

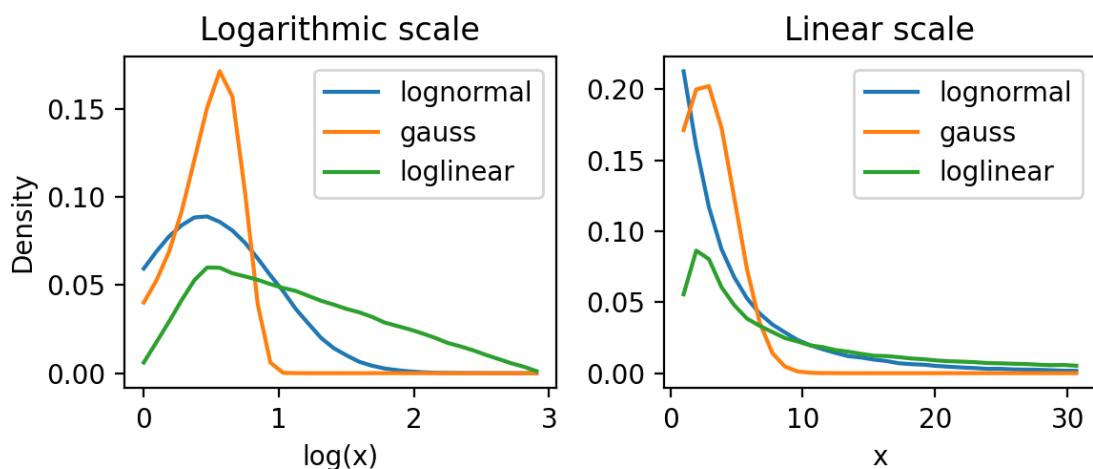
# supermodel

January 12, 2022

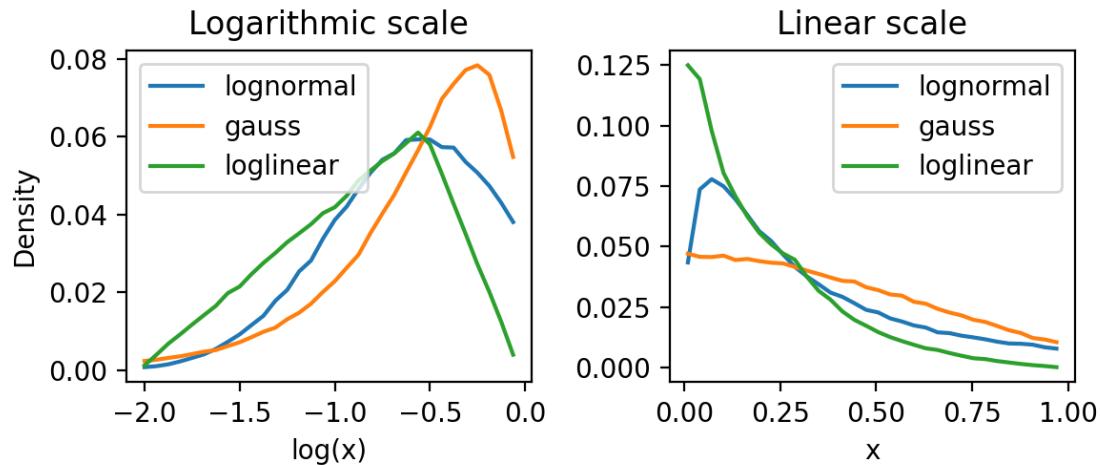
```
[1]: from pca import cluster
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import warnings
warnings.filterwarnings("ignore")

# primeri vseh treh porazdelitev v primeru povprečja večjega in manjšega od 1,
# ob tem so najprej predstavljene porazdelitve za N v primeru večje možnosti
# za širitev na druge planete
```

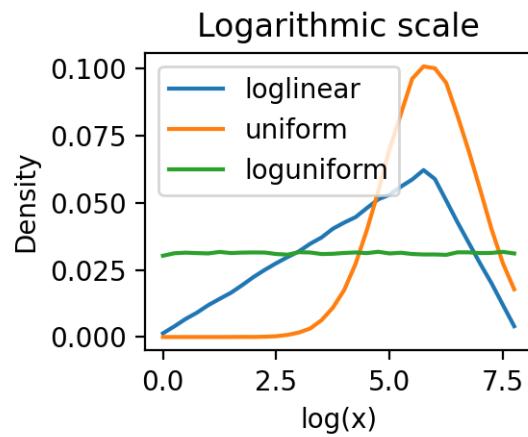
Distributions of x from 1 to 1000 with mean (peak) at 3.16



Distributions of  $x$  from 0.01 to 1 with mean (peak) at 0.32



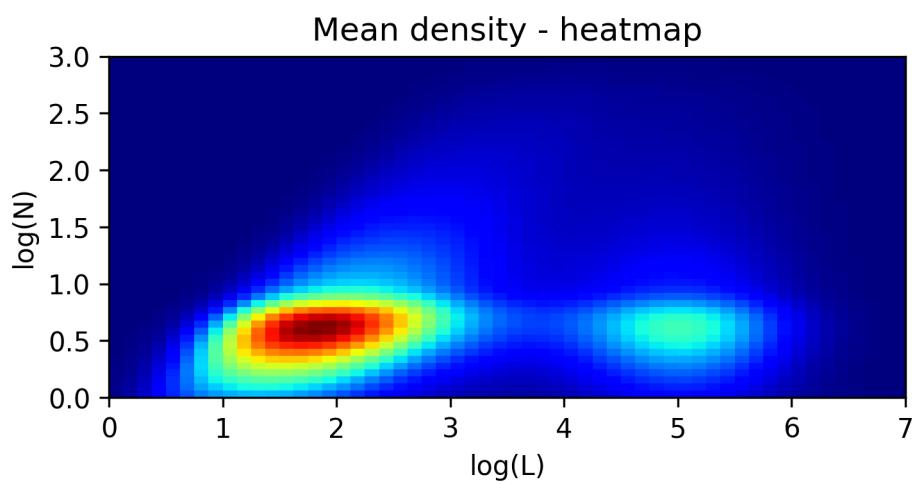
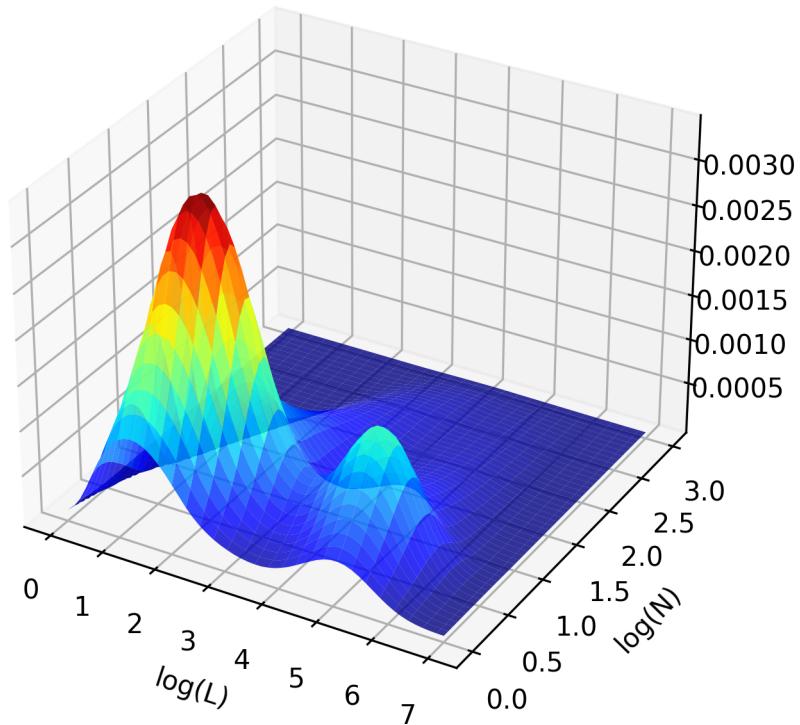
Distributions of  $x$  from 1 to  $1e8$   
with mean (peak) at  $1e6$

