NISMOD

Hands-On 8 – Evaluating infrastructure adaptation options

This exercise takes the risk results from the analysis from previous hands-on sessions, introduces some road-improvement adaptation options, and runs through a cost-benefit analysis, where the costs are the costs of improving and maintaining roads, and the benefits are taken as the value of risks avoided.

Learning objectives

- Quantify the potential risk reduction of adaptation options
- Prioritise assets based on cost-benefit analysis for different adaptation options.

Load risk results

Open the notebook “04-evaluate-adaptation-options.ipynb”. This contains code to implement each of the steps in this tutorial.

Read in roads and join regions as in hands-on 7.

Read in risk results and exposure.

Sum over any segments exposed within the same return period:

```
exposure = exposure \
    .groupby(['road_id', 'rcp', 'gcm', 'rp']) \
    .sum()
```

Then pick the max length exposed over all return periods:

```
exposure = exposure \
    .groupby(['road_id', 'rcp', 'gcm']) \
    .max() \
    .reset_index()
```

Finally join roads and risk results and exposure, so we end up with a table with a row for each road / climate model / climate scenario combination that contains expected annual damages and an upper bound on the length of road exposed.

Introduce adaptation options

Introduce road upgrade options, with costs. These costs are taken purely as an example, and further research is required to make reasonable estimates. They are intended to represent upgrade to a bituminous or concrete road design, with a single-lane design for currently unpaved roads. The routine maintenance costs are estimated for rehabilitation and routine maintenance that should take place every year. The periodic maintenance costs are estimated for resurfacing and surface treatment that may take place approximately every five years.

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

```
options = pd.DataFrame({
    'kind':                      ['four_lane', 'two_lane', 'single_lane'],
    'initial_cost_usd_per_km': [ 1_000_000,     500_000,  125_000     ],
    'routine_usd_per_km':      [    20_000,      10_000,    5_000     ],
    'periodic_usd_per_km':     [   100_000,      50_000,   25_000     ],
})
```

Next, set a discount rate. This will be used to discount the cost of annual and periodic maintenance, as well as the present value of future expected annual damages.

```
discount_rate_percentage = 3
```

This is another sensitive parameter which will affect the net present value calculations for both costs and benefits. As an exercise, try re-running the remainder of the analysis with different values here. What economic or financial justification could there be for assuming different discount rates?

Given initial and routine costs and a discount rate, we can calculate the net present value for each adaptation option.

- start by calculating the normalised discount rate for each year over the time horizon.
- add the initial costs for each option.
- calculate the discounted routine costs for each option (assumed to be incurred each year).
- calculate the discounted periodic costs for each option (assumed to be incurred every five years).

```
# set up a costs dataframe
costs = pd.DataFrame()

# create a row per year over the time-horizon of interest
costs['year'] = np.arange(2020, 2081)
costs['year_from_start'] = costs.year - 2020

# calculate the normalised discount rate
discount_rate = 1 + discount_rate_percentage / 100
costs['discount_rate_norm'] = costs.year_from_start.apply(lambda y:
1.0/math.pow(discount_rate, y))
```

```
# calculate the sum over normalised discount rates for the time horizon
# this will be useful later, to calculate NPV of expected damages
discount_rate_norm = costs.discount_rate_norm.sum()

# link each of the options, so we have a row per-option, per-year
costs['link'] = 1
options['link'] = 1
costs = costs.merge(options, on='link').drop(columns='link')

# set initial costs to zero in all years except start year
costs.loc[costs.year_from_start > 0, 'initial_cost_usd_per_km'] = 0

# discount routine and periodic maintenance costs
costs.routine_usd_per_km = costs.discount_rate_norm *
costs.routine_usd_per_km
costs.periodic_usd_per_km = costs.discount_rate_norm *
costs.periodic_usd_per_km
# set periodic costs to zero except for every five years
costs.loc[costs.year_from_start == 0, 'periodic_usd_per_km'] = 0
costs.loc[costs.year_from_start % 5 != 0, 'periodic_usd_per_km'] = 0
costs
```

This table can then be summarised by summing over all years in the time horizon, to calculate the net present value of all future investment in maintenance.

Estimate costs and benefits

Apply some assumptions about the kind of adaptation option which would be applied to each class of road in our dataset. These are all assumed to be “climate-resilient” engineering options, differing by number of lanes and assumed level of use.

Join the adaptation cost estimates (per km) to the table of exposed roads, then calculate the total cost estimate given the length of road exposed:

```
roads_with_costs['total_adaptation_cost_usd'] = \
    roads_with_costs.total_cost_usd_per_km / 1e3 \
    * roads_with_costs.flood_length_m
```

Calculate net present value of avoided damages over the time horizon:

```
roads_with_costs['total_adaptation_benefit_usd'] = \
    roads_with_costs.ead_usd \
    * discount_rate_norm
```

Finally calculate the benefit-cost ratio (BCR):

```
roads_with_costs['bcr'] = \
    roads_with_costs.total_adaptation_benefit_usd \
    / roads_with_costs.total_adaptation_cost_usd
```

Filter to pull out just the historical climate scenario, and roads with BCR greater than one:

```
candidates = roads_with_costs[
    (roads_with_costs.rcp == 'historical' )
```

```
    & (roads_with_costs.bcr > 1)
]
```

Summarise by region to explore where cost-beneficial adaptation options might be located.

We need to sum over exposed lengths of road, costs and benefits, while finding the mean benefit-cost ratio.

```
candidates.groupby('ADM1_EN') \
    .agg({
        'flood_length_m' : np.sum,
        'total_adaptation_benefit_usd': np.sum,
        'total_adaptation_cost_usd': np.sum,
        'bcr': np.mean
    })
```

Given the aggregation, filtering and plotting you've seen throughout these tutorials, what other statistics would be interesting to explore from these results?

Summary

In this exercise, we read in the results of the flood risk and exposure calculations, using the geopandas “sjoin” method to add information about which admin-1 region each exposed road is within. Then we introduced some adaptation options, example costs, and used a discount rate to calculate the net present value (NPV) of investment in improvement and maintenance.

We applied those per-kilometre costs to the roads exposed to flooding, then compared those costs to the benefits of avoiding the discounted value of expected annual damages over the same period.

Finally, we filtered the results to select the most cost-beneficial options and summarised them to indicate the regional distribution.