RDM_analysis

December 8, 2015

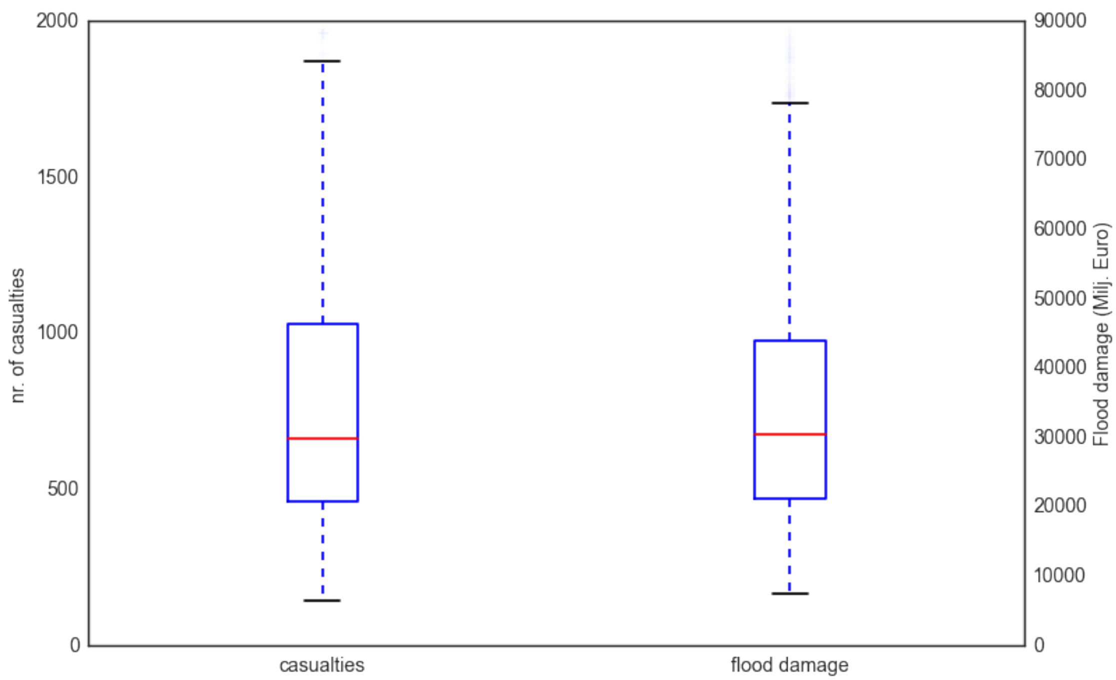
```
In [41]: def save_fig(fig, i):
             plt.savefig('./figs/fig{}_lowres.png'.format(i), dpi=75, bbox_inches='tight', figsi)
             plt.savefig('./figs/fig{}_highres.png'.format(i), dpi=300, bbox_inches='tight')

         def change_fontsize(fig, fs=14):

             for ax in fig.axes:
                 for item in ([ax.title, ax.xaxis.label, ax.yaxis.label] +
                              ax.get_xticklabels() + ax.get_yticklabels()):
                     item.set_fontsize(fs)

                 try:
                     parasites = ax.parasites
                 except AttributeError:
                     pass
                 else:
                     for parisite in parasites:
                         for axis in parisite.axis.values():
                             axis.major_ticklabels.set_fontsize(fs)
                             axis.label.set_fontsize(fs)

                     for axis in ax.axis.values():
                         axis.major_ticklabels.set_fontsize(fs)
                         axis.label.set_fontsize(fs)
```

```
In [42]: from util.util import load_results

         fn = r'./data/no policy 5000 runs.tar.gz'
         results = load_results(fn)
         experiments, outcomes = results
```

```
[INFO] results loaded succesfully from ./data/no policy 5000 runs.tar.gz
```

```
In [43]: with sns.axes_style('white'):
             oois = outcomes.keys()
             oois.pop(oois.index('Costs'))
             data = []

             for ooi in oois:
                 value = outcomes[ooi]
                 if len(value.shape)>1:
                     value = np.sum(value, axis=1)
```

```
            value = value/np.max(value)
            data.append(value)

        fig = plt.figure()

        casualties = np.sum(outcomes['Number of casualties'],axis=1)
        ax_casualties = fig.add_subplot(111)
        ax_casualties.boxplot([casualties,[]])
        ax_casualties.set_ylabel('nr. of casualties')

        damages = np.sum(outcomes['Flood damage (Milj. Euro)'],axis=1)
        ax_damage = ax_casualties.twinx()
        ax_damage.boxplot([[],damages])
        ax_damage.set_ylabel('Flood damage (Milj. Euro)')

        ax_casualties.set_xticklabels(['casualties', 'flood damage'])
        ax_casualties.set_ylim(ymin=0)

    change_fontsize(fig)
    save_fig(fig, 5)

    plt.show()
```




```
In [44]: for ooi in oois:
             value = outcomes[ooi]
             value = np.sum(value, axis=1)
             print ooi, np.mean(value), np.std(value)
```

```
Number of casualties 756.9814067 388.78367684
Flood damage (Milj. Euro) 34608.543 17107.6871672
```

The above figure shows boxplots for both casualties and flood damage. As can be seen, without any policy, there are quite a large number of casualties as well as a substantial amount of damages. The next question is then, under which combination of debelopments do we observe a high amount of casualties and or flood damage? To simplify this question, first let's take a quick look at the correlation between casuatlies and flood damage. If this correlation is high, we might be able to use only one or the other in classifying our experiments.

```
In [45]: print np.corrcoef(casualties, damages)
         print

         # returns the correlation and the p value
         print sp.stats.stats.pearsonr(casualties, damages)
```

```
[[ 1.          0.80732637]
 [ 0.80732637  1.        ]]

(0.80732637205751356, 0.0)
```

There is a statistically significant correlation between the number of casualties and the amount of damage, we can thus simplify the scneario discovery by using either the number of casualties or the amount of flood damage in the classify function.

0.1 First iteration scenario discovery

We can now perform scenario discovery.

\$ f(x) =

$$\begin{cases} 1 & \text{if } x > 50.000 \\ 0 & \text{otherwise} \end{cases}$$

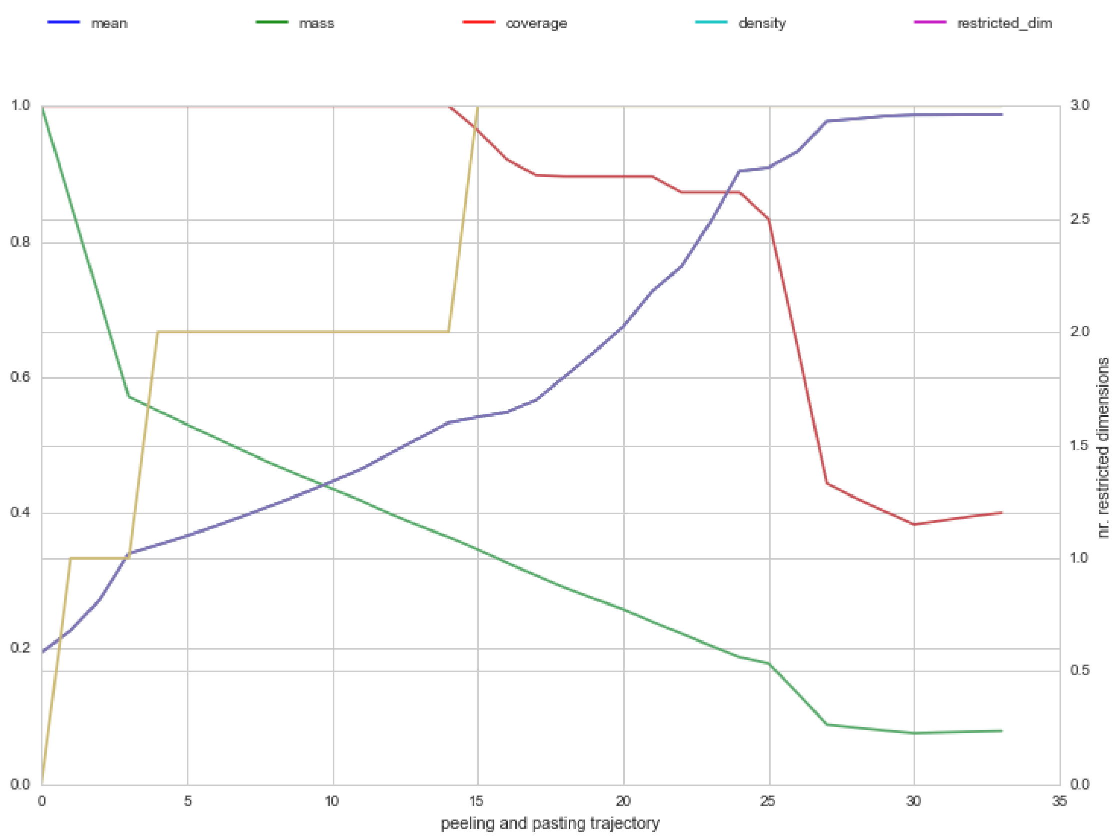
\$\$ \$

where x is the amount of flood damage

```
In [46]: from analysis import prim
         from util import ema_logging
         ema_logging.log_to_stderr(ema_logging.INFO)

         def classify(data):
             ooi = 'Flood damage (Milj. Euro)'
             outcome = np.sum(outcomes[ooi], axis=1)
             classes = np.zeros(outcome.shape[0])
             classes[outcome>50000] = 1
             return classes

         prim_obj = prim.setup_prim(results, classify, threshold=0.75)
         box_1 = prim_obj.find_box()
```

```
[INFO] 5000 points remaining, containing 972 cases of interest
[INFO] mean: 0.98730964467, mass: 0.0788, coverage: 0.400205761317, density: 0.98730964467 restricted_di
```

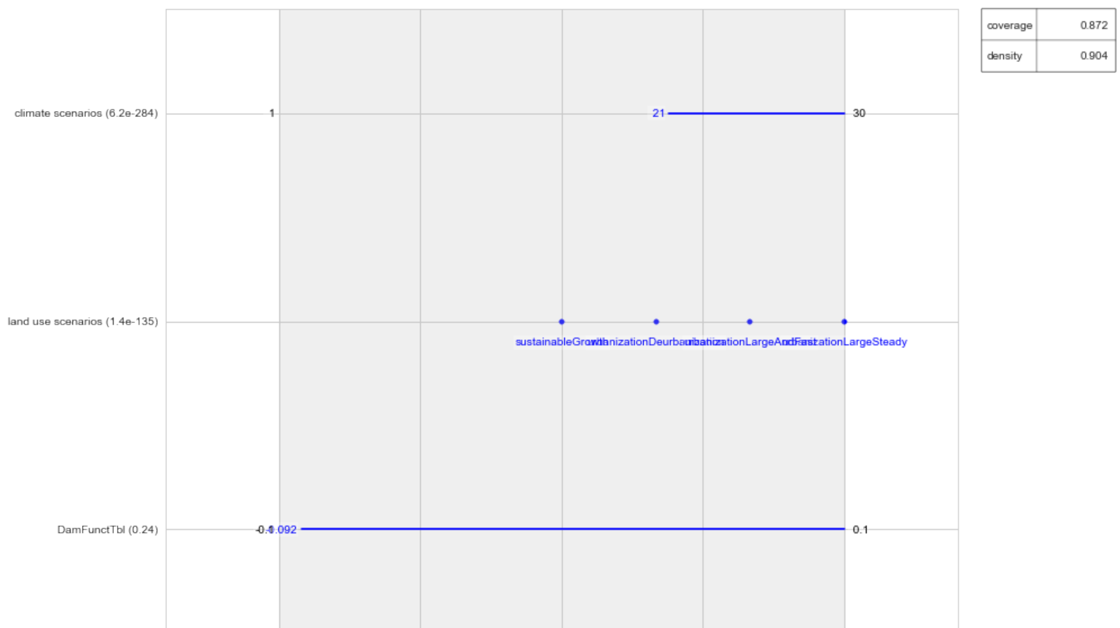
```
In [47]: import mpld3
         box_1.show_ppt()
         plt.show()
         box_1.show_tradeoff()
         mpld3.display()
```




```
Out[47]: <IPython.core.display.HTML object>

In [48]: box_1.inspect(24)
         box_1.select(24)

coverage    0.872428
density     0.904051
mass        0.187600
mean        0.904051
res dim     3.000000
Name: 24, dtype: float64

                                                               box 24  \
                                                                  min
climate scenarios                                                  21
land use scenarios  set([urbanizationLargeSteady, urbanizationDeur...
DamFunctTbl                                               -0.09171426

                                                                       \
                                                                  max
climate scenarios                                                  30
land use scenarios  set([urbanizationLargeSteady, urbanizationDeur...
DamFunctTbl                                                 0.0999638
```

```
                        qp values
climate scenarios   6.158837e-284
land use scenarios  1.427703e-135
DamFunctTbl             0.2375261
```

```
In [49]: box_1.inspect(style='graph')
         plt.show()
```



Using scenario discovery, we are able to find a single box that contains 87% of all the cases of interest, with a density of 90&. This box thus explains with high fidelity the conditions under which the most sever economic damages occur. This box is composes of climate scenarios 21-30, these are different realizations of the most sever climate change scenario, in combination with a growing population as represented by the selected land use scenarios. The parameter `DamFuncTbl` is a model specific uncertainy related to the relationship between water levels and econmic damages. Given that this paramater is not singificant as indicated by the quasi-p value, we drop it from the box for interpretation reasons.

```
In [50]: box_1.drop_restriction('DamFunctTbl')
         box_1.inspect()
```

```
coverage    0.907407
density     0.896341
mass        0.196800
mean        0.896341
res dim     2.000000
Name: 34, dtype: float64

                                                               box 34  \
                                                                  min
climate scenarios                                                  21
land use scenarios  set([urbanizationLargeSteady, urbanizationDeur...

                                                                       \
```

```
                                                                    max
climate scenarios                                                    30
land use scenarios  set([urbanizationLargeSteady, urbanizationDeur...


                        qp values
climate scenarios   3.639663e-291
land use scenarios   6.34335e-137
```

This changes coverage and density slightly. Coverage increases from 87% to 91%, while density remains stable. Droping this parameter from the box limits thus improved the overall quality of the box.