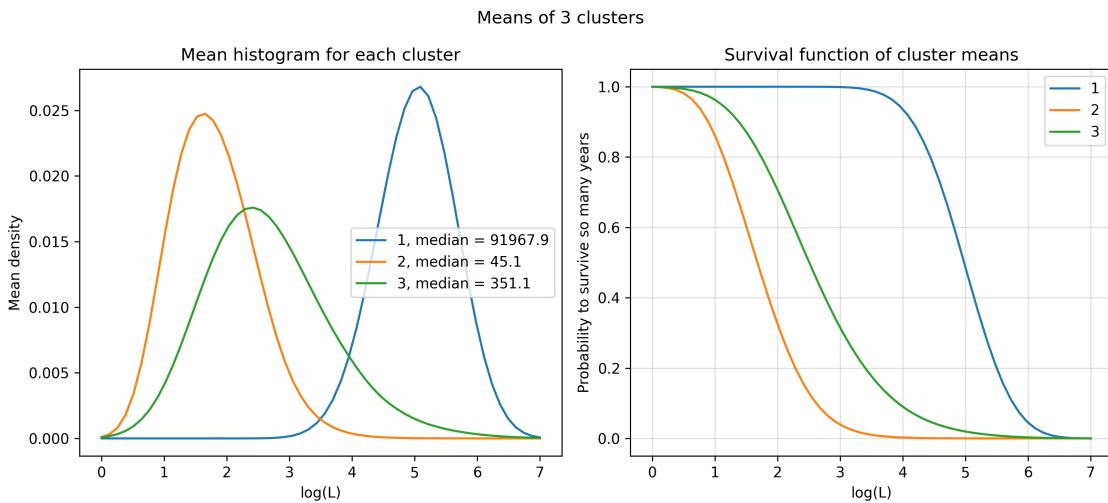
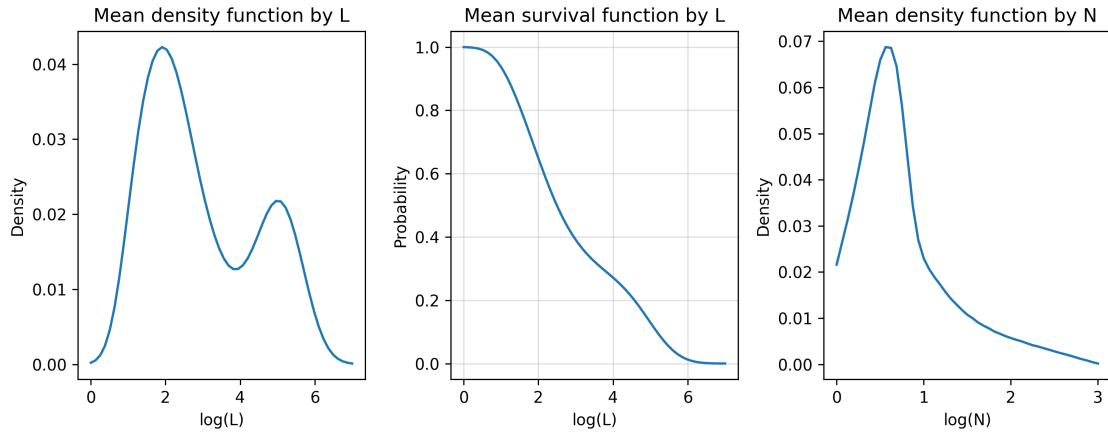


```
[2]: cluster(model=0, ks=[3, 5], supermodel=1) # supermodel  
cluster(model=0, ks=[5], supermodel=2) # supermodel 2
```

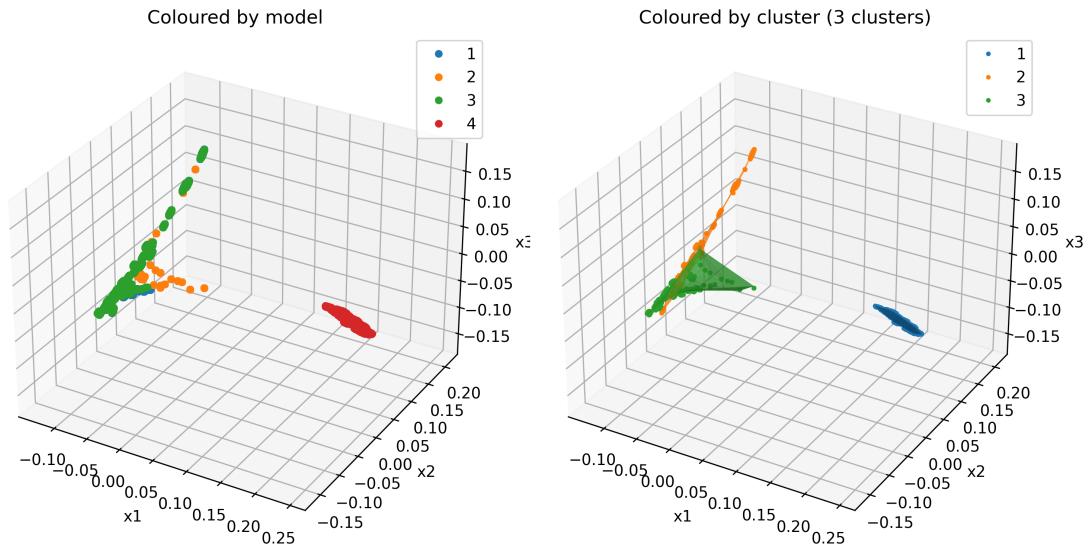
# Supermodel

Mean density

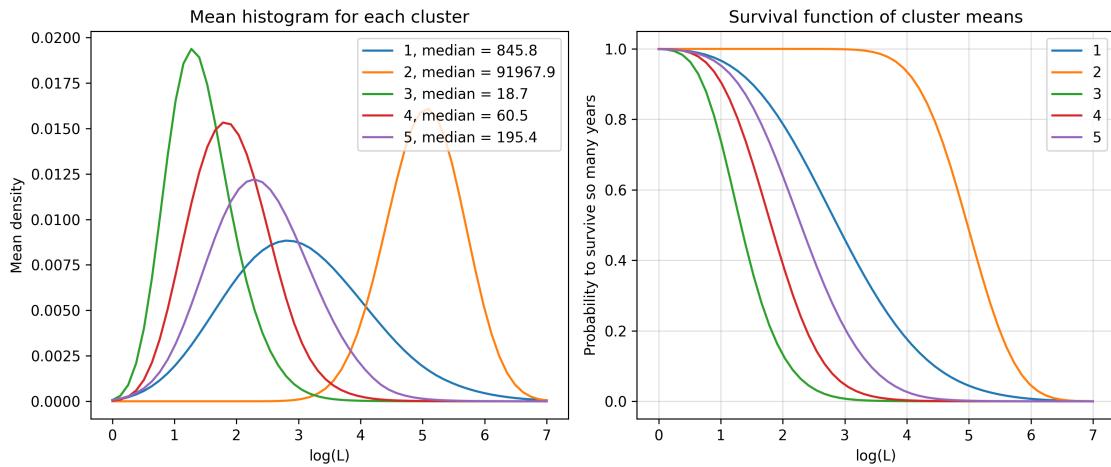




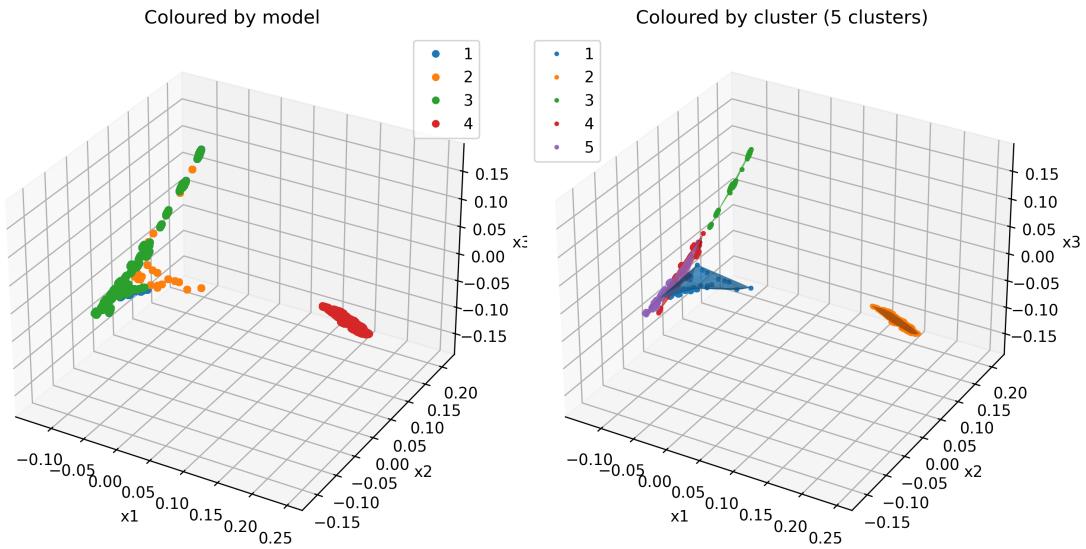
### Supermodel after Principal component analysis (PCA)



