Infrastructure for sustainable development

Modelling infrastructure exposure and risk

This notebook forms the basis of "Hands-On 6" in the CCG course.

It uses the road network and flood dataset extracted in the previous tutorial.

1. Exposure - overlay sample flood extent with the network and estimate flood depth of exposure
2. Vulnerability - assume depth-damage curve (fragility curve) for the road and
    - show how the exposure is translated to damage
    - create a table with probability, flood depth, length exposed, fragility, cost/km, direct damage
3. Risk - show a risk calculation on the table and generate the result
4. Future risk - repeat with climate projections and compare with baseline

By the end of this tutorial you should be able to:

- Assess direct damage and indirect disruptions to infrastructure assets
- Apply the risk calculation to understand how to generate loss-probability curves
- Show how different flood hazards introduce uncertainty in risk estimations

```
# Imports from Python standard library
import os
from pathlib import Path

# see https://docs.python.org/3/library/glob.html
from glob import glob

# Imports from other Python packages
import geopandas as gpd

# numpy is used by pandas and geopandas to store data in efficient arrays
# we use it in this notebook to help with trapezoidal integration
# see https://numpy.org/
import numpy as np
import pandas as pd

# seaborn helps produce more complex plots
# see https://seaborn.pydata.org/
import seaborn as sns

from scipy.integrate import simpson
```

```
import snail.damages
import snail.intersection
import snail.io

from pyproj import Geod

# tqdm lets us show progress bars (and    means "progress" in Arabic)
# see https://tqdm.github.io/
from tqdm.notebook import tqdm
```

Change this to point to your data folder as in the previous tutorial:

```
data_folder = Path("Path/to/folder/ghana_tutorial")
```

1. Exposure

List all the hazard files in the `flood_layer` folder:

```
hazard_paths = sorted(
    glob(str(data_folder / "flood_layer/gha/wri_aqueduct_version_2/wri*.tif"))
)
hazard_files = pd.DataFrame({"path": hazard_paths})
hazard_files["key"] = [Path(path).stem for path in hazard_paths]
hazard_files, grids = snail.io.extend_rasters_metadata(hazard_files)

hazard_files.head(5)
```

```
                                                path  \
0  /Users/ivannschlosser/Documents/oxford/ghana_t...
1  /Users/ivannschlosser/Documents/oxford/ghana_t...
2  /Users/ivannschlosser/Documents/oxford/ghana_t...
3  /Users/ivannschlosser/Documents/oxford/ghana_t...
4  /Users/ivannschlosser/Documents/oxford/ghana_t...

                                                 key  grid_id bands
0  wri_aqueduct-version_2-inuncoast_historical_wt...        0  (1,)
1  wri_aqueduct-version_2-inuncoast_historical_wt...        0  (1,)
2  wri_aqueduct-version_2-inuncoast_historical_wt...        0  (1,)
3  wri_aqueduct-version_2-inuncoast_historical_wt...        0  (1,)
4  wri_aqueduct-version_2-inuncoast_historical_wt...        0  (1,)
```

```
assert len(grids) == 1
grid = grids[0]
```

