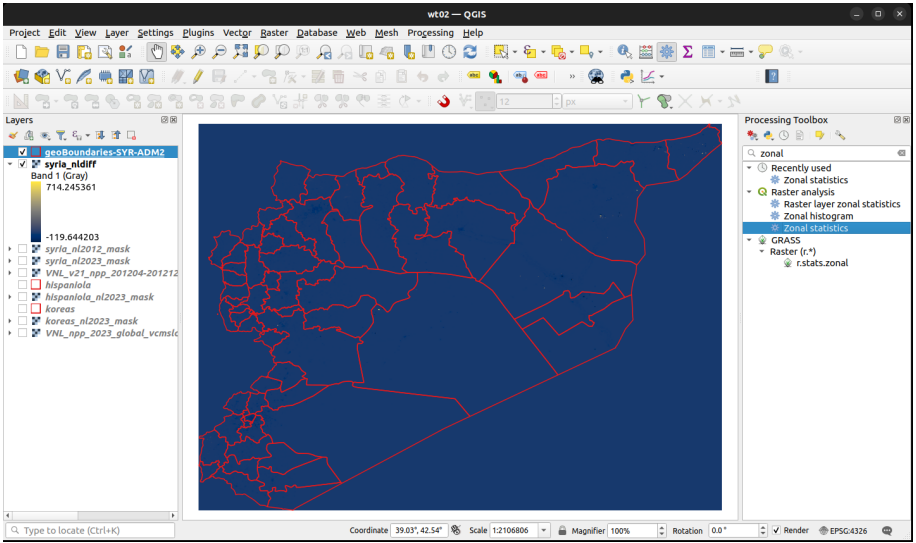
Set the expression to `"syria_nl2023_mask@1" - "syria_nl2012_mask@1"`, save output layer as `syria_nldiff.tif`



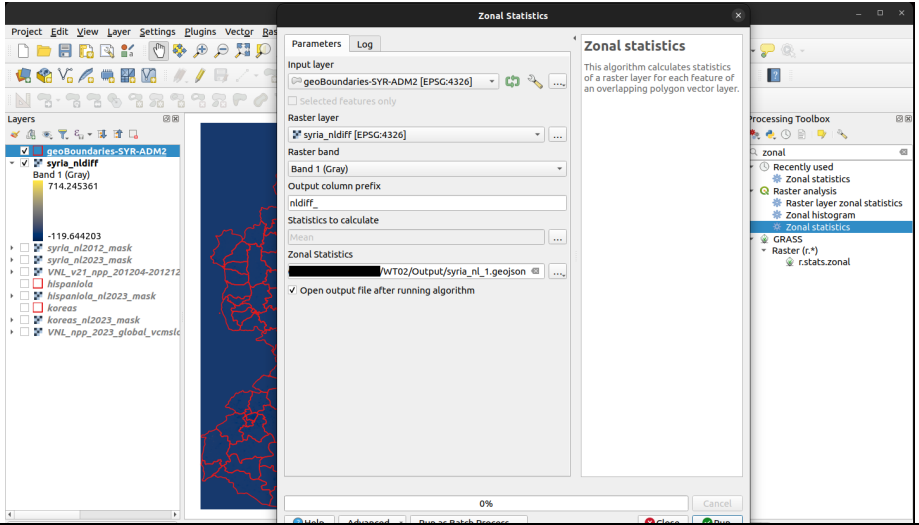
Explore the distribution of this new raster by modifying the color scheme
(here, purple areas lost luminosity, orange areas gained luminosity)



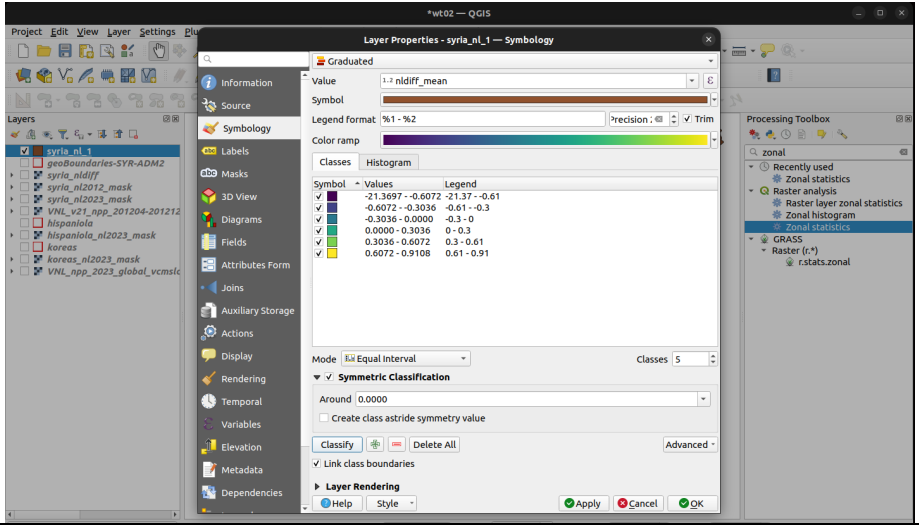
We can now calculate average differences in luminosity per district, using `Zonal statistics` (in the `Processing Toolbox`)