Means of 5 clusters

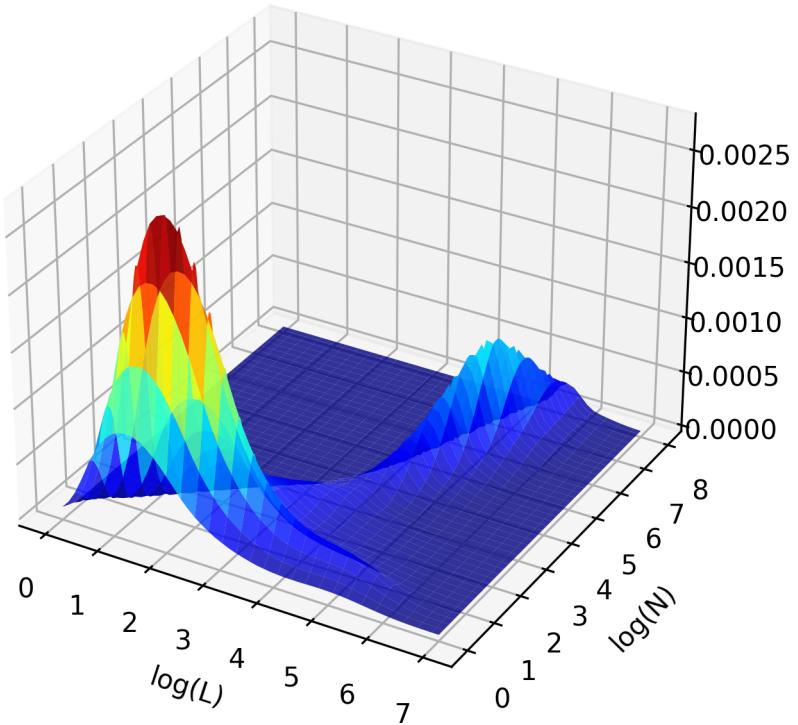


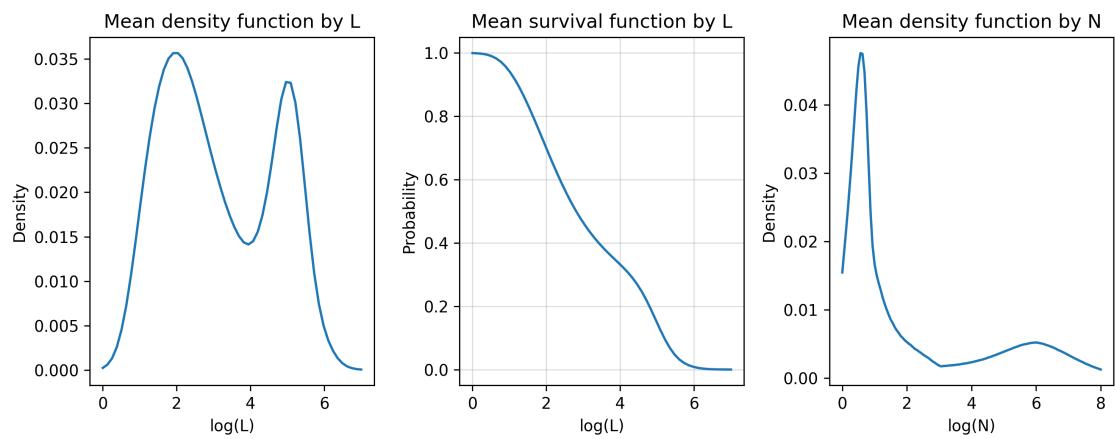
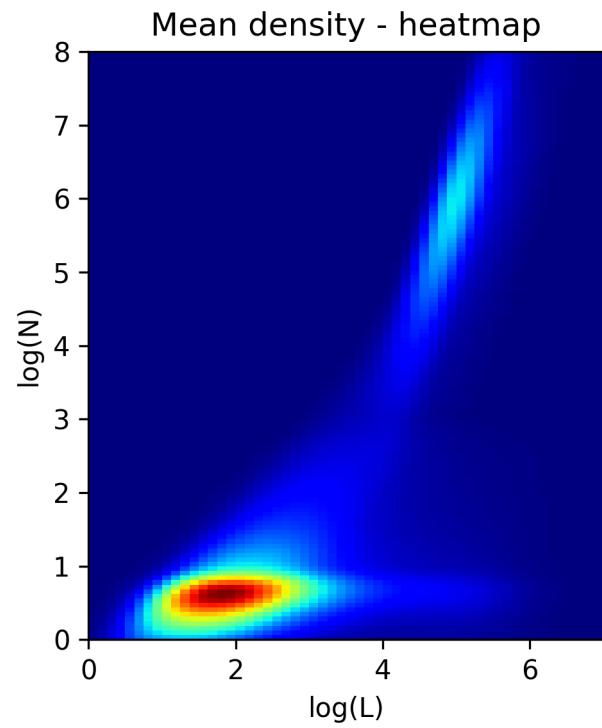
Supermodel after Principal component analysis (PCA)

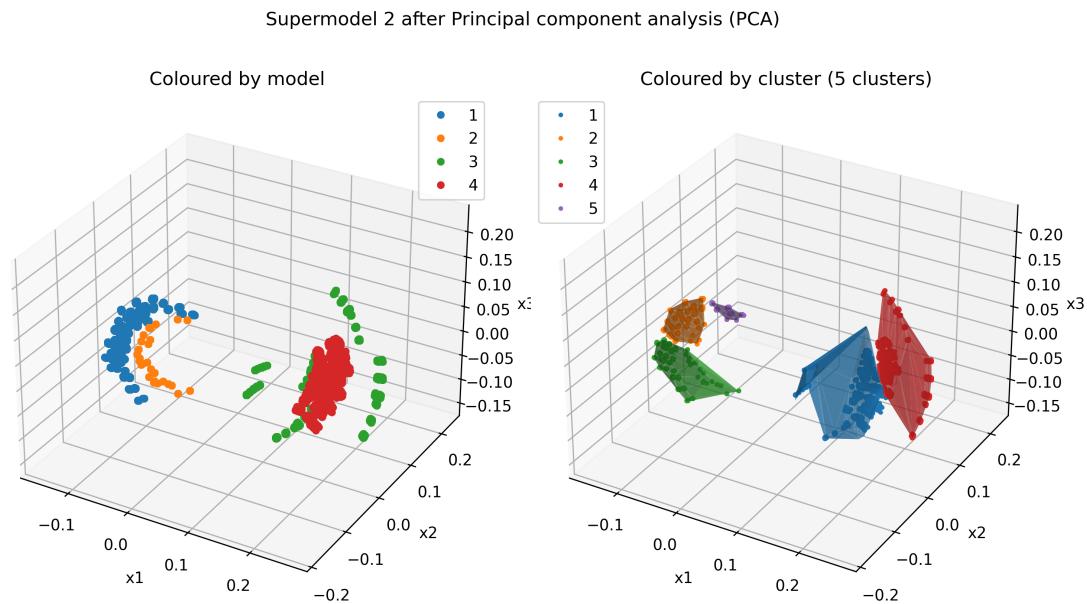
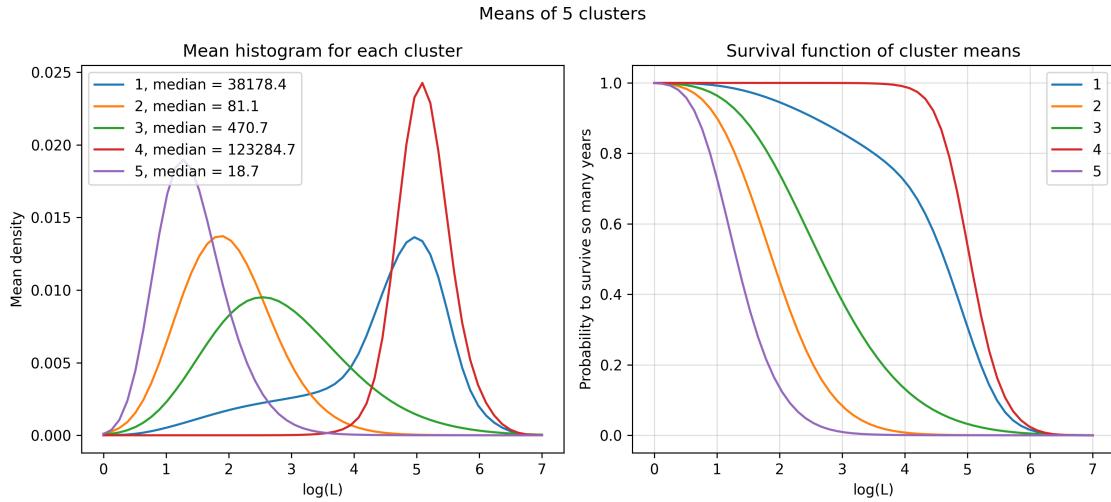