Read in roads again, then do intersections against all hazard scenarios.

```
roads_file = data_folder / "GHA_OSM_roads.gpkg"
roads = gpd.read_file(roads_file, layer="edges")
roads.head(2)
```

```
    osm_id road_type                    name       id  from_id        to_id  \
0  4790594  tertiary           Airport Road  roade_0  roadn_0      roadn_1
1  4790599  tertiary  South Liberation Link  roade_1  roadn_2  roadn_10807

     length_m                                           geometry
0  236.526837  LINESTRING (-0.17544 5.60550, -0.17418 5.60555...
1   18.539418    LINESTRING (-0.17889 5.59979, -0.17872 5.59977)
```

```
# split roads along hazard data grid

# TODO top-level "overlay_rasters"
# TODO for vector in vectors / for raster in rasters "overlay_raster"


# push into split_linestrings, flag to disable
prepared = snail.intersection.prepare_linestrings(roads)

flood_intersections = snail.intersection.split_linestrings(prepared, grid)

# push into split_linestrings
flood_intersections = snail.intersection.apply_indices(
    flood_intersections, grid, index_i="i_0", index_j="j_0"
)

flood_intersections = snail.io.associate_raster_files(
    flood_intersections, hazard_files
)

# calculate the length of each stretch of road
# don't include in snail wrapper top-level function
geod = Geod(ellps="WGS84")
flood_intersections["length_m"] = flood_intersections.geometry.apply(
    geod.geometry_length
)
```

```
# save to file
output_file = os.path.join(
    data_folder,
    "results",
    str(roads_file.name).replace(".gpkg", "_edges___exposure.geoparquet"),
)

flood_intersections.to_parquet(output_file)
```

```
flood_intersections.columns
```

```
Index(['osm_id', 'road_type', 'name', 'id', 'from_id', 'to_id', 'length_m',
       'geometry', 'split', 'i_0',
       ...
```

```
       'wri_aqueduct-version_2-inunriver_rcp8p5_MIROC-ESM-CHEM_2050_rp01000-gha',
       'wri_aqueduct-version_2-inunriver_rcp8p5_MIROC-ESM-CHEM_2080_rp00002-gha',
       'wri_aqueduct-version_2-inunriver_rcp8p5_MIROC-ESM-CHEM_2080_rp00005-gha',
       'wri_aqueduct-version_2-inunriver_rcp8p5_MIROC-ESM-CHEM_2080_rp00010-gha',
       'wri_aqueduct-version_2-inunriver_rcp8p5_MIROC-ESM-CHEM_2080_rp00025-gha',
       'wri_aqueduct-version_2-inunriver_rcp8p5_MIROC-ESM-CHEM_2080_rp00050-gha',
       'wri_aqueduct-version_2-inunriver_rcp8p5_MIROC-ESM-CHEM_2080_rp00100-gha',
       'wri_aqueduct-version_2-inunriver_rcp8p5_MIROC-ESM-CHEM_2080_rp00250-gha',
       'wri_aqueduct-version_2-inunriver_rcp8p5_MIROC-ESM-CHEM_2080_rp00500-gha',
       'wri_aqueduct-version_2-inunriver_rcp8p5_MIROC-ESM-CHEM_2080_rp01000-gha'],
      dtype='object', length=390)
```

```
data_cols = [col for col in flood_intersections.columns if "wri" in col]
```

```
# find any max depth and filter > 0
all_intersections = flood_intersections[
    flood_intersections[data_cols].max(axis=1) > 0
]
# subset columns
all_intersections = all_intersections.drop(
    columns=["osm_id", "name", "from_id", "to_id", "geometry", "i_0", "j_0"]
)
# melt and check again for depth
all_intersections = all_intersections.melt(
    id_vars=["id", "split", "road_type", "length_m"],
    value_vars=data_cols,
    var_name="key",
    value_name="depth_m",
).query("depth_m > 0")

all_intersections.head(5)
```

```
             id  split road_type    length_m  \
439  roade_1429      9  tertiary  153.153316
440  roade_1429     10  tertiary   28.151241
444  roade_1447      9  tertiary  412.834012
450  roade_1452      3   primary  929.965564
452  roade_1452      5   primary  921.598630

                                                   key   depth_m
439  wri_aqueduct-version_2-inuncoast_historical_wt...  0.466355
440  wri_aqueduct-version_2-inuncoast_historical_wt...  1.349324
444  wri_aqueduct-version_2-inuncoast_historical_wt...  0.006246
450  wri_aqueduct-version_2-inuncoast_historical_wt...  0.516396
452  wri_aqueduct-version_2-inuncoast_historical_wt...  0.407549
```

```
river = all_intersections[all_intersections.key.str.contains("inunriver")]
coast = all_intersections[all_intersections.key.str.contains("inuncoast")]
```

```
coast_keys = coast.key.str.extract(
    r"wri_aqueduct-version_2-(?P<hazard>\w+)_(?P<rcp>[^_]+)_(?P<sub>[^_]+)_(?P<epoch>[^_]+)_r
)
coast = pd.concat([coast, coast_keys], axis=1)
river_keys = river.key.str.extract(
    r"wri_aqueduct-version_2-(?P<hazard>\w+)_(?P<rcp>[^_]+)_(?P<gcm>[^_]+)_(?P<epoch>[^_]+)_r
)
river = pd.concat([river, river_keys], axis=1)
```

```
coast.rp = coast.rp.apply(lambda rp: float(rp.replace("_", ".").lstrip("0")))
coast.head(5)
```

```
            id  split road_type    length_m  \
439  roade_1429      9  tertiary  153.153316
440  roade_1429     10  tertiary   28.151241
444  roade_1447      9  tertiary  412.834012
450  roade_1452      3   primary  929.965564
452  roade_1452      5   primary  921.598630

                                                   key   depth_m     hazard  \
439  wri_aqueduct-version_2-inuncoast_historical_wt...  0.466355  inuncoast
440  wri_aqueduct-version_2-inuncoast_historical_wt...  1.349324  inuncoast
444  wri_aqueduct-version_2-inuncoast_historical_wt...  0.006246  inuncoast
450  wri_aqueduct-version_2-inuncoast_historical_wt...  0.516396  inuncoast
452  wri_aqueduct-version_2-inuncoast_historical_wt...  0.407549  inuncoast

           rcp    sub epoch   rp
439  historical  wtsub  2030  1.5
440  historical  wtsub  2030  1.5
444  historical  wtsub  2030  1.5
450  historical  wtsub  2030  1.5
452  historical  wtsub  2030  1.5
```

```
# river.rp = river.rp.apply(lambda rp: float(rp.replace("_", ".").lstrip("0")))
river.gcm = river.gcm.str.replace("0", "")
river.head(5)
```

```
              id  split road_type    length_m  \
550753   roade_56      0     trunk  256.660267
550755  roade_126      0     trunk  364.644366
550756  roade_126      1     trunk  158.050565
550757  roade_127      0     trunk   54.297481
550758  roade_128      0     trunk  715.652789

                                                    key   depth_m  \
550753  wri_aqueduct-version_2-inunriver_historical_00...  2.243539
550755  wri_aqueduct-version_2-inunriver_historical_00...  0.073757
550756  wri_aqueduct-version_2-inunriver_historical_00...  0.073757
550757  wri_aqueduct-version_2-inunriver_historical_00...  0.073757
```

```
550758  wri_aqueduct-version_2-inunriver_historical_00...  0.073757

          hazard         rcp    gcm epoch     rp
550753  inunriver  historical  WATCH  1980  00005
550755  inunriver  historical  WATCH  1980  00005
550756  inunriver  historical  WATCH  1980  00005
550757  inunriver  historical  WATCH  1980  00005
550758  inunriver  historical  WATCH  1980  00005
```