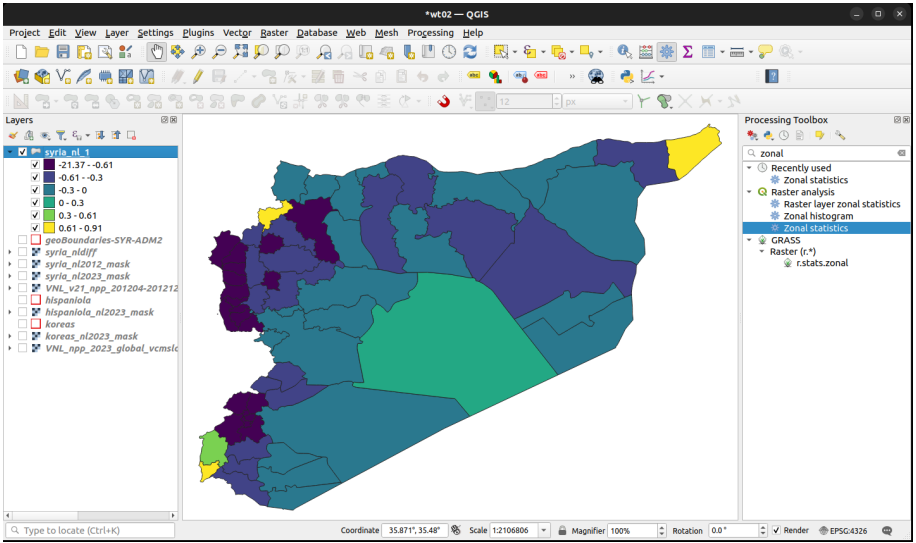
Set the `Input layer` = `geoBoundaries-SYR-ADM2`, `Raster layer` = `syria_nldiff`, `Output column prefix` = `nldiff_`. Save the output as `syria_nl_1.geojson`



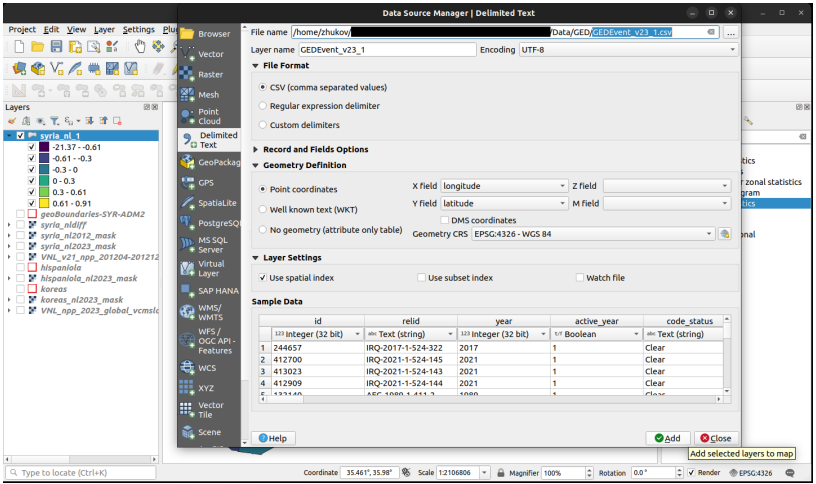
Adjust the symbology in the new `syria_nl_1` layer to visualize the `nldiff_mean` variable with graduated colors, `Equal Interval` mode and `Symmetric Classification` around `0.00`