So, what kind of vulnerability does this box represent? In essence, under extreme climate change and growing population, you get a lot of problems. This is hardly a surprising result. It also indicates that the system in its current state is already in need of additional actions.

1 second iteration, 5 policies

There is a variety of ways in which the identified vulnerability can be handeld. These options include heightening the dikes, room for the river, strenghtening the dikes by making them wider (so called climate dikes), upstream collaboration, and earlier evacuation. These five policy options are not identical in their effect. For example, earlier evacuation will not change the damages but only reduce casualties. We ran 5000 experiments for each of these policy options. For heightening the dikes and room for the river, we start with a medium sized option. That is, we give some space to the river, or modestly increase the height of the dikes. In light of the following analysis, we might explore whether a smaller or larger scale version of this policy option is in order. Because we now include policy options, we added costs as a third indicator.

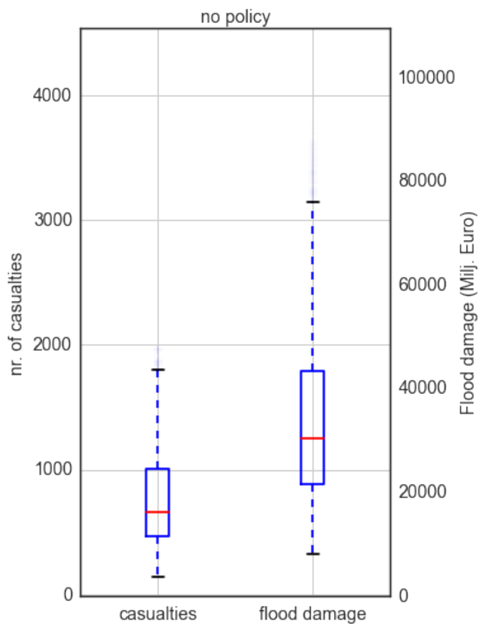
```
In [51]: from util.util import load_results

         # load the data and split it by policy
         # we end up with a dict with policy as key
         # and the associated experiments and outcomes
         # as value
         results_dict = {}

         fn  = r'./data/6 policies 5000 runs.tar.gz'
         experiments, outcomes = load_results(fn)

         policies = list(set(experiments['policy']))

         for policy in policies:
             logical = experiments['policy']==policy

             temp_exp = experiments[logical]
             temp_outcomes = {}
             for key, value in outcomes.iteritems():
                 temp_outcomes[key] = value[logical]
             results_dict[policy] = (temp_exp, temp_outcomes)
```

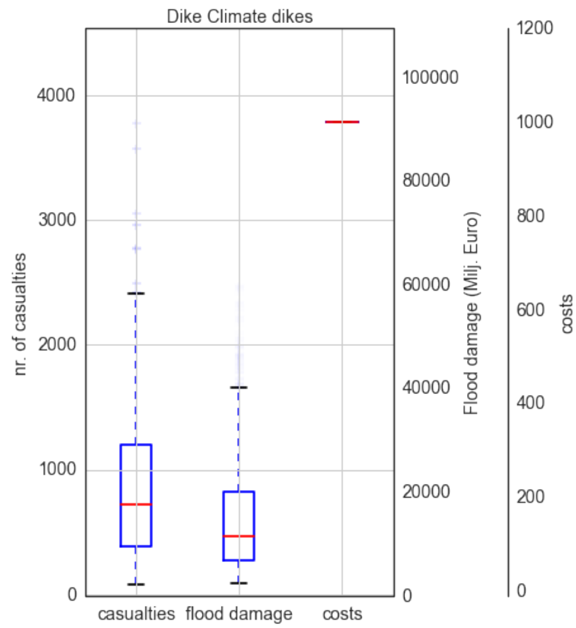
```
[INFO] results loaded succesfully from ./data/6 policies 5000 runs.tar.gz
```

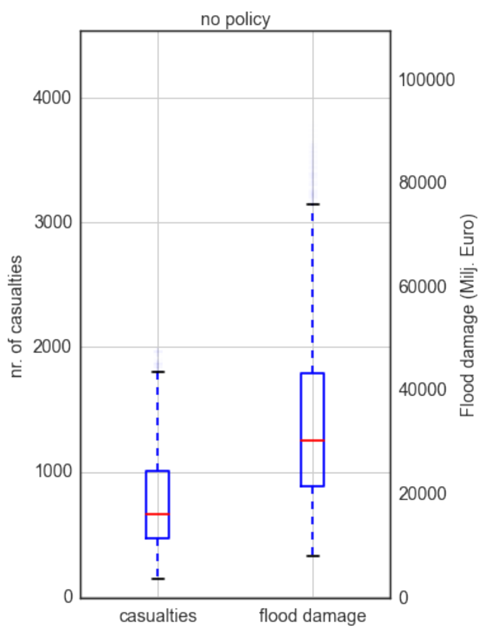
```
In [52]: from mpl_toolkits.axes_grid1 import host_subplot
         import mpl_toolkits.axisartist as AA

         policies = list(set(experiments['policy']))
```

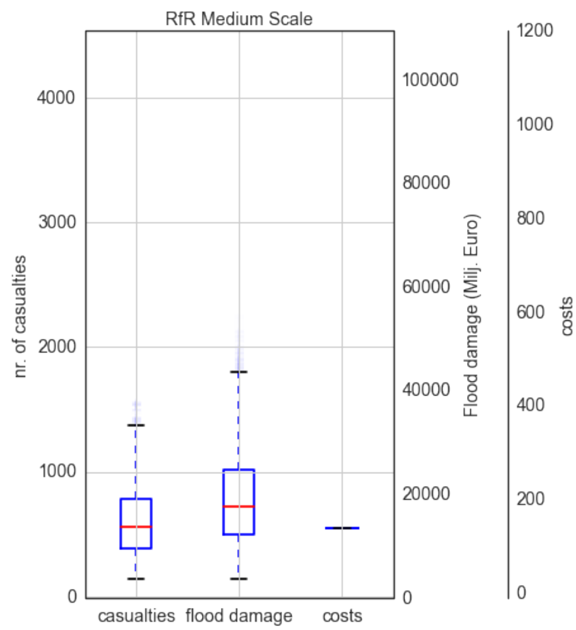
```python
policies.remove('no policy')

#determine maxima across all policies
costs = outcomes['Costs']
costs[costs==1e31] = 0
costs = np.sum(costs, axis=1)
max_costs = np.max(costs)

casualties = outcomes['Number of casualties']
casualties[casualties==1e31] = 0
casualties = np.sum(casualties, axis=1)
max_casualties = np.max(casualties)

damages = outcomes['Flood damage (Milj. Euro)']
damages[damages==1e31] = 0
damages = np.sum(damages, axis=1)
max_damages = np.max(damages)

def do_boxplot(results_dict, policy, compare_with='no policy'):
    fig = plt.figure()

    # no policy
    outcomes = results_dict[compare_with][1]
    casualties1 = np.sum(outcomes['Number of casualties'],axis=1)
    ax_casualties1 = fig.add_subplot(121)
    ax_casualties1.boxplot([casualties1,[]])
    ax_casualties1.set_ylabel('nr. of casualties')

    damages1 = np.sum(outcomes['Flood damage (Milj. Euro)'],axis=1)
    ax_damage1 = ax_casualties1.twinx()
    ax_damage1.boxplot([[],damages1])
    ax_damage1.set_ylabel('Flood damage (Milj. Euro)')

    ax_casualties1.set_xticklabels(['casualties', 'flood damage'])
    ax_casualties1.set_ylim(ymin=0)
    ax_casualties1.set_title(compare_with)
    ax_casualties1.grid(True)

    # policy
    outcomes = results_dict[policy][1]
    casualties2 = np.sum(outcomes['Number of casualties'],axis=1)
    ax_casualties2 = host = host_subplot(122, axes_class=AA.Axes)
    ax_casualties2.boxplot([casualties2,[],[]])
    ax_casualties2.set_ylabel('nr. of casualties')

    damages2 = np.sum(outcomes['Flood damage (Milj. Euro)'],axis=1)
    ax_damage2 = ax_casualties2.twinx()
    ax_damage2.boxplot([[],damages2,[]])
    ax_damage2.set_ylabel('Flood damage (Milj. Euro)')

    costs = np.sum(outcomes['Costs'],axis=1)
    ax_costs = ax_casualties2.twinx()
    offset = 90
```

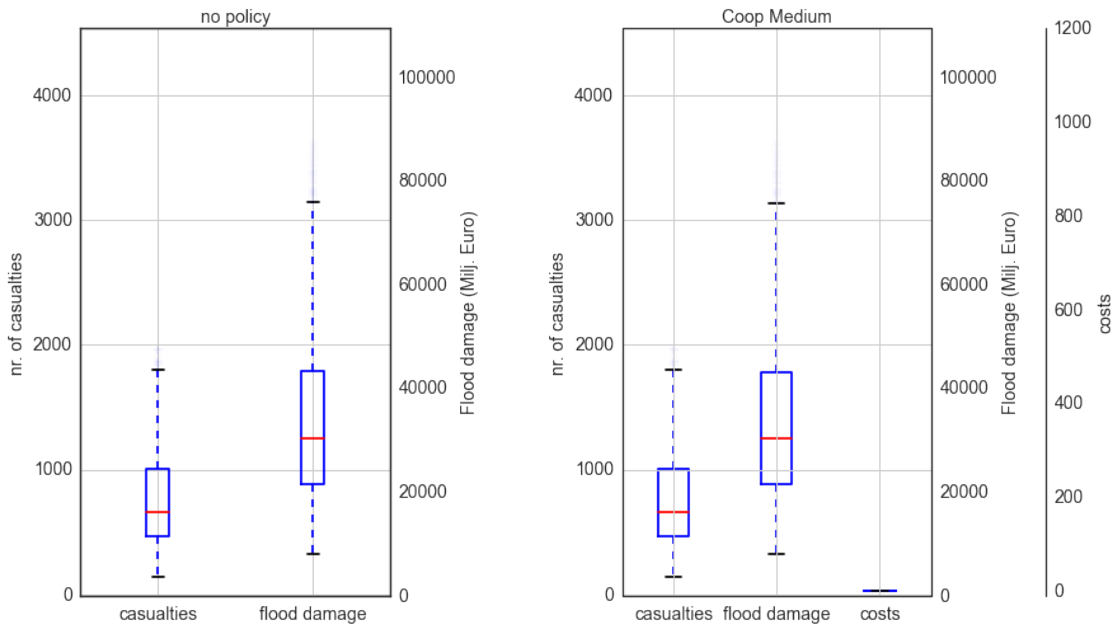
```
    new_fixed_axis = ax_costs.get_grid_helper().new_fixed_axis
    ax_costs.axis["right"] = new_fixed_axis(loc="right",
                                            axes=ax_costs,
                                            offset=(offset, 0))

    ax_costs.axis["right"].toggle(all=True)
    ax_costs.boxplot([[],[], costs])
    ax_costs.set_ylabel('costs')

    ax_casualties2.set_xticklabels(['casualties', 'flood damage','costs'])
    ax_casualties2.set_ylim(ymin=0)
    ax_casualties2.set_title(policy)
    ax_casualties2.grid(True)

    # the xaxis for must be set to the same limits
    ax_casualties1.set_ylim(ymin=-10, ymax=1.2*max_casualties)
    ax_casualties2.set_ylim(ymin=-10, ymax=1.2*max_casualties)

    ax_damage1.set_ylim(ymin=-10, ymax=1.2*max_damages)
    ax_damage2.set_ylim(ymin=-10, ymax=1.2*max_damages)

    ax_costs.set_ylim(ymin=-10, ymax=1.2*max_costs)


    plt.subplots_adjust(wspace = .75)

    return fig

for policy in policies:
    with sns.axes_style('white'):
        fig = do_boxplot(results_dict, policy)
        change_fontsize(fig)


    plt.show()
```

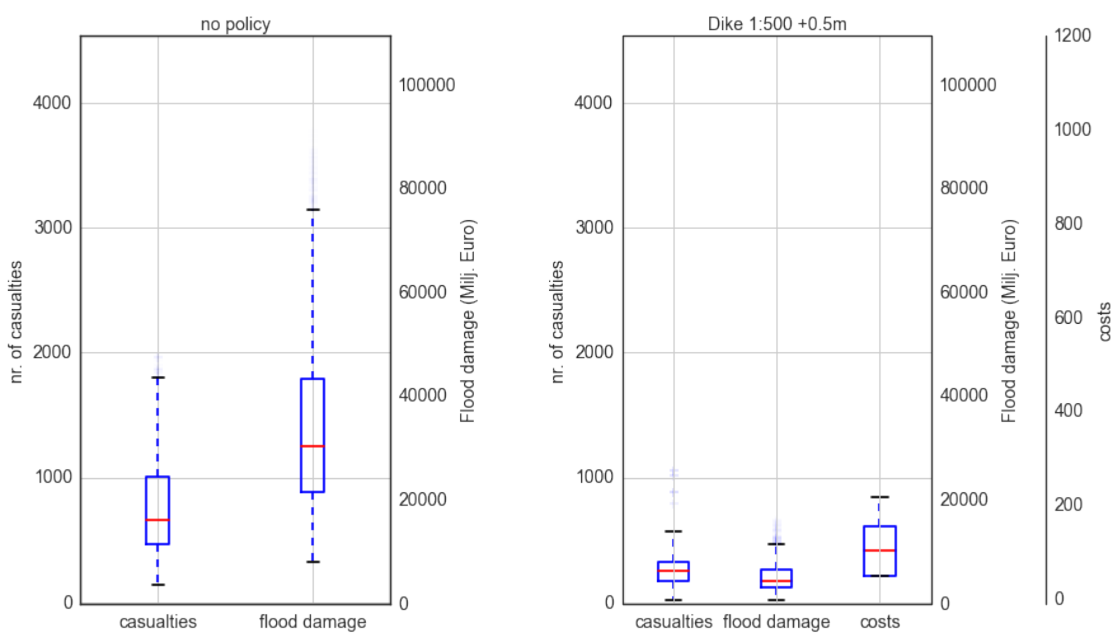

no policy
nr. of casualties
Flood damage (Milj. Euro)
0
1000
2000
3000
4000
0
20000
40000
60000
80000
100000
casualties
flood damage