Summarise total length of roads exposed to depth 2m or greater river flooding, under different return periods and climate scenarios:

```
summary = (
    river[river.depth_m >= 2.0]
    .drop(columns=["id", "split", "road_type", "key"])
    .groupby(["hazard", "rcp", "gcm", "epoch", "rp"])
    .sum()
    .drop(columns=["depth_m"])
)

summary
```

```
                                                 length_m
hazard    rcp        gcm       epoch rp
inunriver historical WATCH     1980  00005  278980.836489
                                       00010  461345.618367
                                       00025  521049.572286
                                       00050  557202.826411
                                       00100  589840.619653
...                                                    ...
          rcp8p5     NorESM1-M 2080  00050  306812.495606
                                       00100  346457.694544
                                       00250  408674.849110
                                       00500  506771.887795
                                       01000  574607.043246

[208 rows x 1 columns]
```

Plot exposure against return period, with separate plot areas for each Representative Concentration Pathway (RCP), and different colours for the different Global Climate Models (GCM):

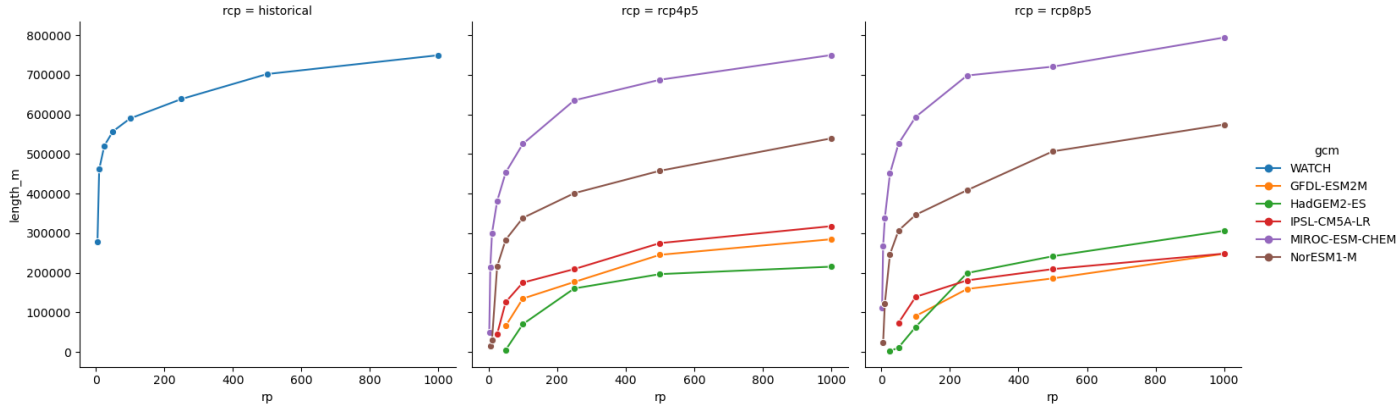
```
plot_data = summary.reset_index()
plot_data = plot_data[plot_data.epoch.isin(["1980", "2080"])]
plot_data.rp = plot_data.rp.apply(lambda rp: int(rp.lstrip("0")))
plot_data["probability"] = 1 / plot_data.rp
plot_data.head(5)
```

```
      hazard         rcp    gcm epoch   rp       length_m  probability
0  inunriver  historical  WATCH  1980    5  278980.836489         0.20
1  inunriver  historical  WATCH  1980   10  461345.618367         0.10
```

```
2  inunriver  historical  WATCH  1980   25  521049.572286         0.04
3  inunriver  historical  WATCH  1980   50  557202.826411         0.02
4  inunriver  historical  WATCH  1980  100  589840.619653         0.01
```

```
sns.relplot(
    data=plot_data,
    x="rp",
    y="length_m",
    hue="gcm",
    col="rcp",
    kind="line",
    marker="o",
)
```

```
<seaborn.axisgrid.FacetGrid at 0x2885e7690>
```