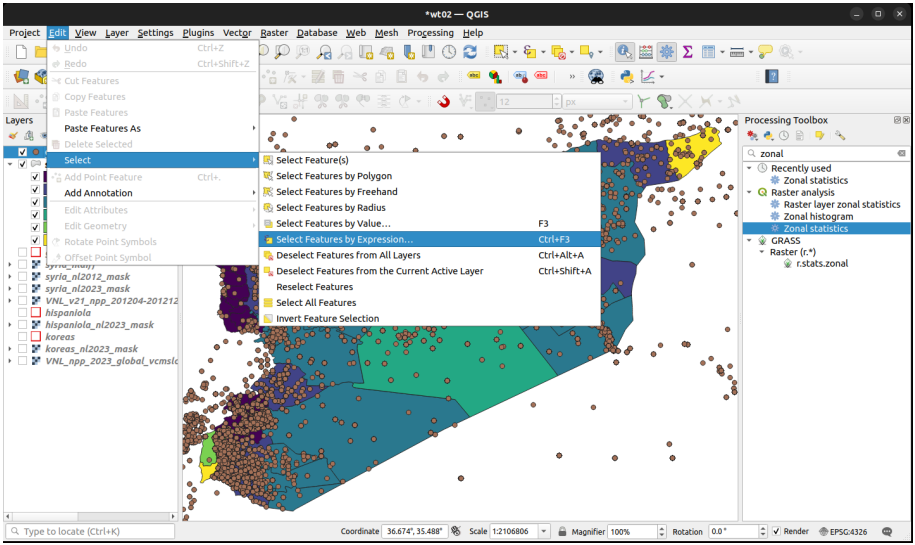
The district-level luminosity differences should look something like this.
Now let's see if places hardest-hit by violence saw the biggest declines...



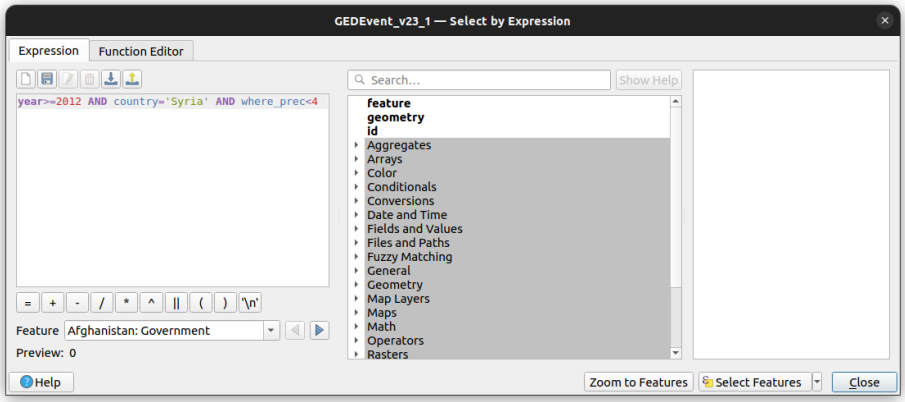
Add the *Syrian Civil War violence data* to the project, using `Add Delimited Text Layer...`. Load the `GEDEvent_v23.csv` file in `Data/GED` folder. Set `X field` = `longitude` and `Y field` = `latitude`. Check box ✓ `Use spatial index`



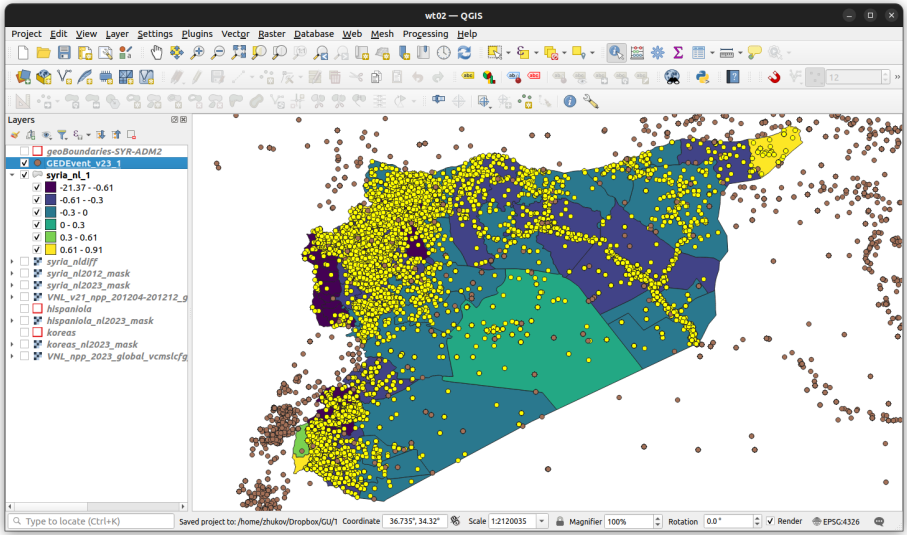
Highlight GED layer and go to `Edit` → `Select` → `Select by Expression...`