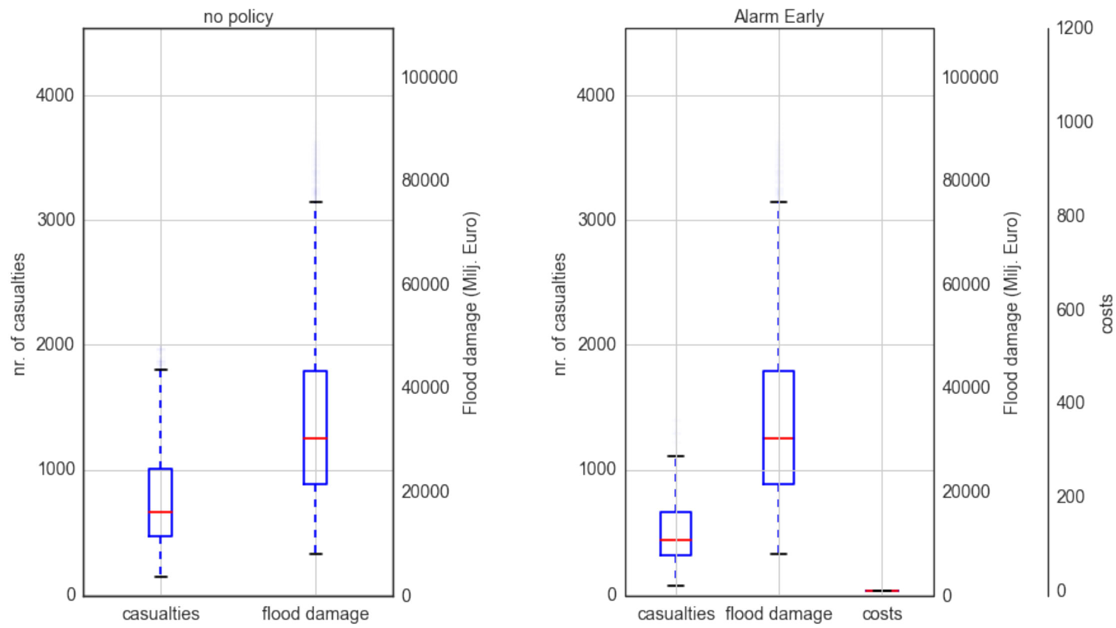

Dike Climate dikes
nr. of casualties
Flood damage (Milj. Euro)
costs
0
1000
2000
3000
4000
0
20000
40000
60000
80000
100000
0
200
400
600
800
1000
1200
casualties
flood damage
costs


no policy
nr. of casualties
Flood damage (Milj. Euro)
0
1000
2000
3000
4000
0
20000
40000
60000
80000
100000
casualties
flood damage


RfR Medium Scale
nr. of casualties
Flood damage (Milj. Euro)
costs
0
1000
2000
3000
4000
0
20000
40000
60000
80000
100000
0
200
400
600
800
1000
1200
casualties
flood damage
costs


no policy
Coop Medium
nr. of casualties
Flood damage (Milj. Euro)
costs
casualties
flood damage
costs


no policy
Dike 1:500 +0.5m
nr. of casualties
Flood damage (Milj. Euro)
costs
casualties
flood damage
costs

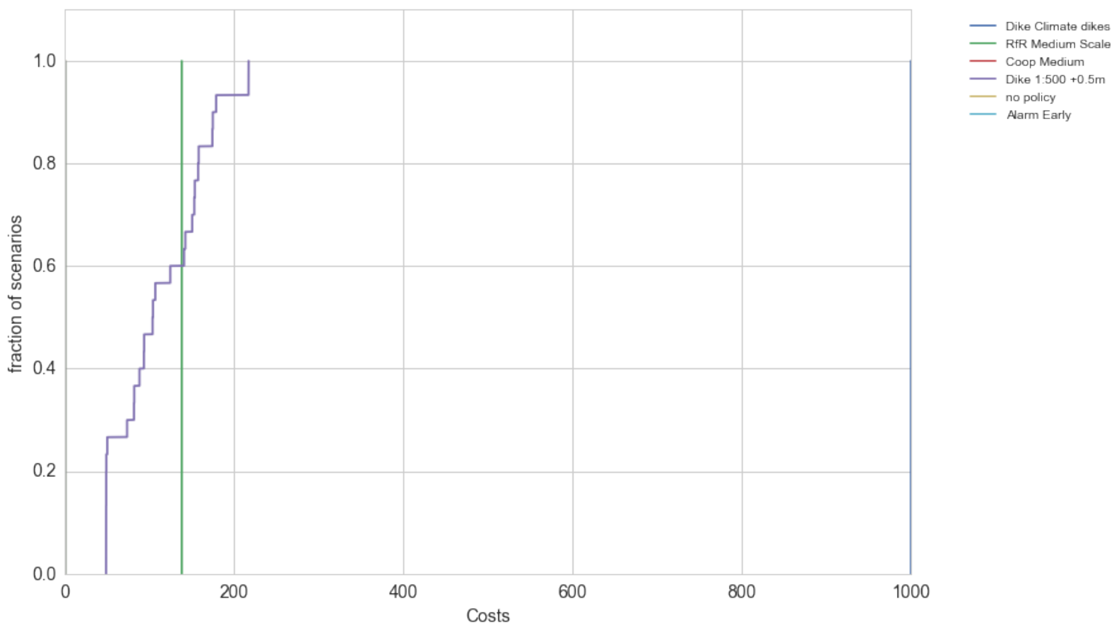


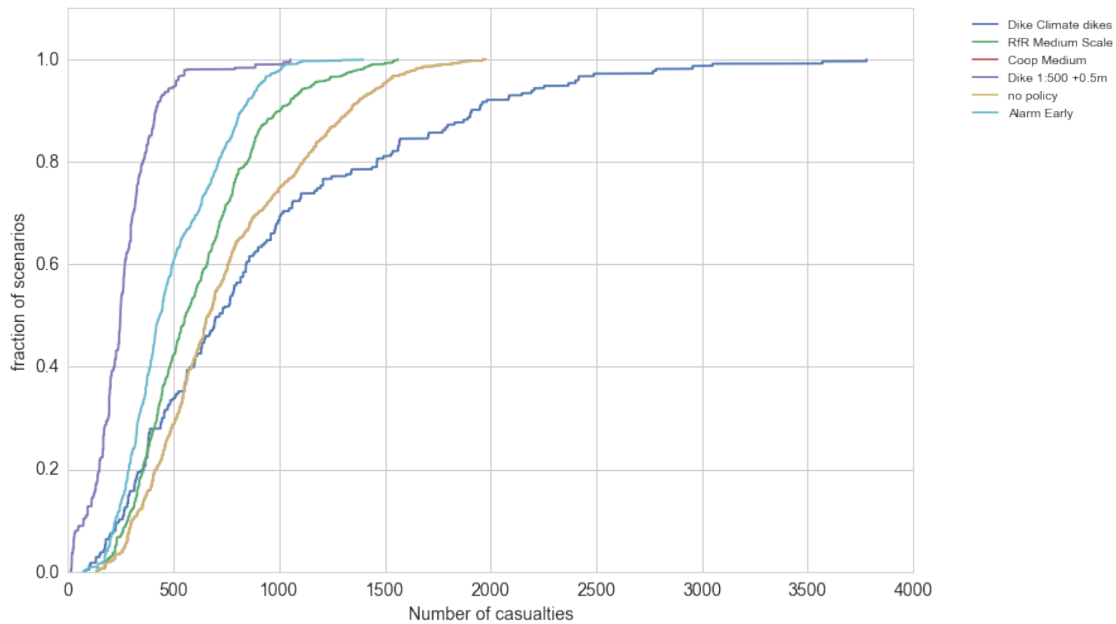
The above figures show a side by side comparison of each of the five policy options and doing nothing. As can be seen, raising the dikes is by far the most effective option. It substantially reduces both casualties and damages. A minor downside is the uncertainty associated with the exact costs. This is due to the fact that the dike height is based on a design discharge, which is continuously updated during the runtime in light of the latest discharge. This is standard practice in the Netherlands. The other policy options are substantially less effective. Climate dikes are broad enought to avoid breaching, but can still be overtopped. They improve the situation slightly, but are not very effective because the dikes are still too low. Medium scale room for the river results in a minor reduction of casualties and flood damage. Upstream collaboration is not effective, because the resulting maximum discharge is still heigher than the dikes can handle. Earlier alarm reduces casualities substantially, but does not affect the damages.

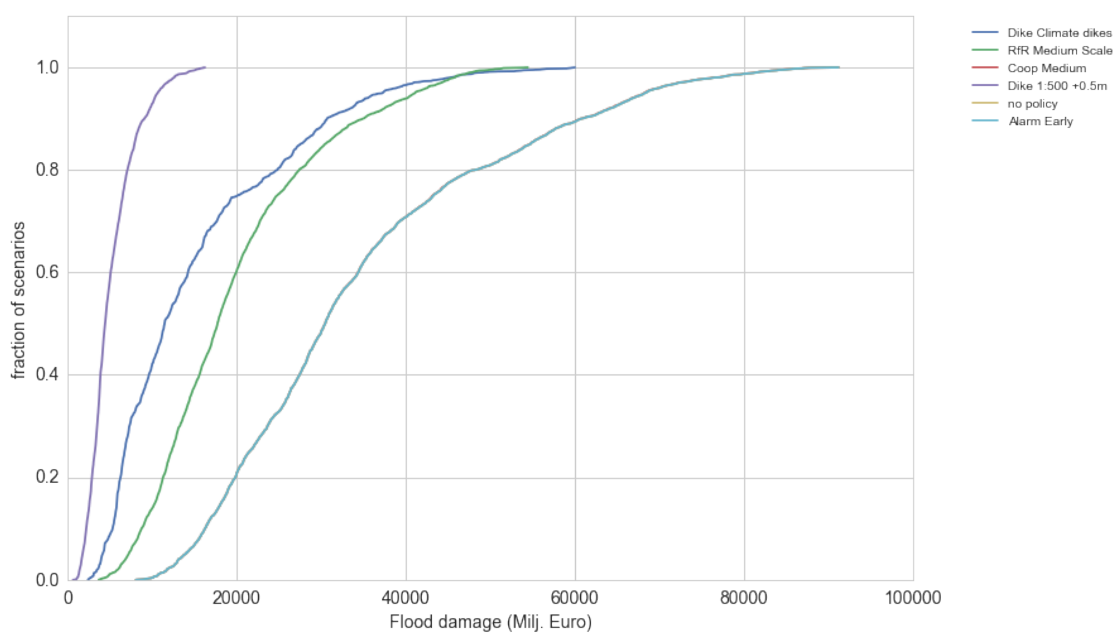
```
In [53]: fn  = r'./data/6 policies 5000 runs.tar.gz'
         experiments, outcomes = load_results(fn)

         policies = list(set(experiments['policy']))

         temp_outcomes = {}
         for key, value in outcomes.items():
             value = np.sum(value, axis=1)
             temp_outcomes[key] = value
         outcomes = temp_outcomes


         for ooi in outcomes.keys():
             fig = plt.figure()
             ax = fig.add_subplot(111)
             ax.set_ylabel('fraction of scenarios')

             for policy in policies:
                 logical = experiments['policy']==policy

                 data = outcomes[ooi][logical]
```

```
            x = np.sort(data)
            y = np.arange(len(x))/float(len(x))

            ax.plot(x, y, label=policy)
            ax.set_xlabel(ooi)
        ax.set_ylim(ymax=1.1)
        ax.legend(loc='upper right', bbox_to_anchor=(1.25,1))

        change_fontsize(fig)

    plt.show()
```

```
[INFO] results loaded succesfully from ./data/6 policies 5000 runs.tar.gz
```