## Supermodel 2

Mean density



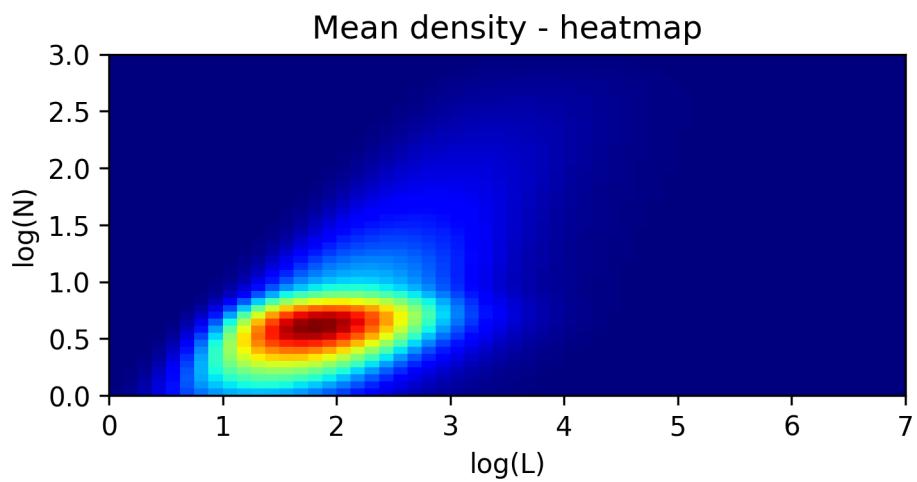
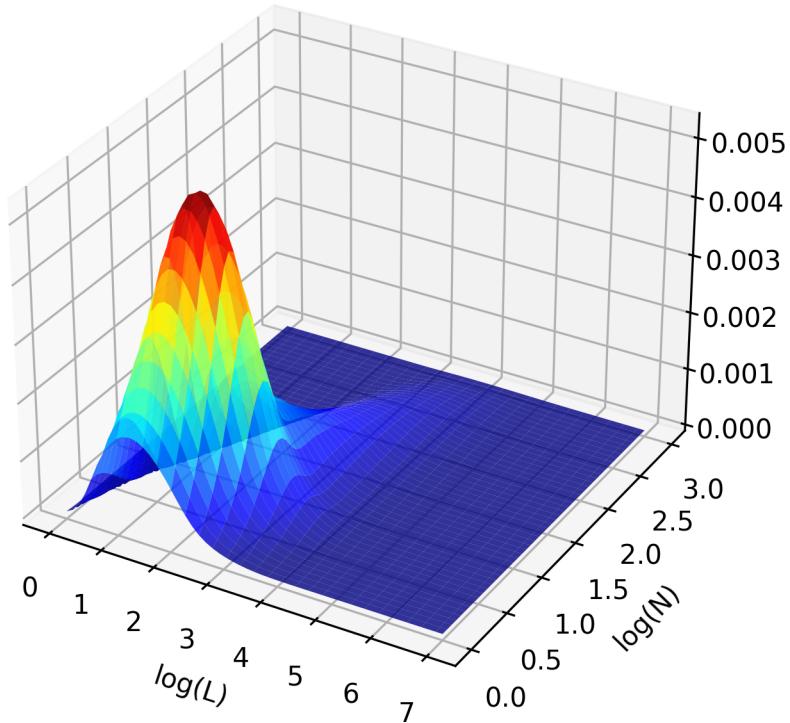


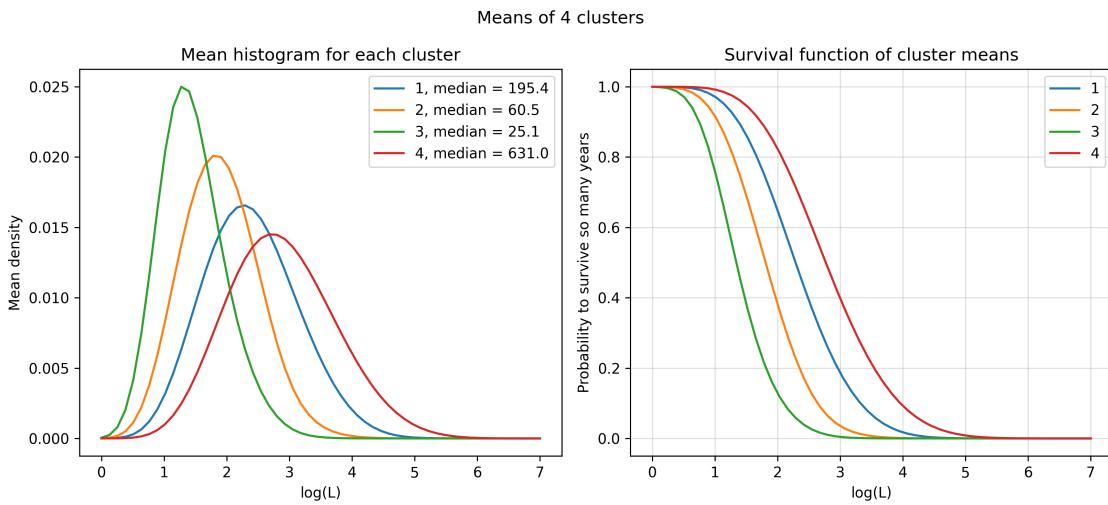
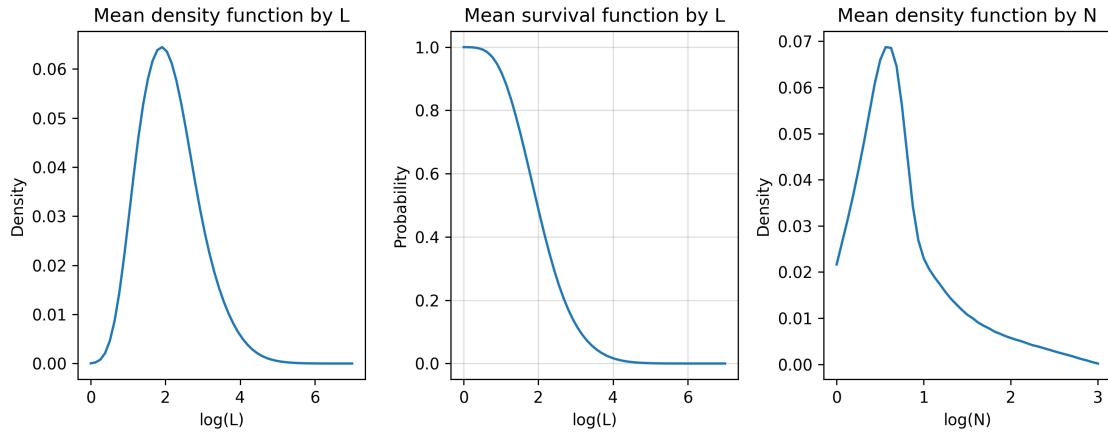


```
[3]: cluster(model=1, ks=[4]) # model 1
```