2. Vulnerability

Set up fragility curve assumptions, where probability of damage (`pfail`) depends on whether a road is paved and the depth of flood it is exposed to.

These assumptions are derived from Koks, E.E., Rozenberg, J., Zorn, C. et al. A global multi-hazard risk analysis of road and railway infrastructure assets. Nat Commun 10, 2677 (2019). https://doi.org/10.1038/s41467-019-10442-3, Figure S3, extrapolated to 2m and 3m depths.

The analysis is likely to be highly sensitive to these assumptions, and this approach is strongly limited by the availability and quality of fragility data, as well as the assumption that fragility can be related to flood depth alone - flood water velocity would be an important factor in a more detailed vulnerability assessment.

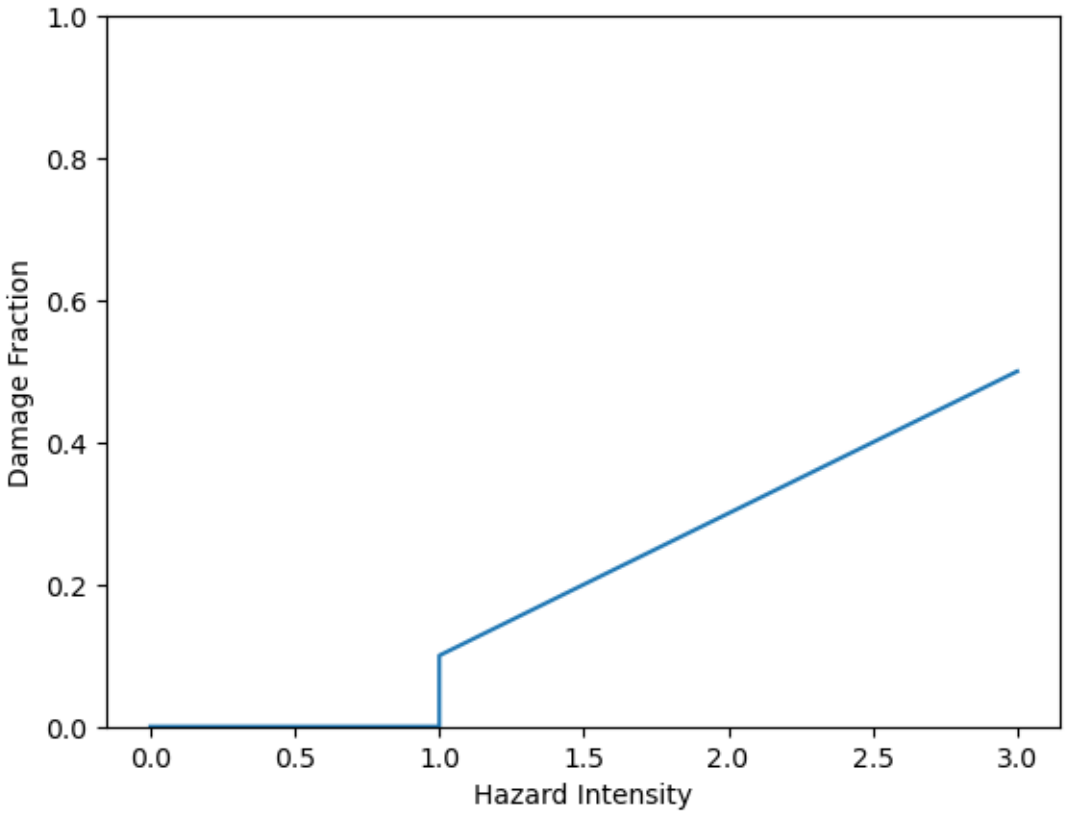
```
paved = snail.damages.PiecewiseLinearDamageCurve(
    pd.DataFrame(
        {
            "intensity": [0.0, 0.999999999, 1, 2, 3],
            "damage": [0.0, 0.0, 0.1, 0.3, 0.5],
        }
    )
)
unpaved = snail.damages.PiecewiseLinearDamageCurve(
```