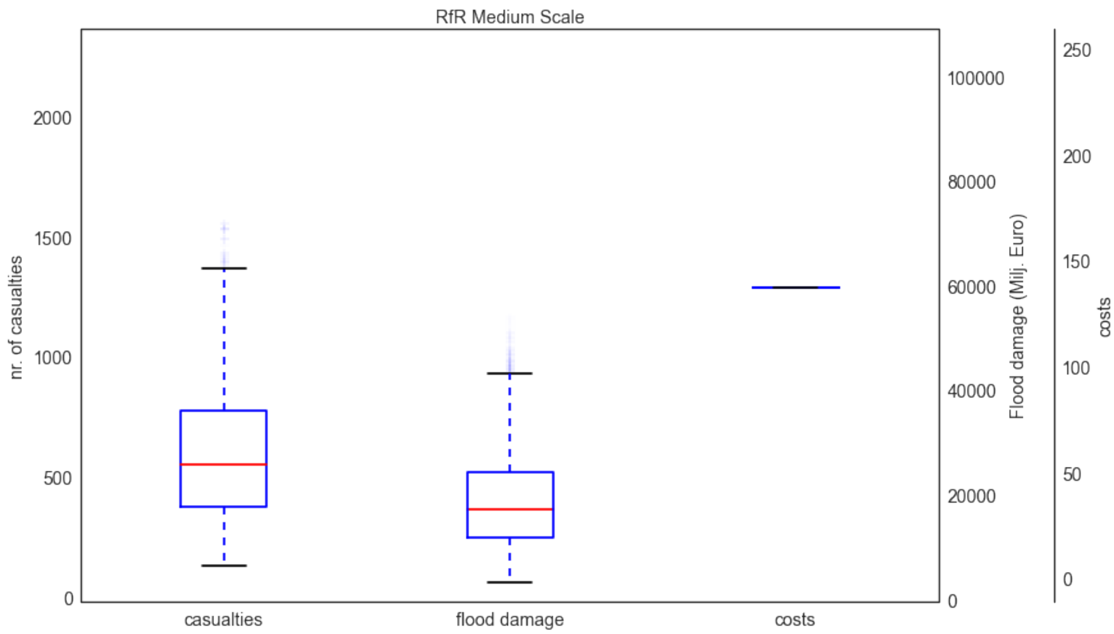


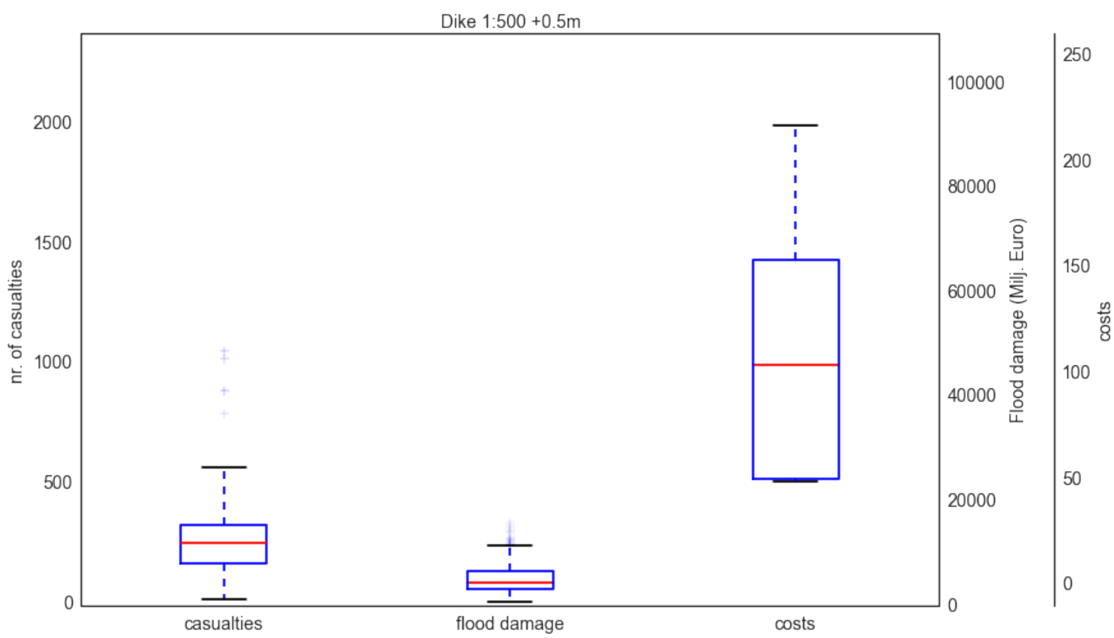

```
In [54]: fn  = r'./data/6 policies 5000 runs.tar.gz'
         experiments, outcomes = load_results(fn)

         outcomes = {key:np.sum(value, axis=1) for key, value in
                     outcomes.items()}
```

```
policies = ['RfR Medium Scale', 'Dike 1:500 +0.5m']

logical = np.zeros(experiments.shape, dtype=np.bool)
for policy in policies:
    logical[experiments['policy']==policy] = True
logical[experiments['policy']=='no policy'] = True

max_casualties = np.max(outcomes['Number of casualties'][logical])
max_damages = np.max(outcomes['Flood damage (Milj. Euro)'][logical])
max_costs = np.max(outcomes['Costs'][logical])


with sns.axes_style('white'):
    for i, policy in enumerate(policies):
        logical = experiments['policy']==policy

        # policy
        casualties = outcomes['Number of casualties'][logical]
        ax_casualties = host = host_subplot(111, axes_class=AA.Axes)
        ax_casualties.boxplot([casualties,[],[]])
        ax_casualties.set_ylabel('nr. of casualties')

        damages = outcomes['Flood damage (Milj. Euro)'][logical]
        ax_damage = ax_casualties.twinx()
        ax_damage.boxplot([[],damages,[]])
        ax_damage.set_ylabel('Flood damage (Milj. Euro)')

        costs = outcomes['Costs'][logical]
        ax_costs = ax_casualties.twinx()
        offset = 90

        new_fixed_axis = ax_costs.get_grid_helper().new_fixed_axis
        ax_costs.axis["right"] = new_fixed_axis(loc="right",
                                                axes=ax_costs,
                                                offset=(offset, 0))

        ax_costs.axis["right"].toggle(all=True)
        ax_costs.boxplot([[],[], costs])
        ax_costs.set_ylabel('costs')

        ax_casualties.set_xticklabels(['casualties', 'flood damage','costs'])
        ax_casualties.set_ylim(ymin=0)
        ax_casualties.set_title(policy)

        # the xaxis for must be set to the same limits
        ax_casualties.set_ylim(ymin=-10, ymax=1.2*max_casualties)

        ax_damage.set_ylim(ymin=-10, ymax=1.2*max_damages)

        ax_costs.set_ylim(ymin=-10, ymax=1.2*max_costs)
        plt.subplots_adjust(wspace = .75)

        fig = plt.gcf()
        change_fontsize(fig)
```

```
        save_fig(fig, '6{}'.format(chr(i + ord('a'))))


        plt.show()
```

```
[INFO] results loaded succesfully from ./data/6 policies 5000 runs.tar.gz
```





1.1 Second iteration scenario discovery

Given that raising the dikes is the most effective solution. we focuss on this option in the next iteration of scenario discovery. The aim is to understand what the remaining vulnerabilities of this policy are.

```
In [55]: from util.util import load_results
         fn  = r'./data/6 policies 5000 runs.tar.gz'
         experiments, outcomes = load_results(fn)

         policies = ['RfR Medium Scale', 'Dike 1:500 +0.5m']
         logical = np.zeros(experiments.shape, dtype=np.bool)
         for policy in policies:
             logical[experiments['policy']==policy]=True

         outcomes = {key:np.sum(value, axis=1)[logical] for key, value in
                     outcomes.items()}
         experiments = experiments[logical]
         results = (experiments, outcomes)
```

```
[INFO] results loaded succesfully from ./data/6 policies 5000 runs.tar.gz
```

```
In [56]: casualties = outcomes['Number of casualties']
         damages = outcomes['Flood damage (Milj. Euro)']

         print np.corrcoef(casualties, damages)
         print

         # returns the correlation and the p value
         print sp.stats.stats.pearsonr(casualties, damages)
```

```
[[ 1.          0.82273562]
 [ 0.82273562  1.        ]]

(0.82273561931990868, 0.0)
```

There still exists a statistically significant correlation,

1.1.1 scenario discovery for damages

We can now perform scenario discovery.

$ f(x) =

$$\begin{cases}1 & \text{if } x > 7.500 \\ 0 & \text{otherwise}\end{cases}$$

$$ $

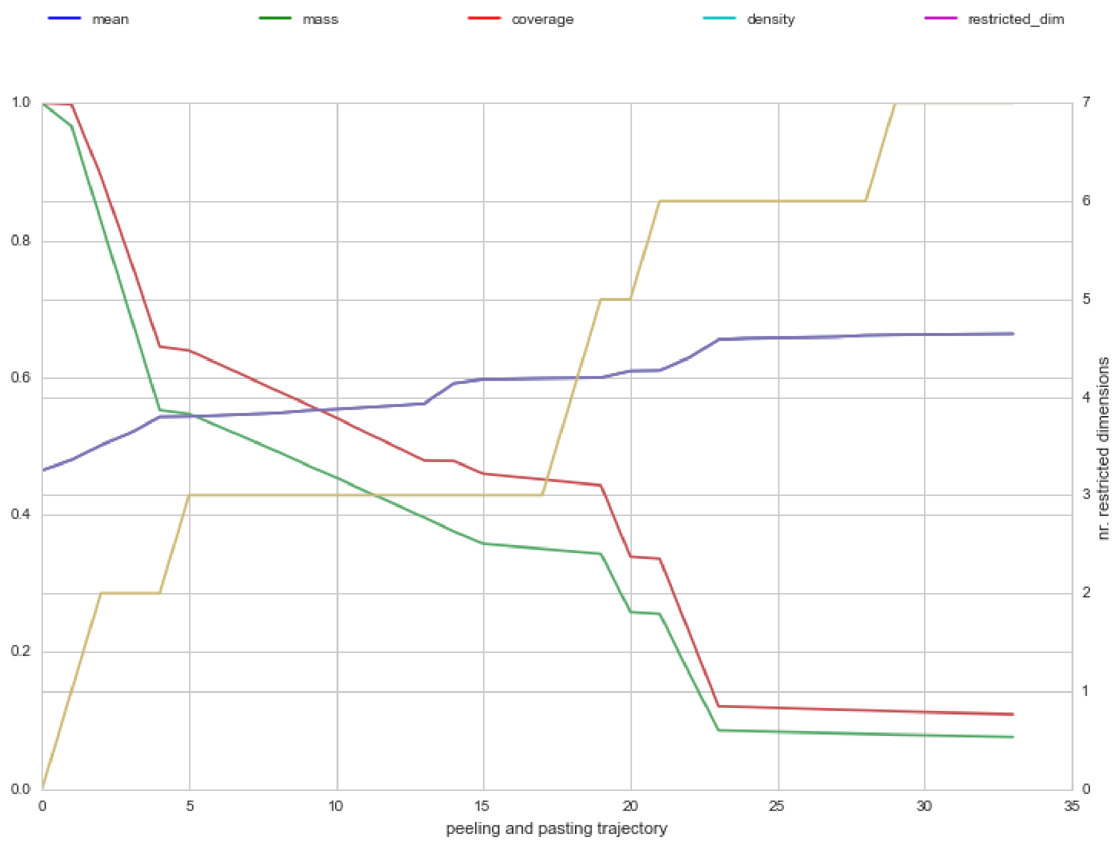
where x is the amount of flood damage

```
In [57]: from analysis import prim
         from util import ema_logging
         ema_logging.log_to_stderr(ema_logging.INFO)

         def classify(data):
             ooi = 'Flood damage (Milj. Euro)'
             outcome = outcomes[ooi]
             classes = np.zeros(outcome.shape[0])
             classes[outcome>10000] = 1
             return classes
```

```
results[0]['policy'] = 'na'

prim_obj = prim.setup_prim(results, classify, threshold=0.5, peel_alpha=0.01)
box_1 = prim_obj.find_box()
```

```
[INFO] 10000 points remaining, containing 4647 cases of interest
[INFO] mean: 0.663612565445, mass: 0.0764, coverage: 0.109102646869, density: 0.663612565445 restricted
```

In [58]:
```
box_1.show_ppt()
plt.show()
box_1.show_tradeoff()
mpld3.display()
```



Out[58]: <IPython.core.display.HTML object>

In [59]:
```
box_1.inspect(14)
box_1.inspect(20)
```

```
coverage    0.478373
density     0.591538
mass        0.375800
mean        0.591538
res dim     3.000000
Name: 14, dtype: float64
```

```
                                                               box 14  \
                                                                  min
climate scenarios                                                  11
land use scenarios  set([urbanizationLargeSteady, urbanizationDeur...
fragility dikes                                           -0.09998227

                                                                       \
                                                                  max
climate scenarios                                                  30
land use scenarios  set([urbanizationLargeSteady, urbanizationDeur...
fragility dikes                                             0.0979795


                       qp values
climate scenarios   1.108469e-15
land use scenarios  1.289178e-12
fragility dikes        0.4948249

coverage    0.338928
density     0.609520
mass        0.258400
mean        0.609520
res dim     5.000000
Name: 20, dtype: float64

                                                               box 20  \
                                                                  min
climate scenarios                                                  12
land use scenarios  set([urbanizationLargeSteady, urbanizationLarg...
fragility dikes                                           -0.09660298
DamFunctTbl                                               -0.09997506
ShipTbl3                                                  -0.09851993

                                                                       \
                                                                  max
climate scenarios                                                  30
land use scenarios  set([urbanizationLargeSteady, urbanizationLarg...
fragility dikes                                             0.0979795
DamFunctTbl                                                0.09768257
ShipTbl3                                                   0.09996198


                       qp values
climate scenarios   3.013309e-14
land use scenarios  6.766745e-10
fragility dikes        0.4534329
DamFunctTbl            0.5020987
ShipTbl3               0.5020987
```

```
In [60]: box_1.select(20)

         # let's drop the insignificant restrictions
         box_1.drop_restriction('fragility dikes')
```

```
        box_1.drop_restriction('DamFunctTbl')
        box_1.drop_restriction('ShipTbl3')
```

In [61]:
```
box_1.inspect()
```

```
coverage    0.354422
density     0.607749
mass        0.271000
mean        0.607749
res dim     2.000000
Name: 36, dtype: float64

                                                                 box 36  \
                                                                    min
climate scenarios                                                    12
land use scenarios  set([urbanizationLargeSteady, urbanizationLarg...

                                                                         \
                                                                    max
climate scenarios                                                    30
land use scenarios  set([urbanizationLargeSteady, urbanizationLarg...


                       qp values
climate scenarios   9.315272e-15
land use scenarios  3.242482e-10
```