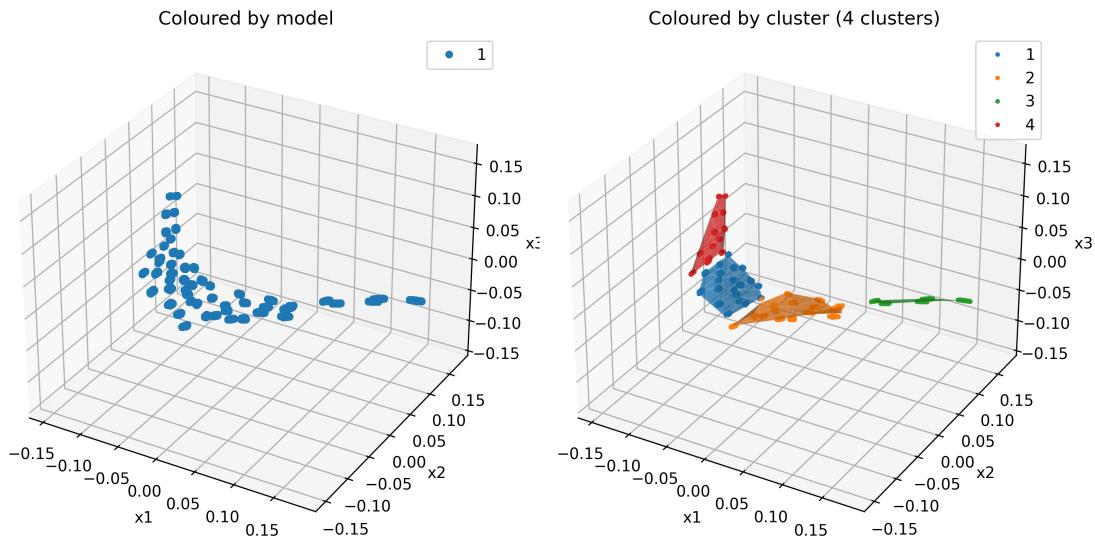
# Model I

Mean density

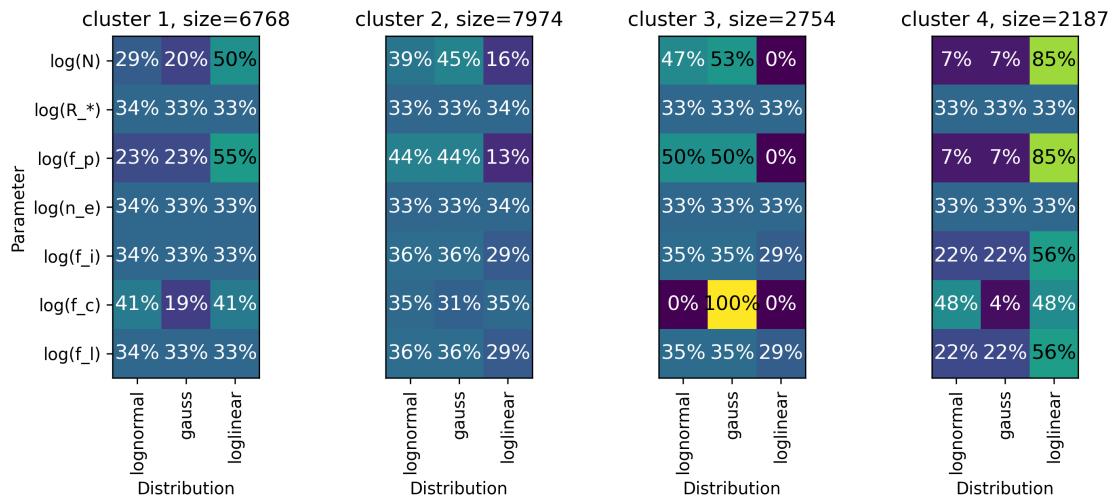




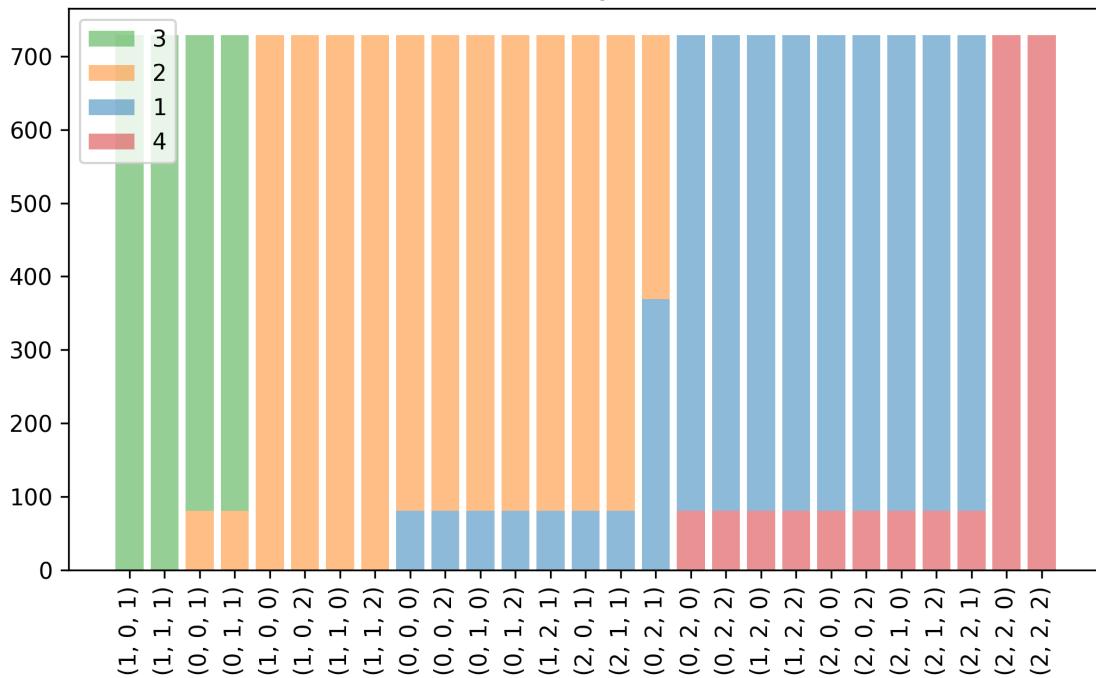
Model I after Principal component analysis (PCA)



Percent of submodels in model 1 distributed with particular distribution on particular parameter in each of 4 clusters



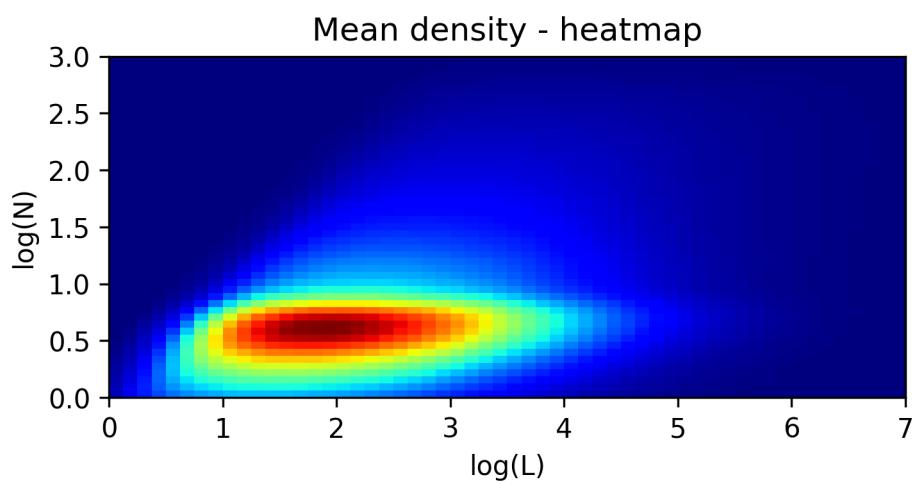
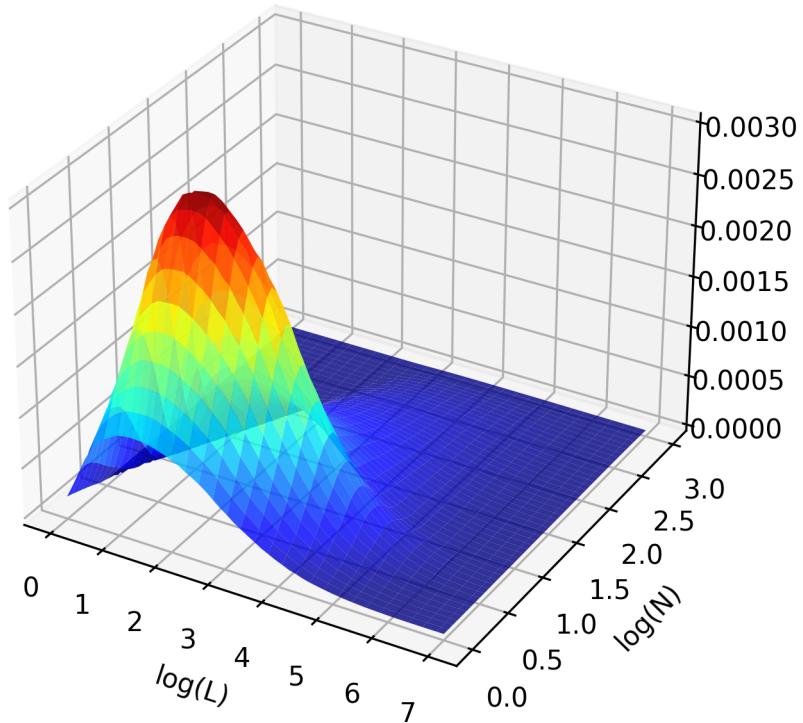
Percentage of distributions  
 $(\log(N), \log(f_p), \log(f_c))$  by (lognormal, gauss, loglinear)  
 coloured by cluster