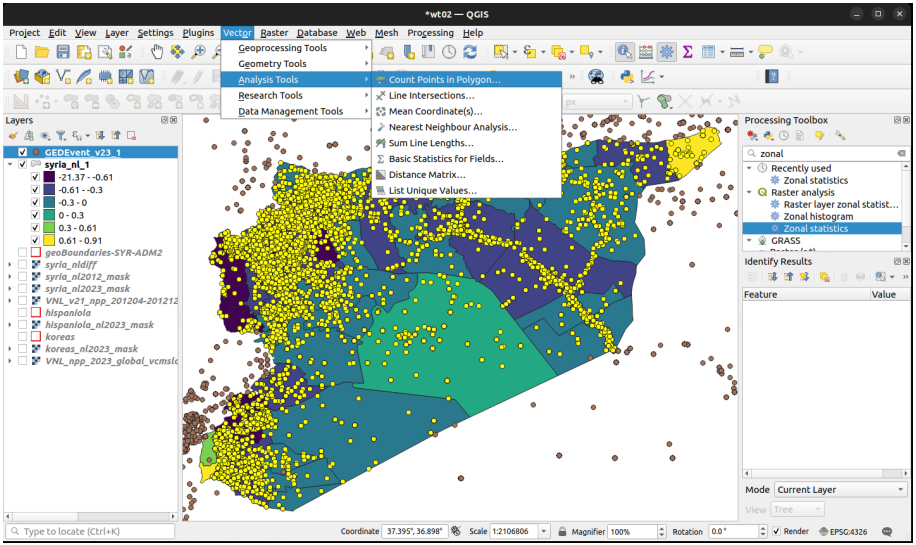
`Expression: year>=2012 AND country='Syria' AND where_prec<4`
Click `Select Features`



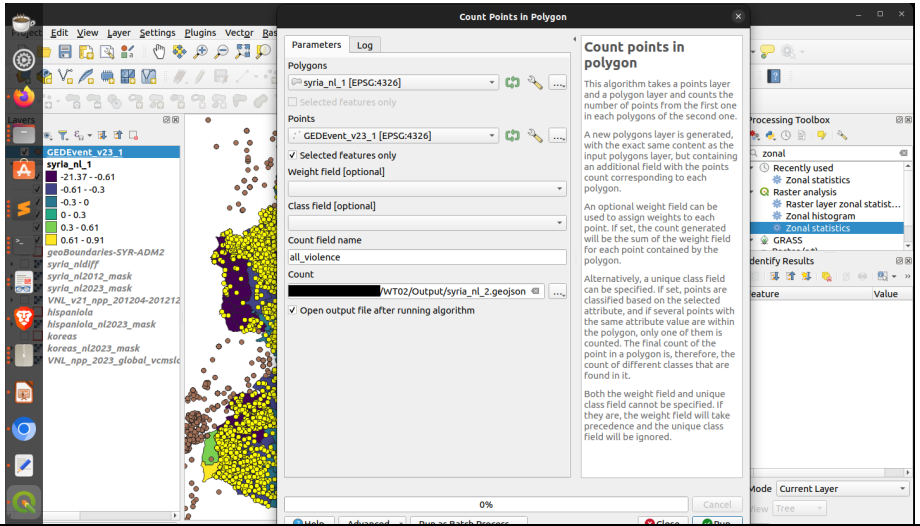
This procedure should have selected about 72 thousand events within Syria. Now let's calculate the **number of violent events per district**