In [62]:
```
box_2 = prim_obj.find_box()
```

```
[INFO] 7290 points remaining, containing 3000 cases of interest
[INFO] mean: 0.611969111969, mass: 0.0518, coverage: 0.0682160533678, density: 0.611969111969 restricte
```

In [63]:
```
box_2.show_tradeoff()
mpld3.display()
```

Out[63]: <IPython.core.display.HTML object>

In [64]:
```
box_2.inspect(8)
box_2.inspect()
```

```
coverage    0.279966
density     0.482209
mass        0.269800
mean        0.482209
res dim     5.000000
Name: 8, dtype: float64

                                                                  box 8  \
                                                                    min
land use scenarios  set([urbanizationLargeSteady, urbanizationDeur...
climate scenarios                                                     2
fragility dikes                                             -0.09998227
ShipTbl2                                                     -0.0979855
DamFunctTbl                                                 -0.09811832

                                                                         \
```

```
                                                               max
land use scenarios  set([urbanizationLargeSteady, urbanizationDeur...
climate scenarios                                               30
fragility dikes                                         0.09804238
ShipTbl2                                                0.09996517
DamFunctTbl                                             0.09831242


                       qp values
land use scenarios  4.401683e-08
climate scenarios    0.004215981
fragility dikes        0.4695582
ShipTbl2               0.4701255
DamFunctTbl            0.4774302

coverage    0.068216
density     0.611969
mass        0.051800
mean        0.611969
res dim     8.000000
Name: 35, dtype: float64

                                                  box 35  \
                                                     min
climate scenarios                                     16
land use scenarios  set([urbanizationDeurbanization])
ShipTbl2                                     -0.09621301
ShipTbl3                                     -0.09999651
collaboration                                   1.006688
fragility dikes                              -0.09744563
DamFunctTbl                                  -0.09811832
ShipTbl1                                     -0.09998611


                                                     max     qp values
climate scenarios                                     27  2.001806e-06
land use scenarios  set([urbanizationDeurbanization])  1.766676e-05
ShipTbl2                                      0.09446498     0.4569208
ShipTbl3                                      0.09772397     0.4875906
collaboration                                    1.59999     0.4954284
fragility dikes                               0.09804238     0.4954284
DamFunctTbl                                   0.09831242     0.5112933
ShipTbl1                                      0.09818923     0.5389885
```

In [65]:
```
box_2.select(8)
box_2.drop_restriction('DamFunctTbl')
box_2.drop_restriction('ShipTbl2')
box_2.drop_restriction('fragility dikes')
box_2.inspect()
```

```
coverage    0.290725
density     0.479759
mass        0.281600
mean        0.479759
res dim     2.000000
```

```
Name: 38, dtype: float64

                                                                    box 38  \
                                                                       min
land use scenarios  set([urbanizationLargeSteady, urbanizationDeur...
climate scenarios                                                        2

                                                                            \
                                                                       max
land use scenarios  set([urbanizationLargeSteady, urbanizationDeur...
climate scenarios                                                       30


                      qp values
land use scenarios  5.919319e-08
climate scenarios     0.00212535
```

- dike raising 1:1000
- dike raising 1:500, combined with alarm early
- dike raising 1:500, combined with room for the river medium
- dike raising 1:500, combined with climate dikes

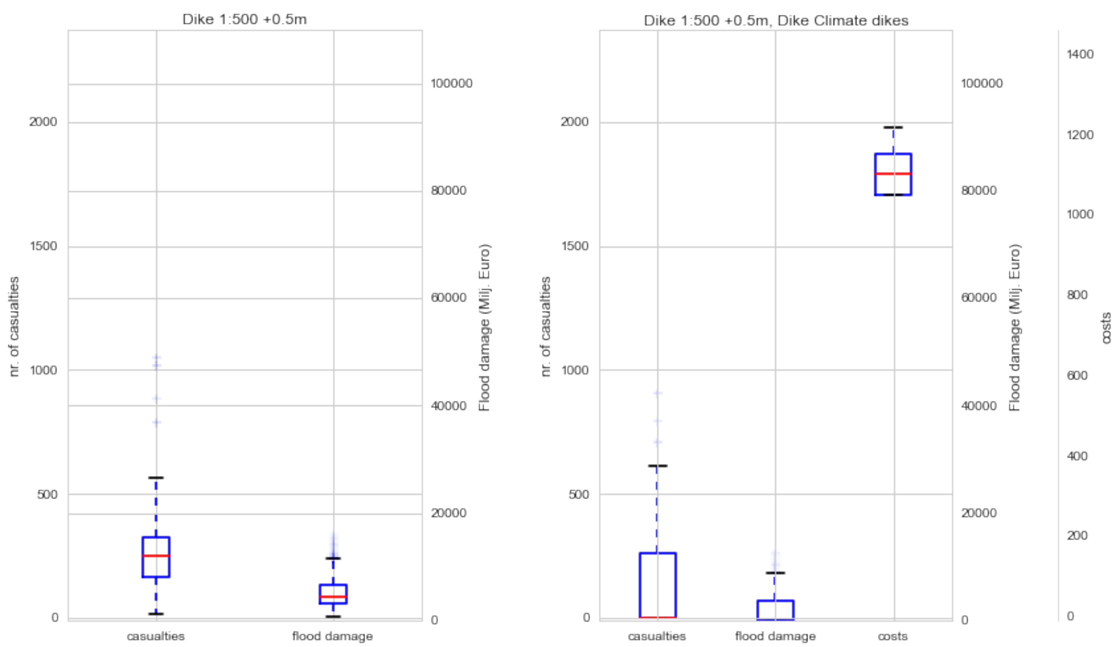
2 third iteration, 5 policies

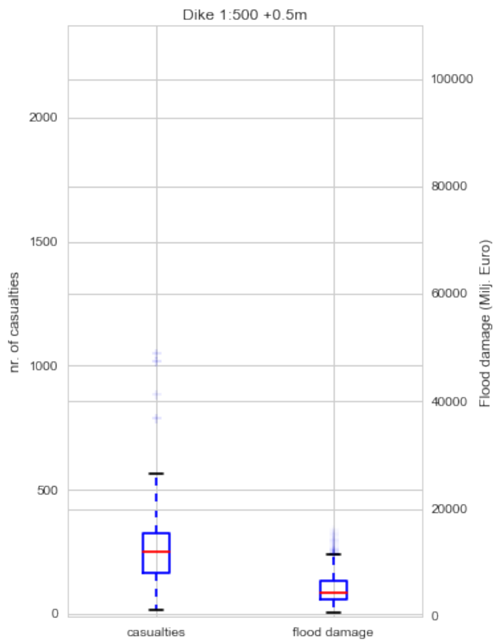
```
In [66]: from mpl_toolkits.axes_grid1 import host_subplot
         import mpl_toolkits.axisartist as AA
         from util.util import load_results

         def do_boxplot(results_dict, policy, compare_with='no policy'):
             fig = plt.figure()

             # no policy
             outcomes = results_dict[compare_with][1]
             casualties1 = outcomes['Number of casualties']
             ax_casualties1 = fig.add_subplot(121)
             ax_casualties1.boxplot([casualties1,[]])
             ax_casualties1.set_ylabel('nr. of casualties')

             damages1 = outcomes['Flood damage (Milj. Euro)']
             ax_damage1 = ax_casualties1.twinx()
             ax_damage1.boxplot([[],damages1])
             ax_damage1.set_ylabel('Flood damage (Milj. Euro)')

             ax_casualties1.set_xticklabels(['casualties', 'flood damage'])
             ax_casualties1.set_ylim(ymin=0)
             ax_casualties1.set_title(compare_with)
             ax_casualties1.grid(True)

             # policy
             outcomes = results_dict[policy][1]
             casualties2 = outcomes['Number of casualties']
             ax_casualties2 = host = host_subplot(122, axes_class=AA.Axes)
             ax_casualties2.boxplot([casualties2,[],[]])
             ax_casualties2.set_ylabel('nr. of casualties')
```

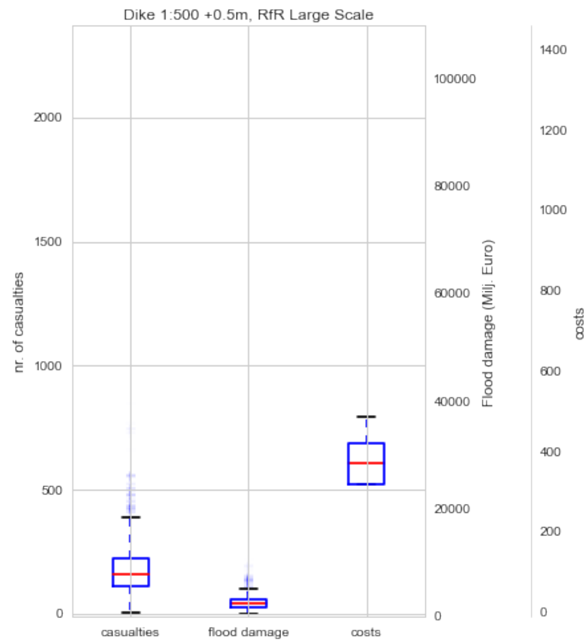
```
    damages2 = outcomes['Flood damage (Milj. Euro)']
    ax_damage2 = ax_casualties2.twinx()
    ax_damage2.boxplot([[],damages2,[]])
    ax_damage2.set_ylabel('Flood damage (Milj. Euro)')


    costs = outcomes['Costs']
    ax_costs = ax_casualties2.twinx()
    offset = 80

    new_fixed_axis = ax_costs.get_grid_helper().new_fixed_axis
    ax_costs.axis["right"] = new_fixed_axis(loc="right",
                                            axes=ax_costs,
                                            offset=(offset, 0))

    ax_costs.axis["right"].toggle(all=True)
    ax_costs.boxplot([[],[], costs])
    ax_costs.set_ylabel('costs')

    ax_casualties2.set_xticklabels(['casualties', 'flood damage','costs'])
    ax_casualties2.set_ylim(ymin=0)
    ax_casualties2.set_title(policy)
    ax_casualties2.grid(True)

    # the xaxis for must be set to the same limits
    ax_casualties1.set_ylim(ymin=-10, ymax=1.2*max_casualties)
    ax_casualties2.set_ylim(ymin=-10, ymax=1.2*max_casualties)

    ax_damage1.set_ylim(ymin=-10, ymax=1.2*max_damages)
    ax_damage2.set_ylim(ymin=-10, ymax=1.2*max_damages)

    ax_costs.set_ylim(ymin=-10, ymax=1.2*max_costs)


    plt.subplots_adjust(wspace = .5)

    return fig

# load the data and split it by policy
# we end up with a dict with policy as key
# and the associated experiments and outcomes
# as value
results_dict = {}

fn  = r'./data/third iteration 7 policies  5000 runs.tar.gz'
policy_results = load_results(fn)

experiments, outcomes = policy_results
policies = list(set(experiments['policy']))
print policies

for policy in policies:
    logical = experiments['policy']==policy
```

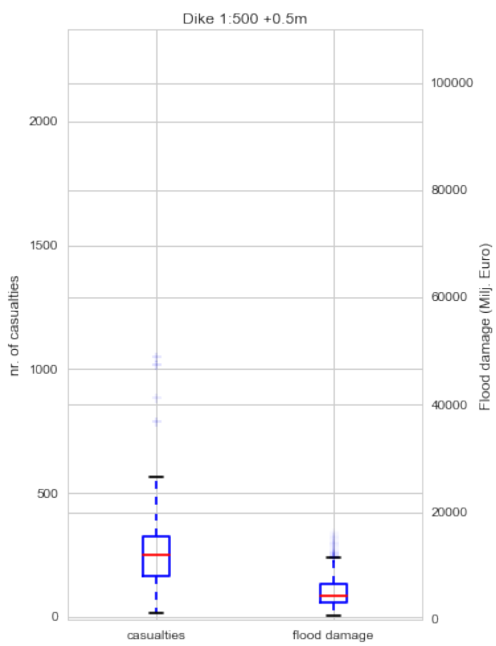
```
    temp_exp = experiments[logical]
    temp_outcomes = {}
    for key, value in outcomes.iteritems():
        temp_outcomes[key] = value[logical]
    results_dict[policy] = (temp_exp, temp_outcomes)

policies = list(set(experiments['policy']))
policies.remove('no policy')

#determine maxima across all policies
costs = outcomes['Costs']
max_costs = np.max(costs)

casualties = outcomes['Number of casualties']
max_casualties = np.max(casualties)

damages = outcomes['Flood damage (Milj. Euro)']
max_damages = np.max(damages)

for policy in policies:
    fig = do_boxplot(results_dict,
                     policy,
                     compare_with='Dike 1:500 +0.5m')
    plt.show()
```

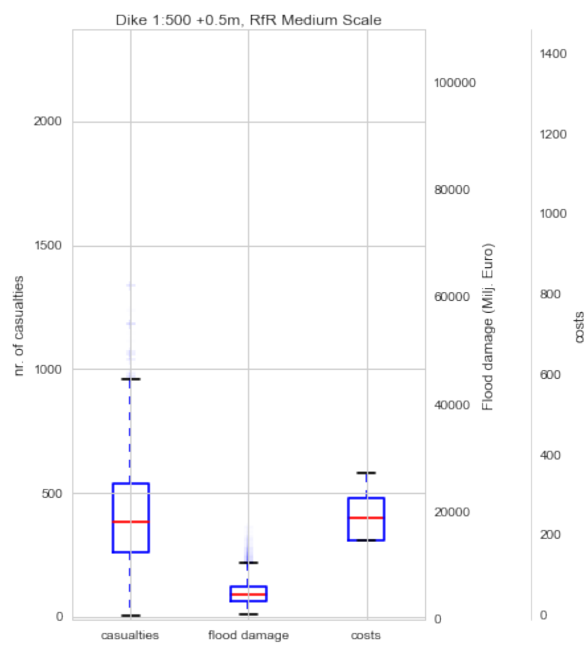
```
[INFO] results loaded succesfully from ./data/third iteration 7 policies  5000 runs.tar.gz

['Dike 1:500 +0.5m, Dike Climate dikes', 'Dike 1:500 +0.5m, RfR Large Scale', 'Dike 1:500 +0.5m, RfR Me
```