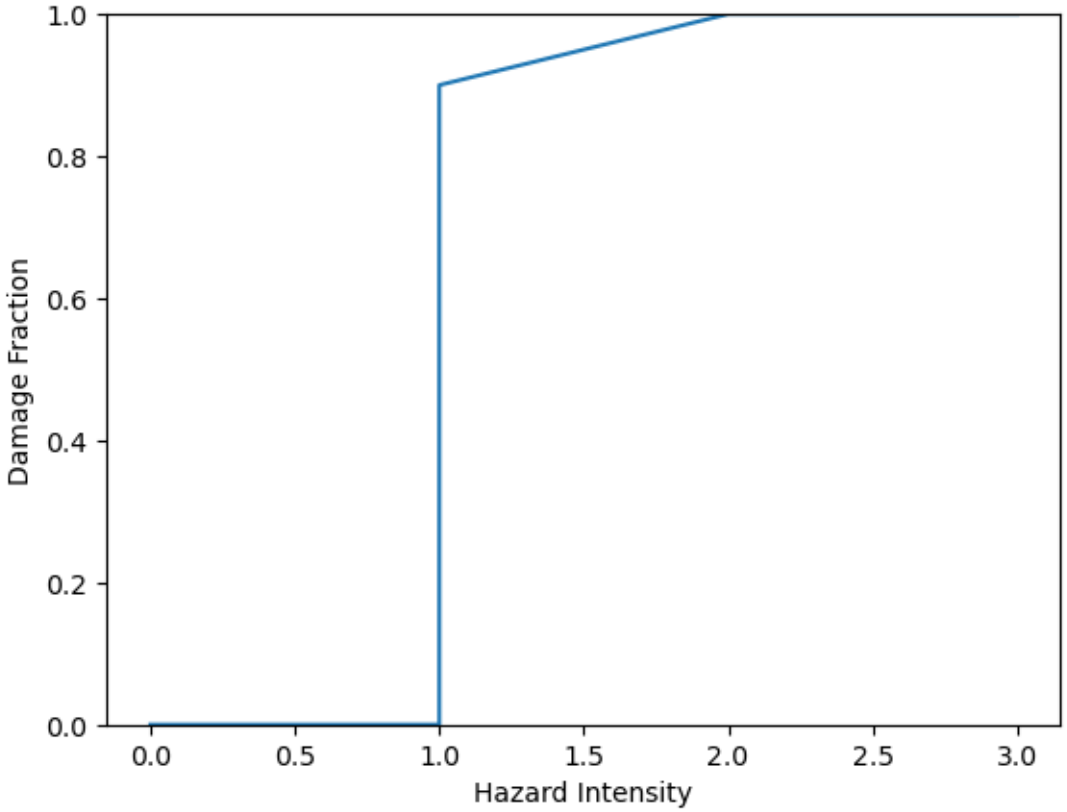
```
    pd.DataFrame(
        {
            "intensity": [0.0, 0.999999999, 1, 2, 3],
            "damage": [0.0, 0.0, 0.9, 1.0, 1.0],
        }
    )
)
paved, unpaved
```

```
(<snail.damages.PiecewiseLinearDamageCurve at 0x2ad859850>,
 <snail.damages.PiecewiseLinearDamageCurve at 0x2ad72a750>)
```

```
paved.plot(), unpaved.plot()
```

```
(<Axes: xlabel='Hazard Intensity', ylabel='Damage Fraction'>,
 <Axes: xlabel='Hazard Intensity', ylabel='Damage Fraction'>)
```





Set up cost assumptions.

These are taken from Koks et al (2019) again, Table S8, construction costs to be assumed as an estimate of full rehabilitation after flood damage.