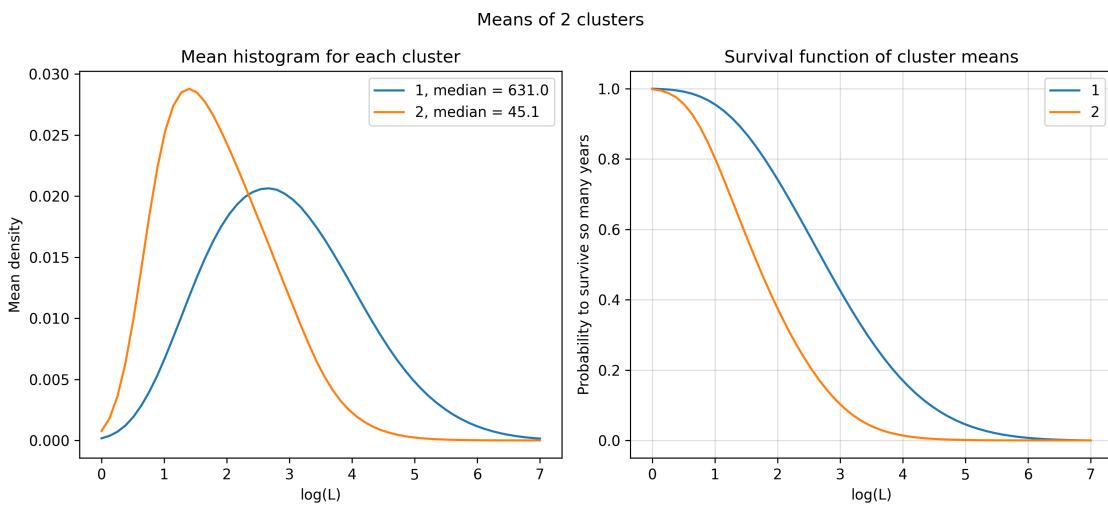
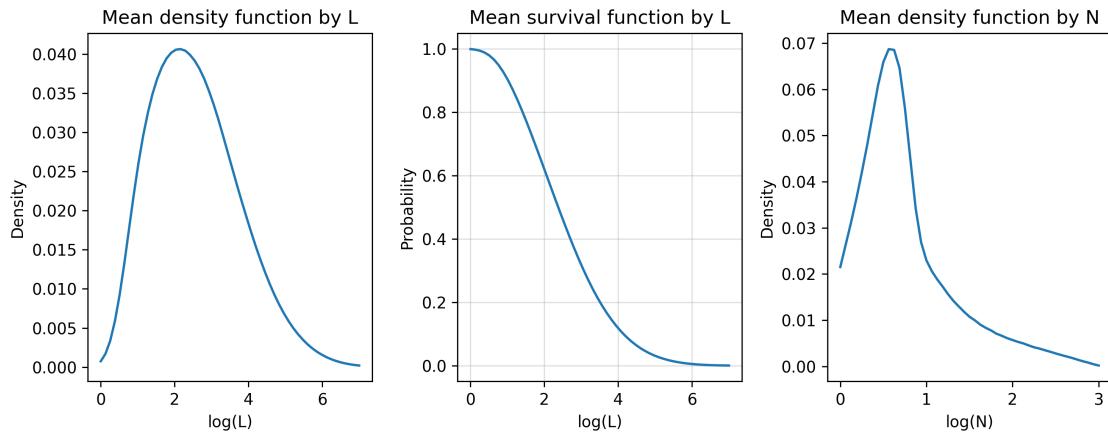


```
[4]: cluster(model=2, ks=[2]) # model 2
```

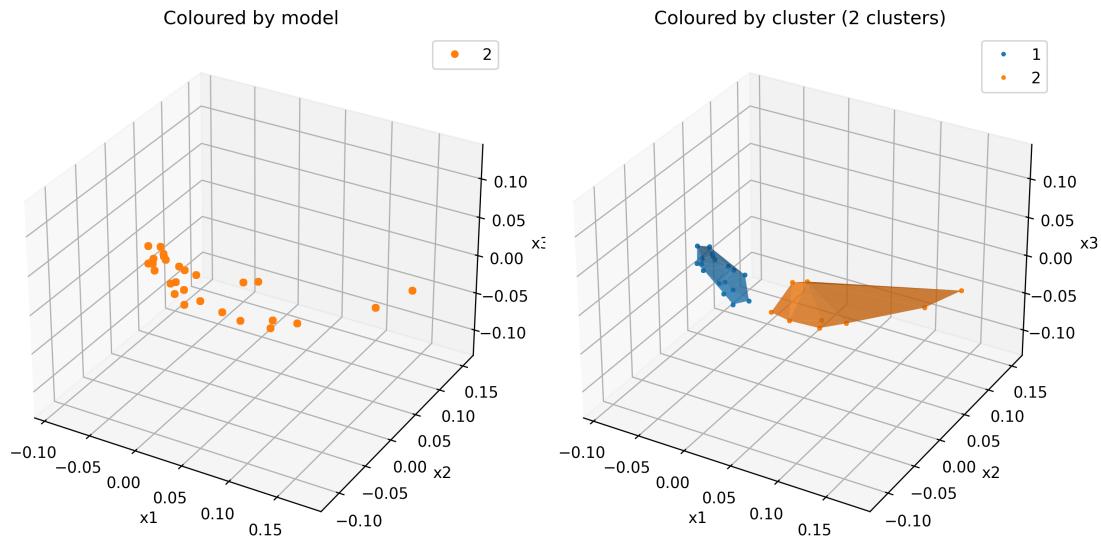
# Model II

Mean density

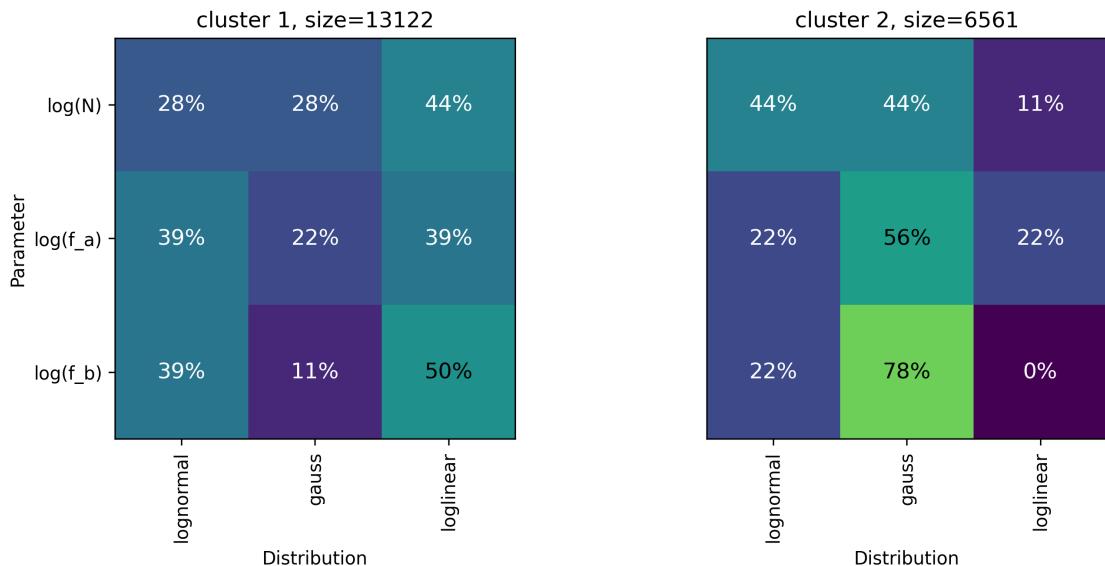




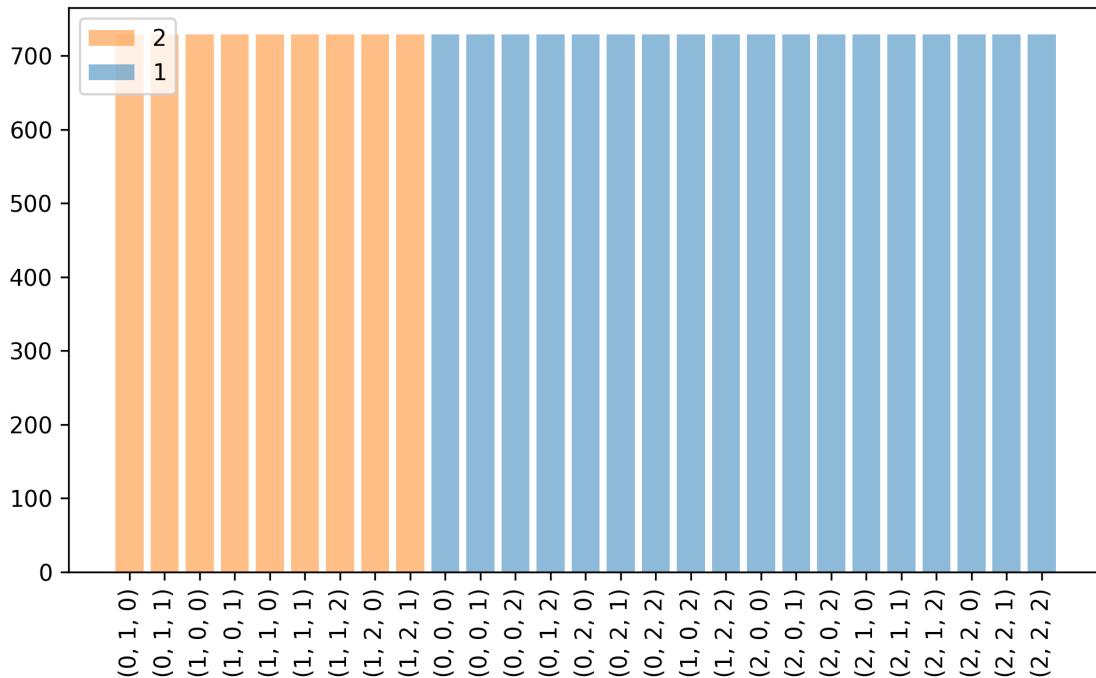
Model II after Principal component analysis (PCA)