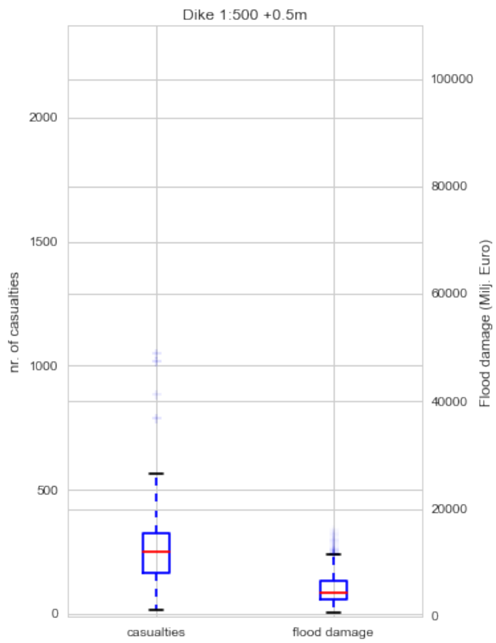


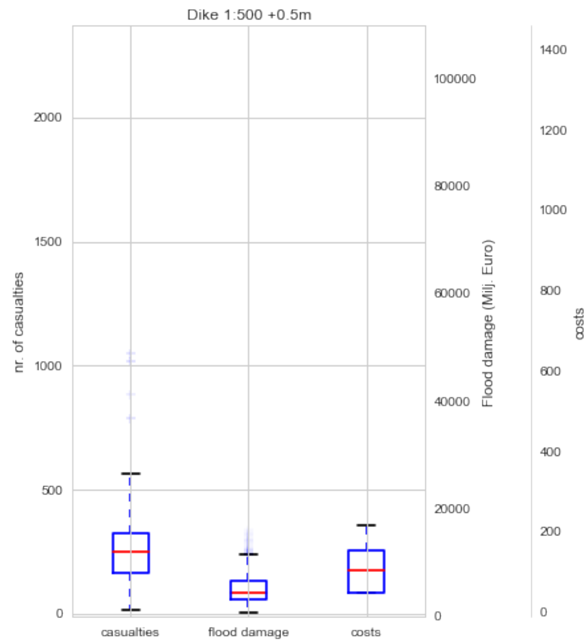

Dike 1:500 +0.5m
nr. of casualties
Flood damage (Milj. Euro)
casualties
flood damage

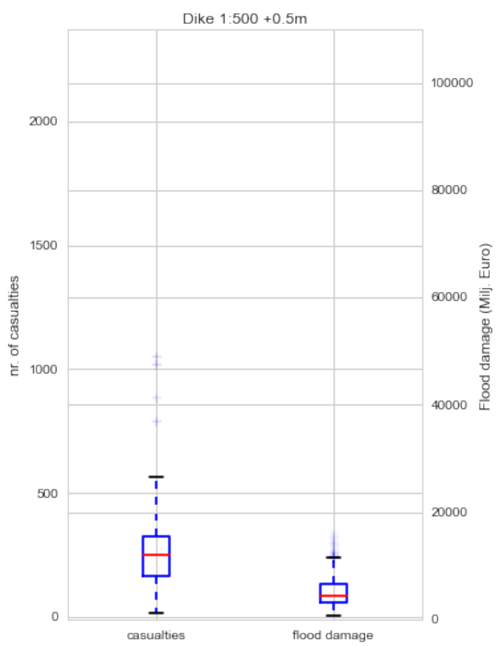

Dike 1:500 +0.5m, RfR Large Scale
nr. of casualties
Flood damage (Milj. Euro)
costs
casualties
flood damage
costs

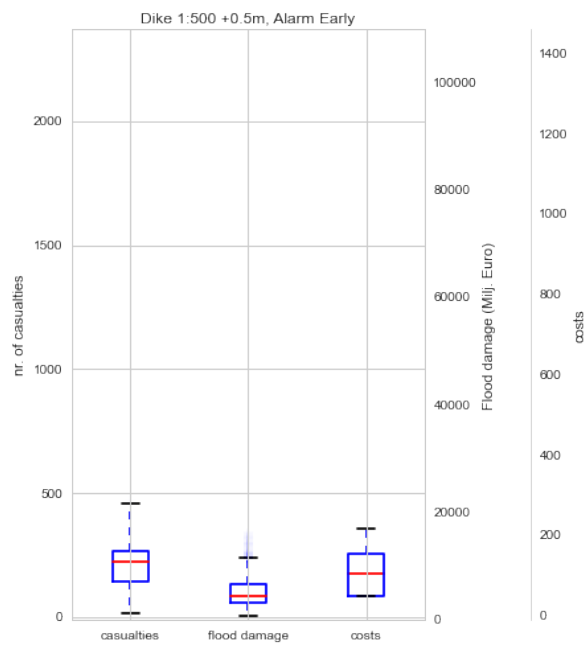

Dike 1:500 +0.5m
nr. of casualties
Flood damage (Milj. Euro)
casualties
flood damage

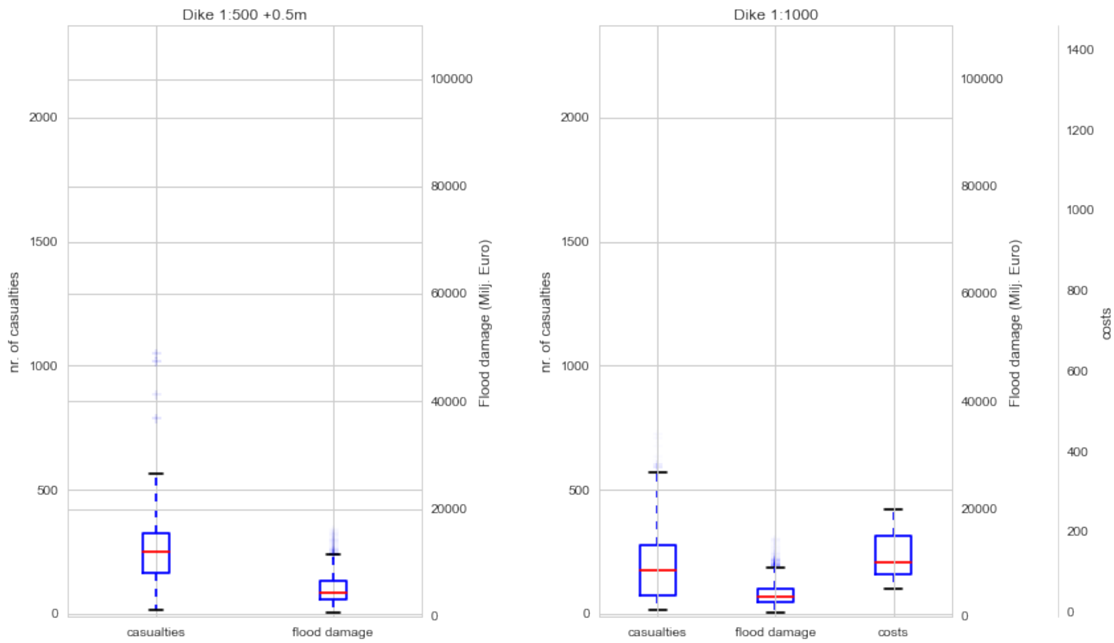

Dike 1:500 +0.5m, RfR Medium Scale
nr. of casualties
Flood damage (Milj. Euro)
costs
casualties
flood damage
costs


Dike 1:500 +0.5m
nr. of casualties
Flood damage (Milj. Euro)
casualties
flood damage


Dike 1:500 +0.5m
nr. of casualties
Flood damage (Milj. Euro)
costs
casualties
flood damage
costs


Dike 1:500 +0.5m
nr. of casualties
Flood damage (Milj. Euro)
casualties
flood damage

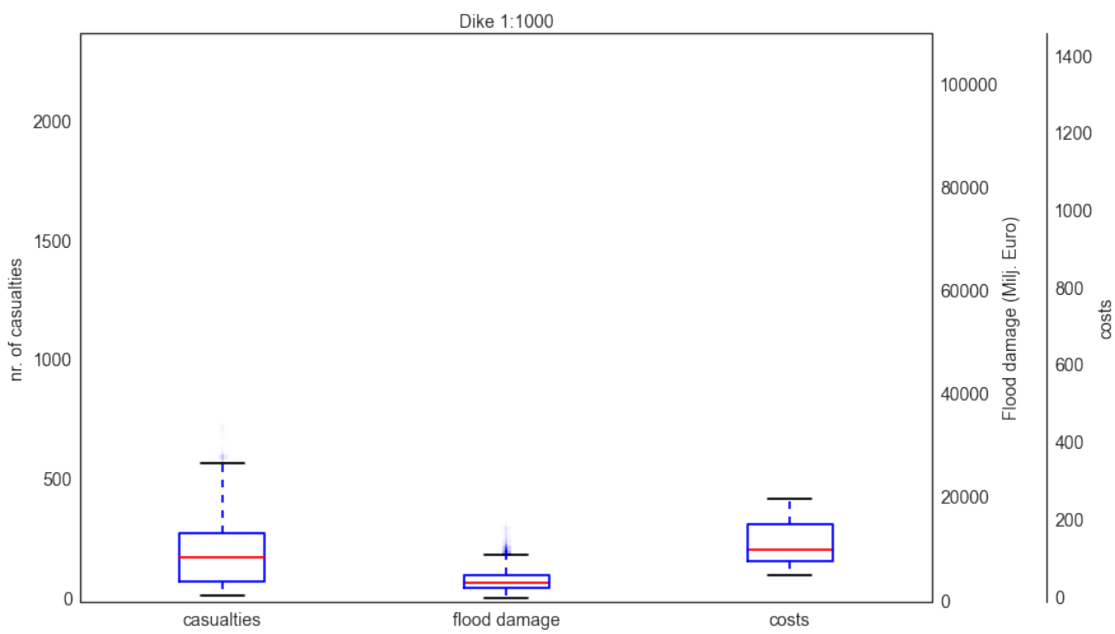

Dike 1:500 +0.5m, Alarm Early
nr. of casualties
Flood damage (Milj. Euro)
costs
casualties
flood damage
costs