Again the analysis is likely to be highly sensitive to these assumptions, which should be replaced by better estimates if available.

```
costs = pd.DataFrame(
    {
        "kind": ["paved_four_lane", "paved_two_lane", "unpaved"],
        "cost_usd_per_km": [3_800_000, 932_740, 22_780],
    }
)
costs
```

	kind	cost_usd_per_km
0	paved_four_lane	3800000
1	paved_two_lane	932740
2	unpaved	22780

Set up assumptions about which roads are paved or unpaved, and number of lanes.

```
sorted(river.road_type.unique())
```

```
['motorway',
 'motorway_link',
 'primary',
```

```
 'primary_link',
 'secondary',
 'secondary_link',
 'tertiary',
 'tertiary_link',
 'trunk',
 'trunk_link']
```

Assume all `tertiary` roads are unpaved, all others are paved.

```
river["paved"] = ~(river.road_type == "tertiary")
```

```
def kind(road_type):
    if road_type in ("trunk", "trunk_link", "motorway"):
        return "paved_four_lane"
    elif road_type in ("primary", "primary_link", "secondary"):
        return "paved_two_lane"
    else:
        return "unpaved"


river["kind"] = river.road_type.apply(kind)
```

```
river = river.merge(costs, on="kind")
```

Use the damage curve to estimate `proportion_damaged` for each exposed section.

```
river.head(2)
```

```
          id  split road_type    length_m  \
0   roade_56      0     trunk  256.660267
1  roade_126      0     trunk  364.644366

                                              key   depth_m     hazard  \
0  wri_aqueduct-version_2-inunriver_historical_00...  2.243539  inunriver
1  wri_aqueduct-version_2-inunriver_historical_00...  0.073757  inunriver

          rcp    gcm epoch     rp  paved             kind  cost_usd_per_km
0  historical  WATCH  1980  00005   True  paved_four_lane          3800000
1  historical  WATCH  1980  00005   True  paved_four_lane          3800000
```

```
paved_depths = river.loc[river.paved, "depth_m"]
paved_damage = paved.damage_fraction(paved_depths)
river.loc[river.paved, "proportion_damaged"] = paved_damage

unpaved_depths = river.loc[~river.paved, "depth_m"]
unpaved_damage = paved.damage_fraction(unpaved_depths)
river.loc[~river.paved, "proportion_damaged"] = unpaved_damage
```

Finally estimate cost of rehabilitation for each exposed section

```
river["damage_usd"] = river.length_m * river.cost_usd_per_km * 1e-3
river.head(2)
```

```
          id  split road_type    length_m  \
0   roade_56      0     trunk  256.660267
1  roade_126      0     trunk  364.644366

                                                 key   depth_m     hazard  \
0  wri_aqueduct-version_2-inunriver_historical_00...  2.243539  inunriver
1  wri_aqueduct-version_2-inunriver_historical_00...  0.073757  inunriver

          rcp    gcm epoch     rp  paved             kind  cost_usd_per_km  \
0  historical  WATCH  1980  00005   True  paved_four_lane          3800000
1  historical  WATCH  1980  00005   True  paved_four_lane          3800000

   proportion_damaged    damage_usd
0            0.348708  9.753090e+05
1            0.000000  1.385649e+06
```

```
river.to_csv(
    os.path.join(data_folder, "results/inunriver_damages_rp.csv"), index=False
)
```

```
summary = (
    river.drop(
        columns=[
            "id",
            "split",
            "length_m",
            "key",
            "depth_m",
            "paved",
            "kind",
            "cost_usd_per_km",
            "proportion_damaged",
        ]
    )
    .groupby(["road_type", "hazard", "rcp", "gcm", "epoch", "rp"])
    .sum()
)
summary
```

```
                                                    damage_usd
road_type  hazard    rcp        gcm       epoch rp
motorway   inunriver historical WATCH     1980  00005  2.848229e+07
                                                00010  2.848229e+07
                                                00025  2.848229e+07
                                                00050  2.848229e+07
                                                00100  2.848229e+07
```

```
...                                                                  ...
trunk_link inunriver rcp8p5     NorESM1-M 2080  00050  1.473414e+07
                                                00100  1.473414e+07
                                                00250  1.473414e+07
                                                00500  1.473414e+07
                                                01000  1.473414e+07

[2780 rows x 1 columns]
```

3. Risk

Calculate expected annual damages for each road under historical hazard.