Percent of submodels in model 2 distributed with particular distribution on particular parameter in each of 2 clusters



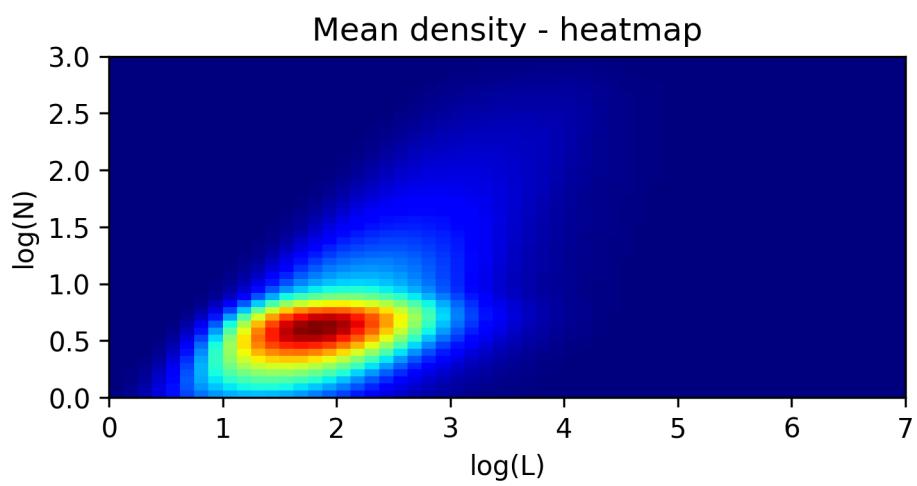
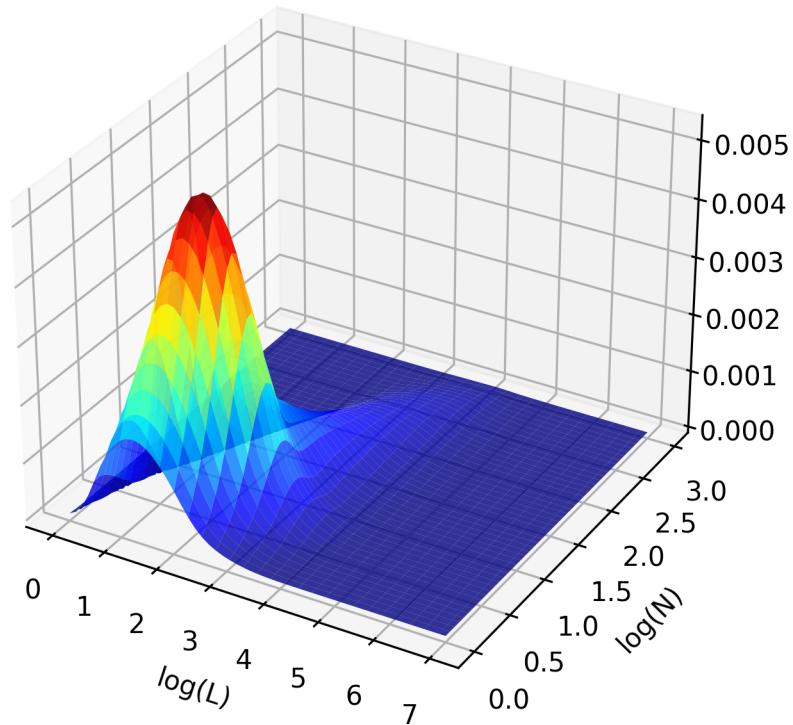
Percentage of distributions  
 $(\log(f_b), \log(f_a), \log(N))$  by (lognormal, gauss, loglinear)  
 coloured by cluster

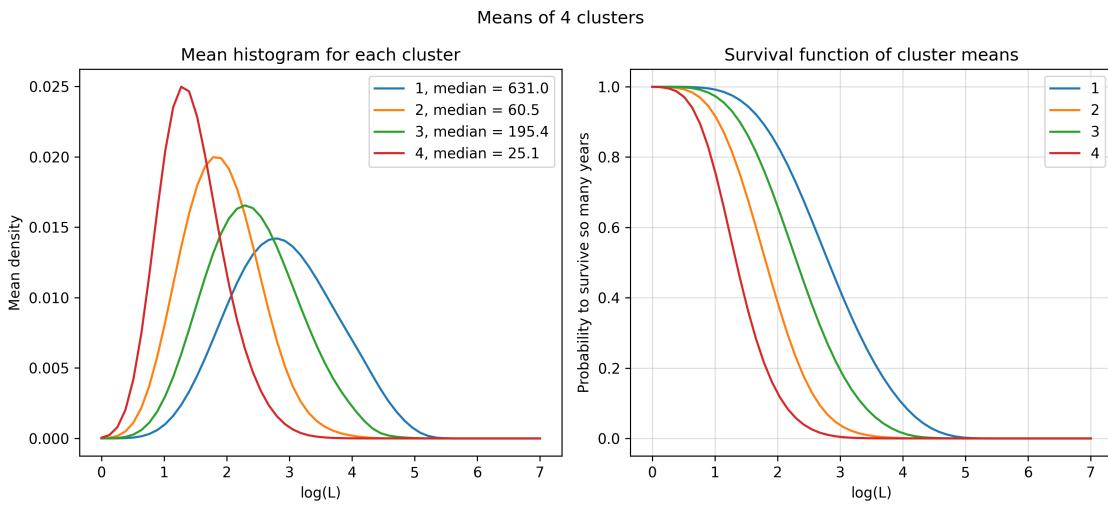
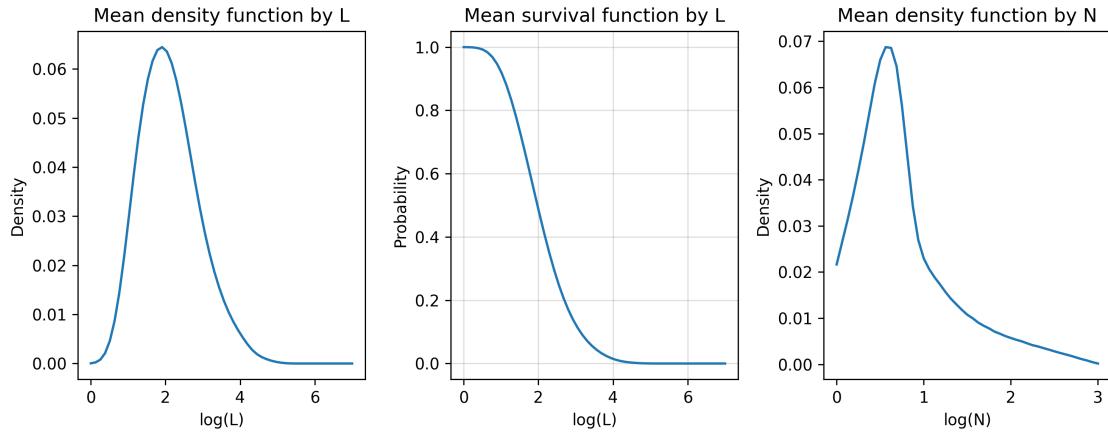


```
[5]: for s in [1, 2]:
    cluster(model=3, ks=[4], supermodel=s) # model 3
```