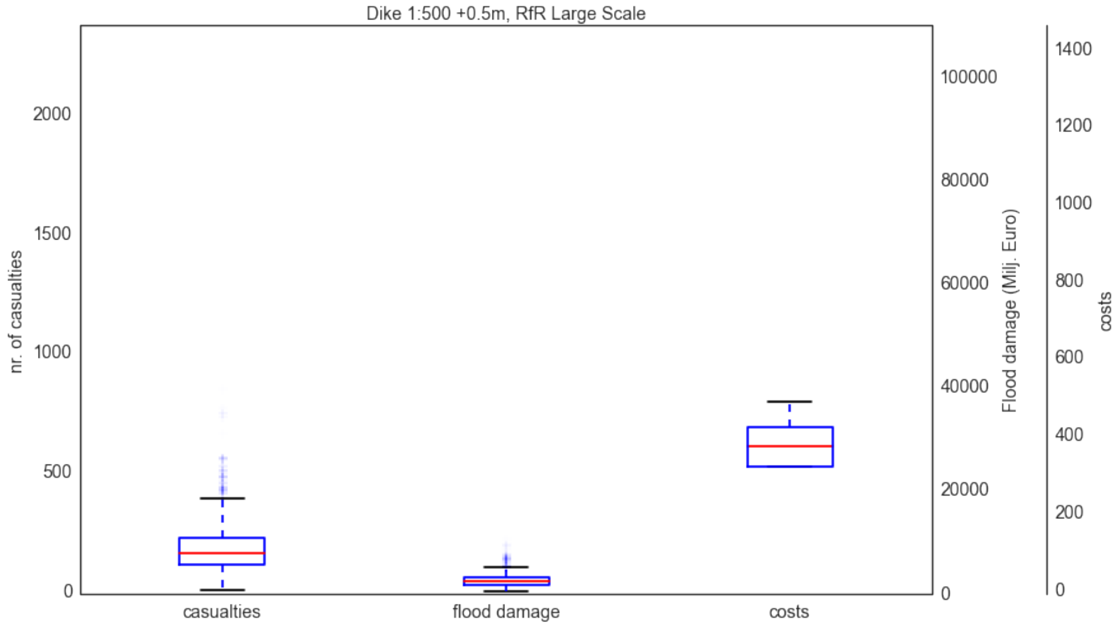


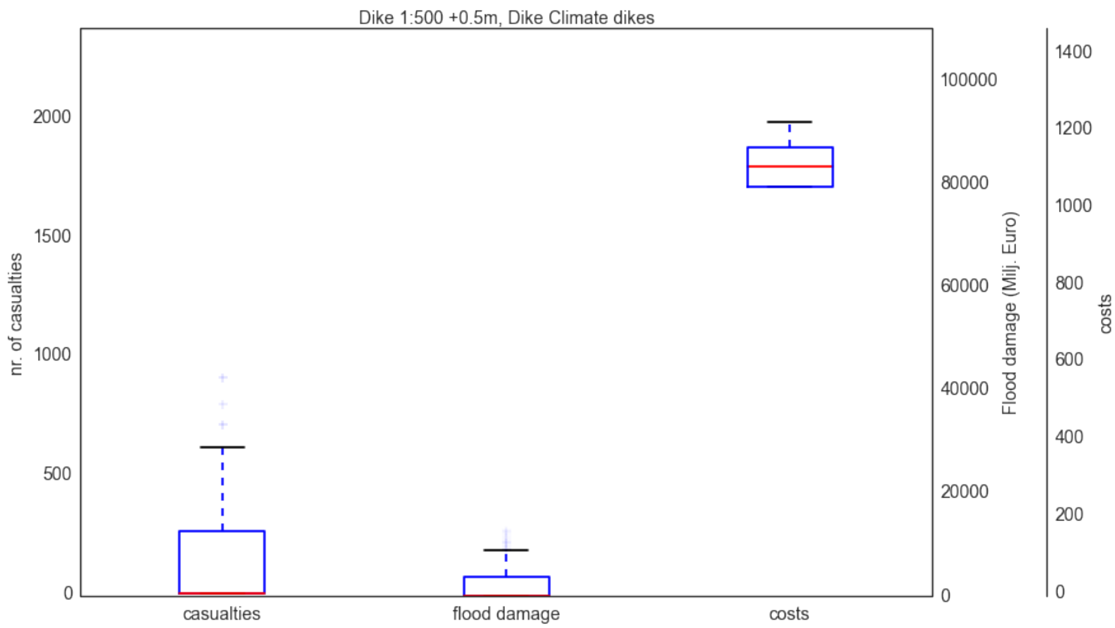

```
In [67]: fn  = r'./data/third iteration 7 policies  5000 runs.tar.gz'
         experiments, outcomes = load_results(fn)

         policies = ['Dike 1:1000','Dike 1:500 +0.5m, RfR Large Scale','Dike 1:500 +0.5m, Dike Climate 

         logical = np.zeros(experiments.shape, dtype=np.bool)
         for policy in policies:
             logical[experiments['policy']==policy] = True
         logical[experiments['policy']=='no policy'] = True

         max_casualties = np.max(outcomes['Number of casualties'][logical])
         max_damages = np.max(outcomes['Flood damage (Milj. Euro)'][logical])
         max_costs = np.max(outcomes['Costs'][logical])


         with sns.axes_style('white'):
             for i, policy in enumerate(policies):
                 logical = experiments['policy']==policy

                 # policy
                 casualties = outcomes['Number of casualties'][logical]
                 ax_casualties = host = host_subplot(111, axes_class=AA.Axes)
                 ax_casualties.boxplot([casualties,[],[]])
                 ax_casualties.set_ylabel('nr. of casualties')

                 damages = outcomes['Flood damage (Milj. Euro)'][logical]
                 ax_damage = ax_casualties.twinx()
                 ax_damage.boxplot([[],damages,[]])
                 ax_damage.set_ylabel('Flood damage (Milj. Euro)')
```

```
costs = outcomes['Costs'][logical]
ax_costs = ax_casualties.twinx()
offset = 90

new_fixed_axis = ax_costs.get_grid_helper().new_fixed_axis
ax_costs.axis["right"] = new_fixed_axis(loc="right",
                                        axes=ax_costs,
                                        offset=(offset, 0))

ax_costs.axis["right"].toggle(all=True)
ax_costs.boxplot([[],[], costs])
ax_costs.set_ylabel('costs')

ax_casualties.set_xticklabels(['casualties', 'flood damage','costs'])
ax_casualties.set_ylim(ymin=0)
ax_casualties.set_title(policy)

# the xaxis for must be set to the same limits
ax_casualties.set_ylim(ymin=-10, ymax=1.2*max_casualties)

ax_damage.set_ylim(ymin=-10, ymax=1.2*max_damages)

ax_costs.set_ylim(ymin=-10, ymax=1.2*max_costs)
plt.subplots_adjust(wspace = .75)

fig = plt.gcf()
change_fontsize(fig)
save_fig(fig, '7{}'.format(chr(i + ord('a'))))


plt.show()
```

```
[INFO] results loaded succesfully from ./data/third iteration 7 policies  5000 runs.tar.gz
```








```
In [68]: print set(experiments['policy'])
```

```
set(['Dike 1:500 +0.5m, Dike Climate dikes', 'Dike 1:500 +0.5m, RfR Large Scale', 'Dike 1:500 +0.5m, RfI
```

```
In [69]: def get_results_for_policies(results, policies):

             experiments, outcomes = results

             logical = np.zeros((experiments.shape[0],), np.bool)

             for policy in policies:
                 logical[experiments['policy']==policy] = True

             temp_exp = experiments[logical]
             temp_out = {key: value[logical] for key, value in outcomes.items()}


             temp_exp['policy'] = 'not relevant'
             logical = temp_exp['climate scenarios']<11
             temp_exp['climate scenarios'][logical] = 0

             logical = (temp_exp['climate scenarios']<21) & (temp_exp['climate scenarios']>10)
             temp_exp['climate scenarios'][logical] = 1

             logical  = temp_exp['climate scenarios']>20
             temp_exp['climate scenarios'][logical] = 2

             return temp_exp, temp_out

         fn  = r'./data/third iteration 7 policies  5000 runs.tar.gz'
         results = load_results(fn)
         policies = ['Dike 1:500 +0.5m, Dike Climate dikes',
                     'Dike 1:1000',
                     'Dike 1:500 +0.5m, RfR Large Scale']
         relevant_results = get_results_for_policies(results, policies)
```

```
[INFO] results loaded succesfully from ./data/third iteration 7 policies  5000 runs.tar.gz
```

2.1 Third iteration prim

based on the results above, we have selected 3 policies

- Dike 1:500 +0.5m, Dike Climate dikes
- ike 1:500 +0.5m, Alarm Early'
- Dike 1:1000

For some reason the results of dike 1:500 and room for the river are off, this needs to be investigated in the next version of this analysis.

2.1.1 scenario discovery for casualties

We can now perform scenario discovery.

$ f(x) =

$$\begin{cases} 1 & \text{if } x > 300 \\ 0 & \text{otherwise} \end{cases}$$

$$ $

where x is the number of casualties

```
In [70]: from analysis import prim
         from util import ema_logging
         ema_logging.log_to_stderr(ema_logging.INFO)

         def classify(data):
             ooi = 'Number of casualties'
             outcome = data[ooi]
             classes = np.zeros(outcome.shape[0])
             classes[outcome>250] = 1
             return classes

         prim_obj = prim.setup_prim(relevant_results, classify, threshold=0.4, peel_alpha=0.05)
         box_1 = prim_obj.find_box()
```

```
[INFO] 15000 points remaining, containing 3773 cases of interest
[INFO] mean: 0.607007575758, mass: 0.0704, coverage: 0.169891333157, density: 0.607007575758 restricted
```

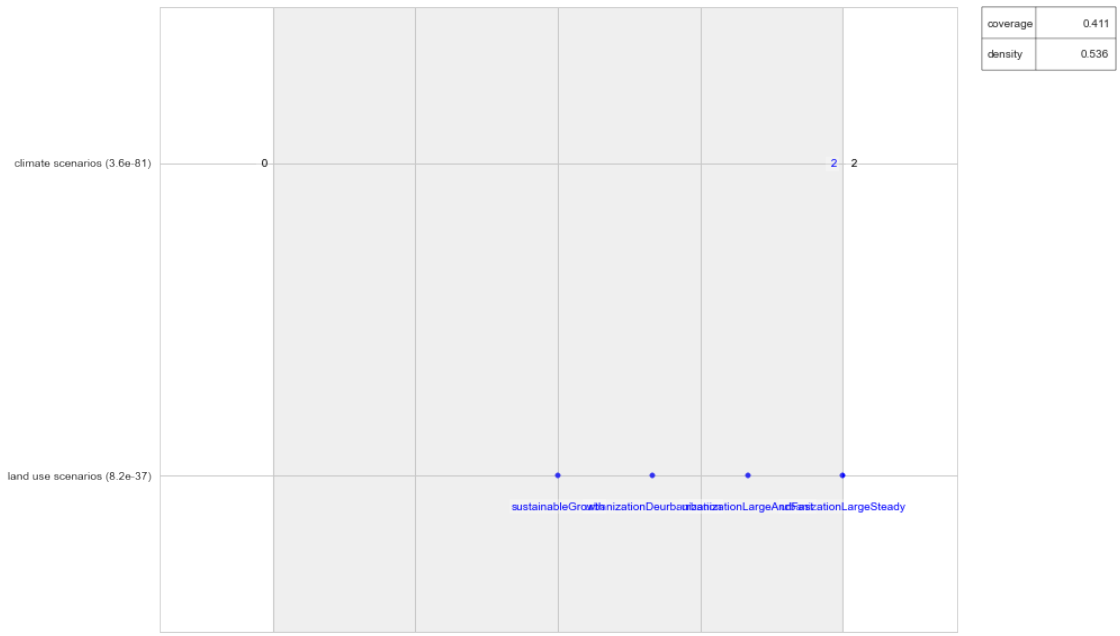
```
In [71]: import mpld3
         box_1.show_tradeoff()
         mpld3.display()
```

```
Out[71]: <IPython.core.display.HTML object>
```

```
In [72]: box_1.inspect(5)
```

```
coverage    0.411344
density     0.535542
mass        0.193200
mean        0.535542
res dim     2.000000
Name: 5, dtype: float64

                                                                     box 5  \
                                                                       min
climate scenarios                                                        2
land use scenarios  set([urbanizationLargeSteady, urbanizationDeur...

                                                                            \
                                                                       max
climate scenarios                                                        2
land use scenarios  set([urbanizationLargeSteady, urbanizationDeur...


                       qp values
climate scenarios     3.5595e-81
land use scenarios  8.225532e-37
```

```
In [73]: box_1.inspect(5, style='graph')
         plt.show()
```




```
In [74]: box_1.select(5)
         box_2 = prim_obj.find_box()
```

```
[INFO] 12102 points remaining, containing 2221 cases of interest
[INFO] box does not meet threshold criteria, value is 0.383480825959, returning dump box
```

2.1.2 Scenario discovery for damages

We can now perform scenario discovery.

$ f(x) =

$$\begin{cases} 1 & \text{if } x > 5000 \\ 0 & \text{otherwise} \end{cases}$$

$$ $

where x is the amount of flood damage

```
In [75]: from analysis import prim
         from util import ema_logging
         ema_logging.log_to_stderr(ema_logging.INFO)

         def classify(data):
             ooi = 'Flood damage (Milj. Euro)'
             outcome = data[ooi]
             classes = np.zeros(outcome.shape[0])
             classes[outcome>5000] = 1
             return classes


         prim_obj = prim.setup_prim(relevant_results, classify, threshold=0.5, peel_alpha=0.01, mass_mi
         box_1 = prim_obj.find_box()
```

```
[INFO] 15000 points remaining, containing 2291 cases of interest
[INFO] mean: 0.598984771574, mass: 0.0394, coverage: 0.15451767787, density: 0.598984771574 restricted_d
```

```
In [76]: import mpld3
         box_1.show_tradeoff()
         mpld3.display()

Out[76]: <IPython.core.display.HTML object>

In [77]: box_1.inspect(10)
```

```
coverage    0.580533
density     0.483988
mass        0.183200
mean        0.483988
res dim     5.000000
Name: 10, dtype: float64

                                                                    box 10  \
                                                                       min
climate scenarios                                                        2
land use scenarios  set([urbanizationLargeSteady, urbanizationDeur...
fragility dikes                                                -0.09597666
ShipTbl1                                                       -0.09608803
collaboration                                                     1.007643

                                                                            \
                                                                       max
climate scenarios                                                        2
land use scenarios  set([urbanizationLargeSteady, urbanizationDeur...
fragility dikes                                                 0.09996334
ShipTbl1                                                        0.09997197
collaboration                                                     1.599963


                       qp values
climate scenarios   8.589929e-186
land use scenarios   1.539981e-54
fragility dikes         0.3891626
ShipTbl1                0.3891626
collaboration           0.4166299
```

It is quite evident that the combination of climate change (W+) and strong urbanization is the main driver for poor outcomes. A next step would be to make an adaptive policy where we strengthen dikes conditional on either a climate signal, or a land use signal, or both. Earlier work on the Rhine suggests that one of the best indicators for detecting climate change is the running average over 30 years of the number of days flows are below 12000 m^3/s.