Start by selecting only historical intersections, and keeping only the road ID, return period, and cost of rehabilitation if damaged.

```
historical = river[river.rcp == "historical"][["id", "rp", "damage_usd"]]
```

Sum up the expected damage for each road, per return period, then pivot the table to create columns for each return period - now there is one row per road.

```
historical = historical.groupby(["id", "rp"]).sum().reset_index()
historical = historical.pivot(index="id", columns="rp").replace(
    float("NaN"), 0
)
historical.columns = [f"rp{int(rp)}" for _, rp in historical.columns]
historical.head(2)
```

```
                     rp5          rp10          rp25          rp50  \
id
roade_1002      0.000000      0.000000      0.000000      0.000000
roade_10029  46079.916698  46079.916698  46079.916698  46079.916698

                    rp100         rp250         rp500        rp1000
id
roade_1002      0.000000      0.000000      0.000000   5788.380563
roade_10029  46079.916698  46079.916698  46079.916698  46079.916698
```

Calculate expected annual damages, integrating under the expected damage curve over return periods.

```
def calculate_ead(df):
    rp_cols = sorted(
        list(df.columns), key=lambda col: 1 / int(col.replace("rp", ""))
    )
    rps = np.array([int(col.replace("rp", "")) for col in rp_cols])
    probabilities = 1 / rps
    rp_damages = df[rp_cols]
    return simpson(rp_damages, x=probabilities, axis=1)


historical["ead_usd"] = calculate_ead(historical)
```

```
historical.head(2)
```

```
                      rp5          rp10          rp25          rp50  \
id
roade_1002       0.000000      0.000000      0.000000      0.000000
roade_10029  46079.916698  46079.916698  46079.916698  46079.916698

                     rp100         rp250         rp500        rp1000  \
id
roade_1002       0.000000      0.000000      0.000000   5788.380563
roade_10029  46079.916698  46079.916698  46079.916698  46079.916698

                 ead_usd
id
roade_1002      0.000000
roade_10029  9169.903423
```

```
historical.to_csv(
    os.path.join(data_folder, "results/inunriver_damages_ead__historical.csv")
)
```

4. Future risk

Calculate expected annual damages under each future scenario (for each global climate model and representative concentration pathway).

This follows the same method as for historical flooding above, with the added variables of climate model and rcp.

```
future = river[["id", "rp", "rcp", "gcm", "epoch", "damage_usd"]].copy()
```

Sum up the expected damage for each road, per return period, gcm and rcp

```
future = (
    future.groupby(["id", "rp", "rcp", "gcm", "epoch"]).sum().reset_index()
)
future.head(2)
```

```
           id     rp     rcp              gcm epoch   damage_usd
0  roade_1002  00005  rcp8p5  MIROC-ESM-CHEM  2080  5788.380563
1  roade_1002  00010  rcp8p5  MIROC-ESM-CHEM  2050  5788.380563
```

Pivot the table to create columns for each return period - now there is one row per road, gcm and rcp.

```
future = future.pivot(
    index=["id", "rcp", "gcm", "epoch"], columns="rp"
).replace(float("NaN"), 0)
future.columns = [f"rp{int(rp)}" for _, rp in future.columns]
future.head(2)
```

```
                                        rp2  rp5  rp10  rp25  rp50  rp100  \
id         rcp        gcm            epoch
```

```
roade_1002 historical WATCH          1980   0.0  0.0   0.0   0.0   0.0    0.0
           rcp4p5     MIROC-ESM-CHEM 2030   0.0  0.0   0.0   0.0   0.0    0.0

                                                  rp250        rp500  \
id         rcp        gcm            epoch
roade_1002 historical WATCH          1980      0.000000     0.000000
           rcp4p5     MIROC-ESM-CHEM 2030   5788.380563  5788.380563

                                                 rp1000
id         rcp        gcm            epoch
roade_1002 historical WATCH          1980   5788.380563
           rcp4p5     MIROC-ESM-CHEM 2030   5788.380563
```

Calculate expected annual damages, integrating under the expected damage curve over return periods.

```
future["ead_usd"] = calculate_ead(future)
```

```
future.to_csv(os.path.join(data_folder, "results/inunriver_damages_ead.csv"))
```