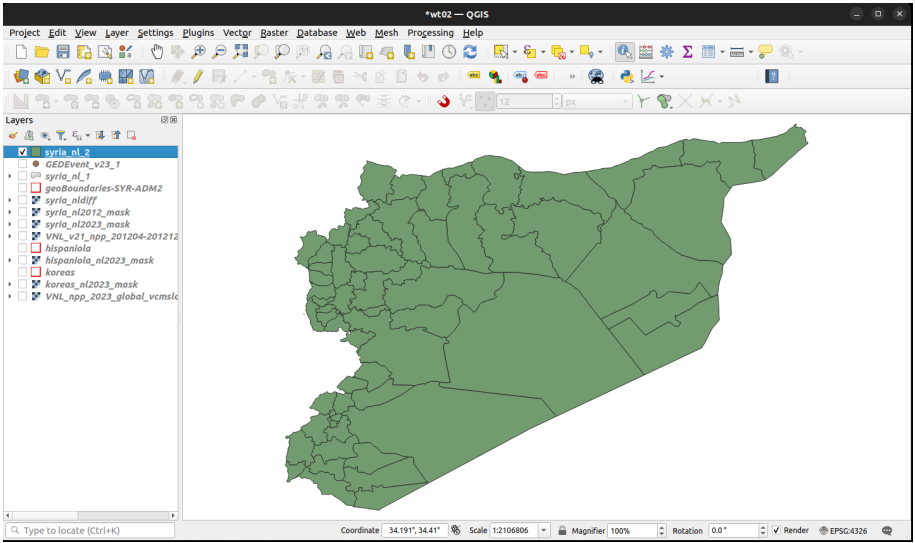
Open the `Count Points in Polygon` tool



Select `Polygons` = `syria_nl_1`, `Points` = `GEDEvent_v23_1`. Make sure the box is checked next to `Selected Features Only` for the points. Name the count field `all_violence`, and save the output file as `syria_nl_2.geojson`. Click `Run`



The new layer `syria_nl_2` should appear in your project window.
Now, let's see if there is a relationship between violence and change in luminosity



Let's run a simple **regression model** in R to see how violence impacted luminosity.

This code chunk imports the `syria_nl_2.geojson` file we created into an object called `syr`, and then lists the variable names:

```
syr = sf::read_sf("Output/syria_nl_2.geojson")
names(syr)
```

```
## [1] "shapeName"    "shapeISO"     "shapeID"      "shapeGroup"   "shapeType"
## [6] "nldiff_mean"  "all_violence" "geometry"
```

This code chunk estimates an **Ordinary Least Squares** model that regresses dependent variable `nldiff_mean` on explanatory variable `all_violence`

```
mod = lm(nldiff_mean~all_violence,data=syr)
summary(mod)
```

```
##
## Call:
## lm(formula = nldiff_mean ~ all_violence, data = syr)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -19.3243   0.0181   0.4239   0.8397   2.6816
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -0.4000160  0.4428367  -0.903   0.3700
## all_violence -0.0004699  0.0002258  -2.081   0.0418 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.754 on 59 degrees of freedom
## Multiple R-squared:  0.06839,    Adjusted R-squared:  0.0526
## F-statistic: 4.331 on 1 and 59 DF,  p-value: 0.04176
```

Let's rescale the variable `all_violence` to make the coefficient more interpretable.

```
mod = lm(nldiff_mean~I(all_violence/100),data=syr)
summary(mod)
```

```
##
## Call:
## lm(formula = nldiff_mean ~ I(all_violence/100), data = syr)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -19.3243   0.0181   0.4239   0.8397   2.6816
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)          -0.40002    0.44284  -0.903   0.3700
## I(all_violence/100) -0.04699    0.02258  -2.081   0.0418 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.754 on 59 degrees of freedom
## Multiple R-squared:  0.06839,    Adjusted R-squared:  0.0526
## F-statistic: 4.331 on 1 and 59 DF,  p-value: 0.04176
```

For every 100 violent events, the change in luminosity falls by 0.047.

You can perform all these steps in R
(see replication code `wt02_demo.R` in `Lab10WT02.zip`)

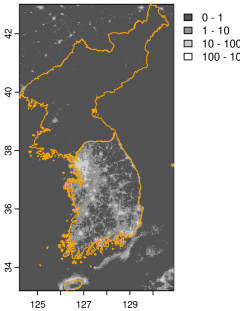


Figure 18: Vignette 1

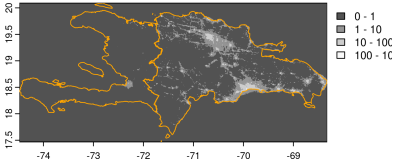


Figure 19: Vignette 2

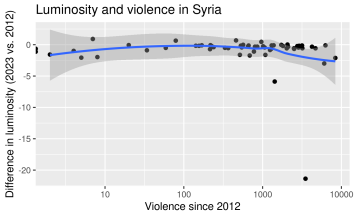


Figure 20: Vignette 3