Using this, we can make an adaptive policy. For demostration purposes, we make two adaptive policies * 1:500, followed by 1:1000 in case of climate change signal * 1:500 with climate dikes, followed by dike strengthening to 1:1000 in case of climate change signal

2.2 fourth iteration, adaptive policy

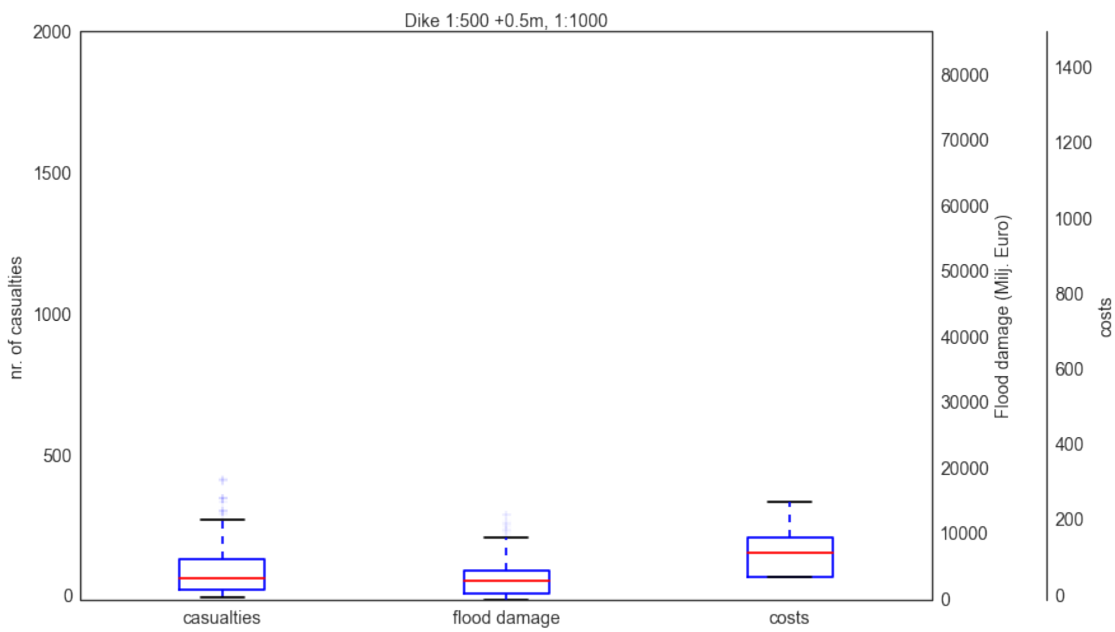
```
In [78]: from util.util import load_results

         experiments, outcomes = load_results('./data/fourth iteration 5 policies  5000 runs.tar.gz')

         for entry in set(experiments['policy']):
```

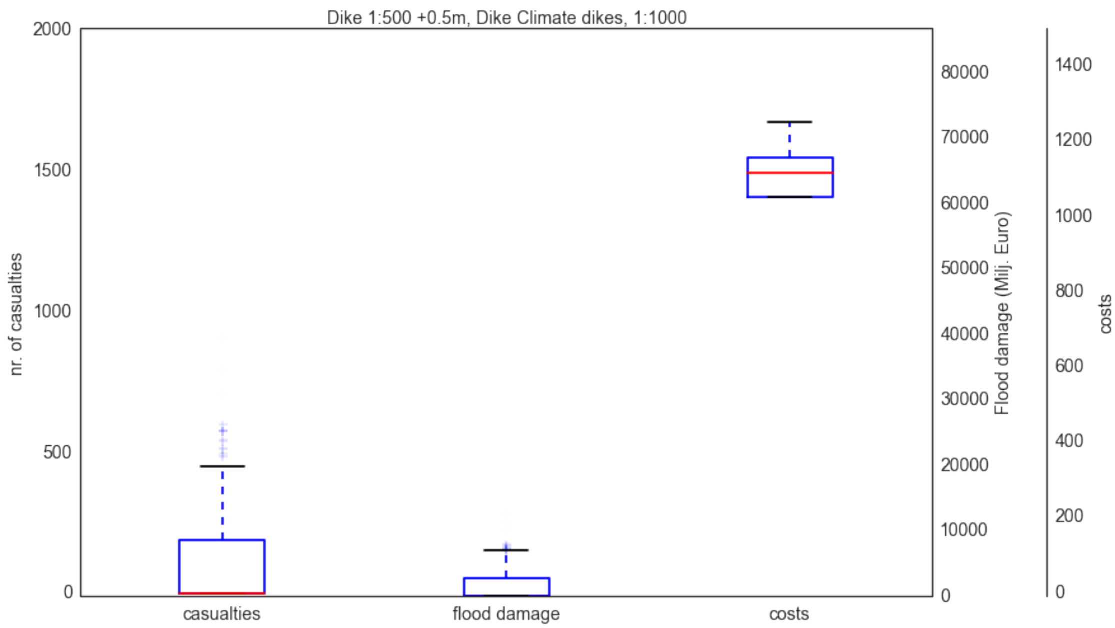
```
            logical = experiments['policy']==entry
            print entry, np.sum(logical)
```

```
[INFO] results loaded succesfully from ./data/fourth iteration 5 policies  5000 runs.tar.gz

Dike 1:500 +0.5m 5000
Dike 1:500 +0.5m, 1:1000 5000
no policy 5000
Dike 1:500 +0.5m, Dike Climate dikes, 1:1000 5000
Dike 1:1000 5000
```

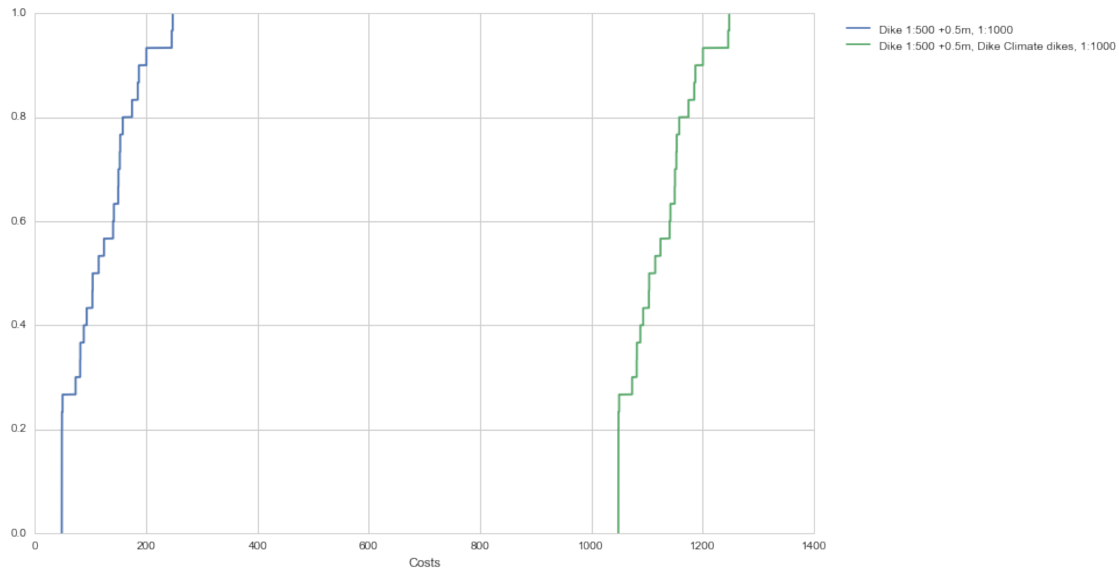
In [79]:
```
from mpl_toolkits.axes_grid1 import host_subplot
import mpl_toolkits.axisartist as AA

policies = ['Dike 1:500 +0.5m, 1:1000','Dike 1:500 +0.5m, Dike Climate dikes, 1:1000']

#determine maxima across all policies
costs = outcomes['Costs']
max_costs = np.max(costs)

casualties = outcomes['Number of casualties']
max_casualties = np.max(casualties)

damages = outcomes['Flood damage (Milj. Euro)']
max_damages = np.max(damages)

with sns.axes_style('white'):
    for i, policy in enumerate(policies):
        logical = experiments['policy']==policy
        temp_outcomes = {key:value[logical] for key, value in outcomes.items()}

        fig = plt.figure()

        # policy

        casualties2 = temp_outcomes['Number of casualties']
        ax_casualties2 = host = host_subplot(111, axes_class=AA.Axes)
        ax_casualties2.boxplot([casualties2,[],[]])
        ax_casualties2.set_ylabel('nr. of casualties')

        damages2 = temp_outcomes['Flood damage (Milj. Euro)']
        ax_damage2 = ax_casualties2.twinx()
        ax_damage2.boxplot([[],damages2,[]])
        ax_damage2.set_ylabel('Flood damage (Milj. Euro)')

        costs = temp_outcomes['Costs']
        ax_costs = ax_casualties2.twinx()
        offset = 90

        new_fixed_axis = ax_costs.get_grid_helper().new_fixed_axis
        ax_costs.axis["right"] = new_fixed_axis(loc="right",
                                                axes=ax_costs,
                                                offset=(offset, 0))
```

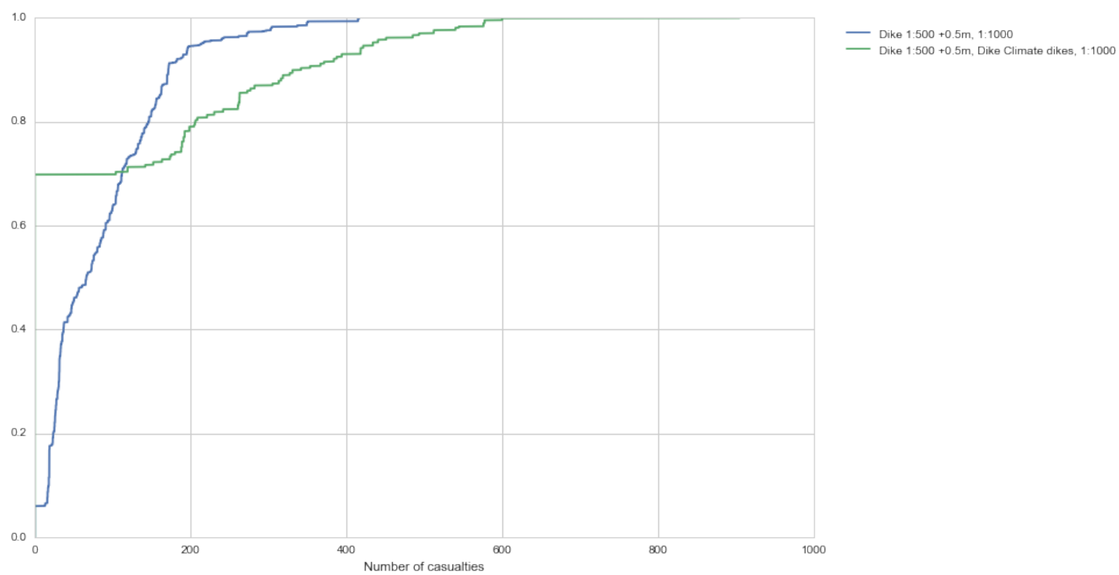
```
ax_costs.axis["right"].toggle(all=True)
ax_costs.boxplot([[],[], costs])
ax_costs.set_ylabel('costs')

ax_casualties2.set_xticklabels(['casualties', 'flood damage','costs'])
ax_casualties2.set_ylim(ymin=0)
ax_casualties2.set_title(policy)

# the xaxis for must be set to the same limits
ax_casualties2.set_ylim(ymin=-10, ymax=1.2*max_casualties)

ax_damage2.set_ylim(ymin=-10, ymax=1.2*max_damages)

ax_costs.set_ylim(ymin=-10, ymax=1.2*max_costs)
plt.subplots_adjust(wspace = .75)

change_fontsize(fig)

save_fig(fig, '8{}'.format(chr(i + ord('a'))))


plt.show()
```

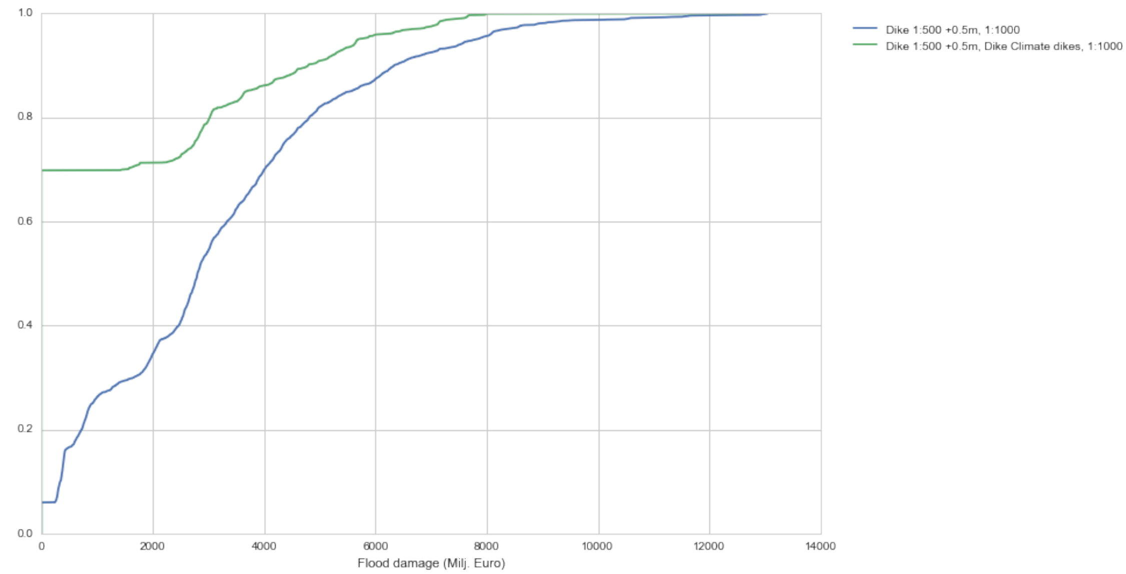





```
In [80]: from analysis.plotting_util import determine_kde

         for ooi in outcomes.keys():

             fig = plt.figure()
             ax = fig.add_subplot(111)
             minima = np.min(outcomes[ooi])
             maxima = np.max(outcomes[ooi])


             for policy in policies:
                 logical = experiments['policy']==policy
                 temp_outcomes = {key:value[logical] for key, value in outcomes.items()}


                 data = temp_outcomes[ooi]
                 x = np.sort(data)
                 y = np.arange(len(x))/float(len(x))

                 ax.plot(x, y, label=policy)
                 ax.set_xlabel(ooi)
             ax.legend(loc='upper right', bbox_to_anchor=(1.4, 1))
         plt.show()
```


1.0
0.8
0.6
0.4
0.2
0.0
0
200
400
600
800
1000
1200
1400
Costs
Dike 1:500 +0.5m, 1:1000
Dike 1:500 +0.5m, Dike Climate dikes, 1:1000


1.0
0.8
0.6
0.4
0.2
0.0
0
200
400
600
800
1000
Number of casualties
Dike 1:500 +0.5m, 1:1000
Dike 1:500 +0.5m, Dike Climate dikes, 1:1000



Dike 1:500 +0.5m, 1:1000
Dike 1:500 +0.5m, Dike Climate dikes, 1:1000
Flood damage (Milj. Euro)


```
In [ ]:
```