Pick out an individual road by id, to spot check uncertainty:

```
future.reset_index().id.unique()
```

```
array(['roade_1002', 'roade_10029', 'roade_1004', ..., 'roade_9962',
       'roade_9963', 'roade_9964'], dtype=object)
```

```
future.loc["roade_1002"]
```

```
                                  rp2          rp5         rp10         rp25  \
rcp        gcm            epoch
historical WATCH          1980   0.0     0.000000     0.000000     0.000000
rcp4p5     MIROC-ESM-CHEM 2030   0.0     0.000000     0.000000     0.000000
                          2050   0.0     0.000000     0.000000     0.000000
                          2080   0.0     0.000000     0.000000  5788.380563
           NorESM1-M      2050   0.0     0.000000     0.000000     0.000000
rcp8p5     MIROC-ESM-CHEM 2030   0.0     0.000000     0.000000     0.000000
                          2050   0.0     0.000000  5788.380563  5788.380563
                          2080   0.0  5788.380563  5788.380563  5788.380563

                                       rp50        rp100        rp250  \
rcp        gcm            epoch
historical WATCH          1980      0.000000     0.000000     0.000000
rcp4p5     MIROC-ESM-CHEM 2030      0.000000     0.000000  5788.380563
                          2050   5788.380563  5788.380563  5788.380563
                          2080   5788.380563  5788.380563  5788.380563
           NorESM1-M      2050      0.000000     0.000000     0.000000
rcp8p5     MIROC-ESM-CHEM 2030      0.000000     0.000000     0.000000
                          2050   5788.380563  5788.380563  5788.380563
                          2080   5788.380563  5788.380563  5788.380563

                                       rp500       rp1000      ead_usd
```

```
rcp        gcm             epoch
historical WATCH           1980      0.000000  5788.380563     0.000000
rcp4p5     MIROC-ESM-CHEM  2030   5788.380563  5788.380563    22.510369
                           2050   5788.380563  5788.380563    32.800823
                           2080   5788.380563  5788.380563   444.418997
           NorESM1-M       2050      0.000000  5788.380563     0.000000
rcp8p5     MIROC-ESM-CHEM  2030   5788.380563  5788.380563    13.023856
                           2050   5788.380563  5788.380563   187.157638
                           2080   5788.380563  5788.380563  2245.248505
```

Summarise total expected annual (direct) damages, showing variation between climate models and representative concentration pathways.

```
summary = (
    future.reset_index()[["rcp", "gcm", "epoch", "ead_usd"]]
    .groupby(["rcp", "gcm", "epoch"])
    .sum()
    .reset_index()
)
summary.epoch = summary.epoch.astype(int)
summary.head()
```

```
           rcp             gcm  epoch       ead_usd
0   historical           WATCH   1980  5.678292e+08
1       rcp4p5       GFDL-ESM2M   2030  6.024297e+08
2       rcp4p5       GFDL-ESM2M   2050  6.015823e+08
3       rcp4p5       GFDL-ESM2M   2080  5.903214e+08
4       rcp4p5       HadGEM2-ES   2030  6.183892e+08
5       rcp4p5       HadGEM2-ES   2050  6.016411e+08
6       rcp4p5       HadGEM2-ES   2080  5.436160e+08
7       rcp4p5     IPSL-CM5A-LR   2030  5.120018e+08
8       rcp4p5     IPSL-CM5A-LR   2050  5.001816e+08
9       rcp4p5     IPSL-CM5A-LR   2080  5.133345e+08
10      rcp4p5  MIROC-ESM-CHEM   2030  6.266596e+08
11      rcp4p5  MIROC-ESM-CHEM   2050  6.179568e+08
12      rcp4p5  MIROC-ESM-CHEM   2080  6.063889e+08
13      rcp4p5        NorESM1-M   2030  5.510785e+08
14      rcp4p5        NorESM1-M   2050  5.646342e+08
15      rcp4p5        NorESM1-M   2080  5.579299e+08
16      rcp8p5       GFDL-ESM2M   2030  5.967260e+08
17      rcp8p5       GFDL-ESM2M   2050  5.920149e+08
18      rcp8p5       GFDL-ESM2M   2080  5.627618e+08
19      rcp8p5       HadGEM2-ES   2030  6.032960e+08
20      rcp8p5       HadGEM2-ES   2050  6.055638e+08
21      rcp8p5       HadGEM2-ES   2080  5.999573e+08
22      rcp8p5     IPSL-CM5A-LR   2030  5.110443e+08
23      rcp8p5     IPSL-CM5A-LR   2050  5.052677e+08
24      rcp8p5     IPSL-CM5A-LR   2080  4.925050e+08
25      rcp8p5  MIROC-ESM-CHEM   2030  6.330736e+08
```

```
26      rcp8p5  MIROC-ESM-CHEM   2050  6.796243e+08
27      rcp8p5  MIROC-ESM-CHEM   2080  6.838621e+08
28      rcp8p5       NorESM1-M   2030  5.240312e+08
29      rcp8p5       NorESM1-M   2050  5.518583e+08
30      rcp8p5       NorESM1-M   2080  5.663191e+08
```

```
sns.lmplot(
    data=summary,
    col="rcp",
    x="epoch",
    y="ead_usd",
    hue="gcm",  # fit_reg=False
)
```

```
<seaborn.axisgrid.FacetGrid at 0x2adabbb10>
```