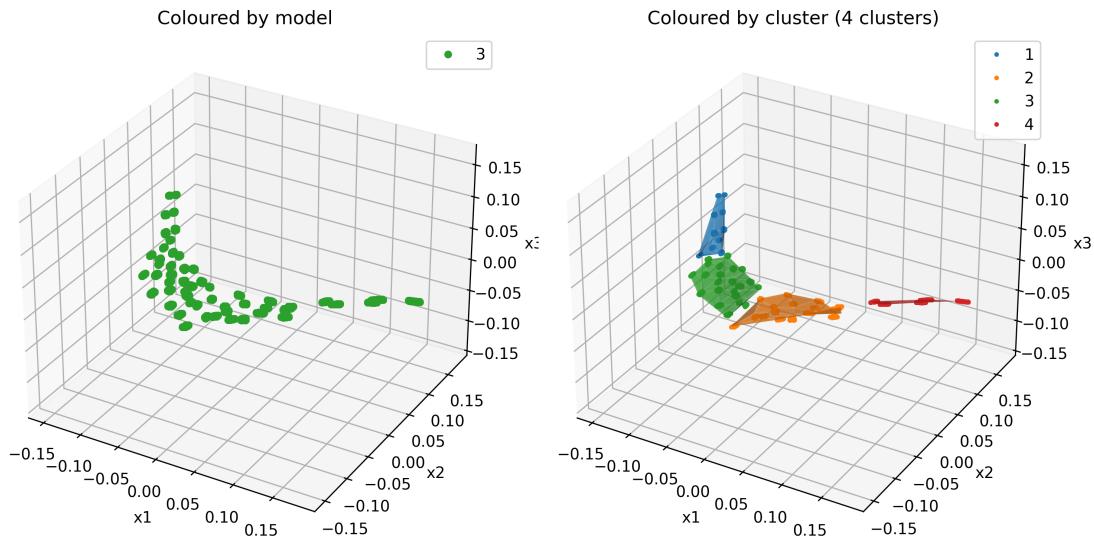
# Model III

Mean density

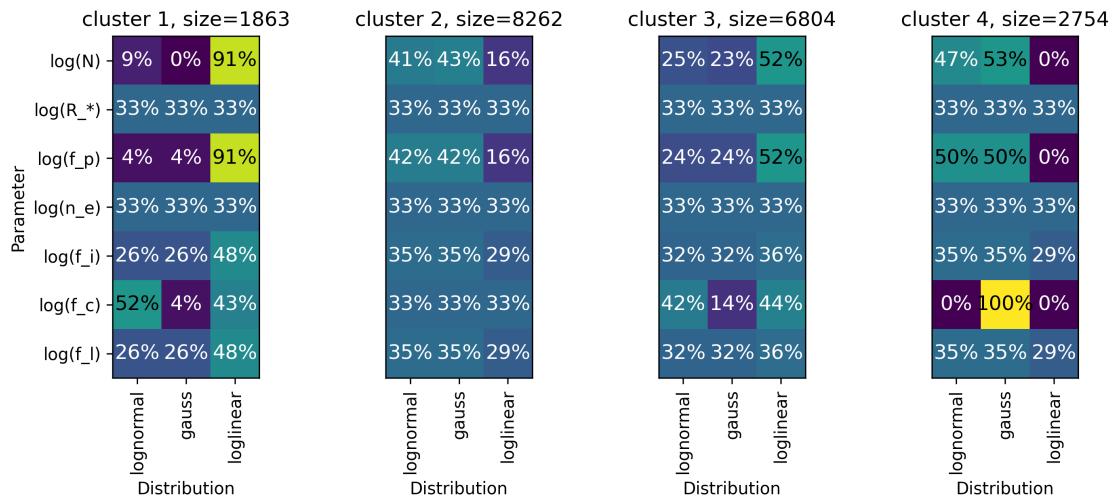




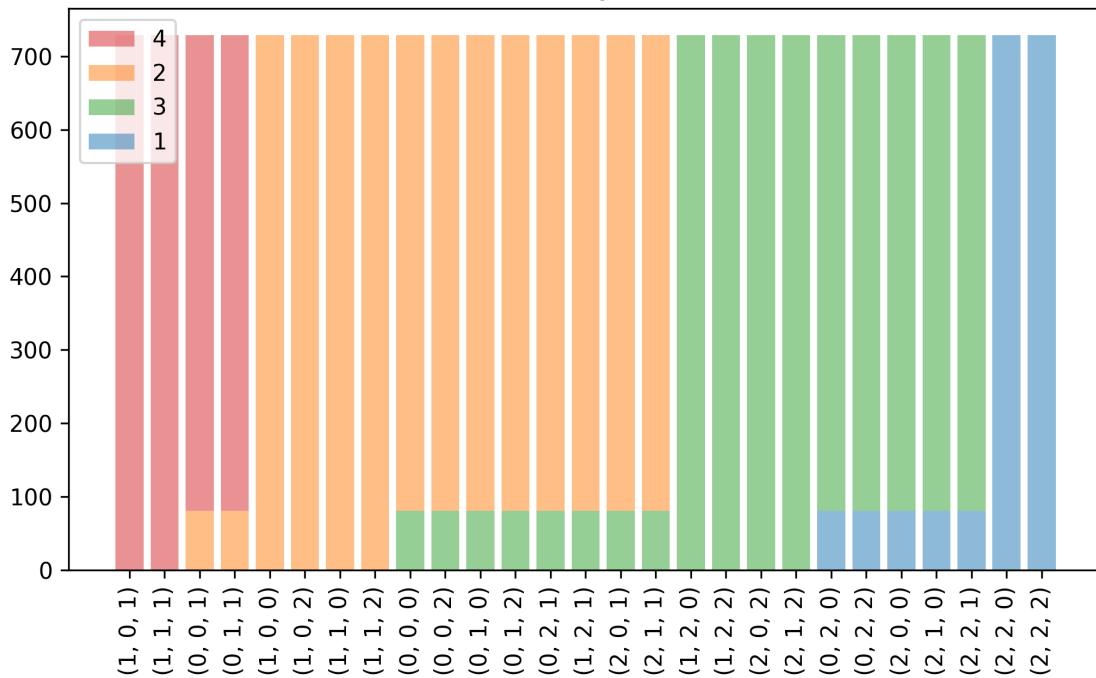
Model III after Principal component analysis (PCA)



Percent of submodels in model 3 distributed with particular distribution on particular parameter in each of 4 clusters

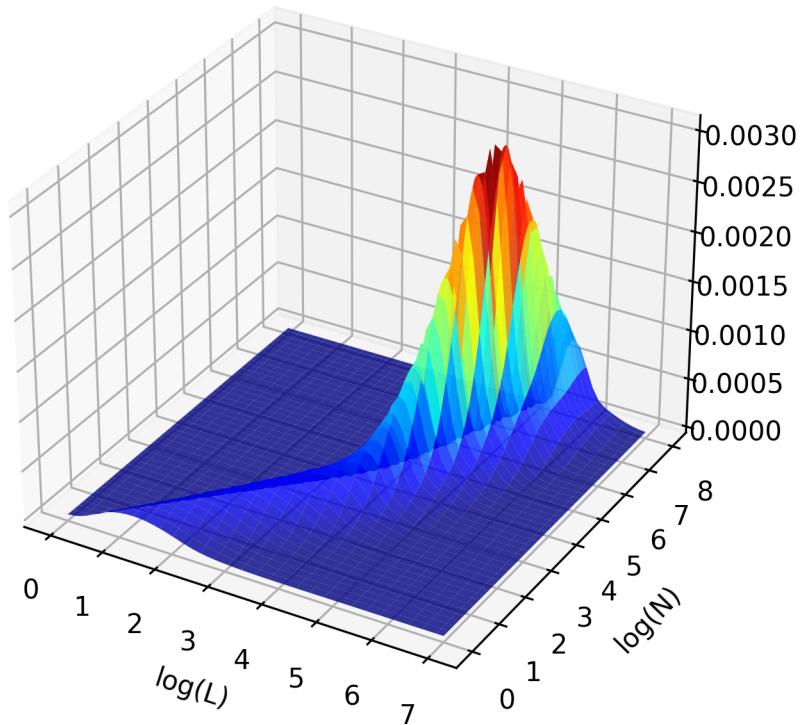


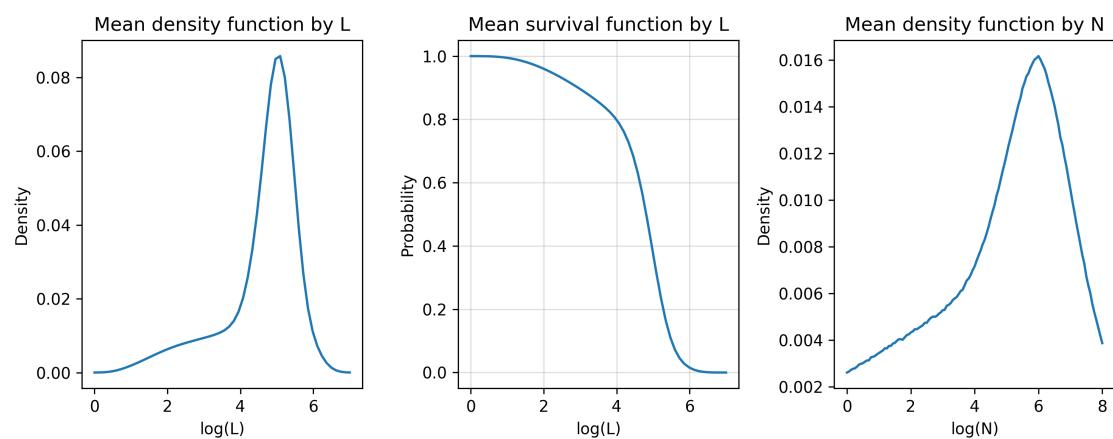
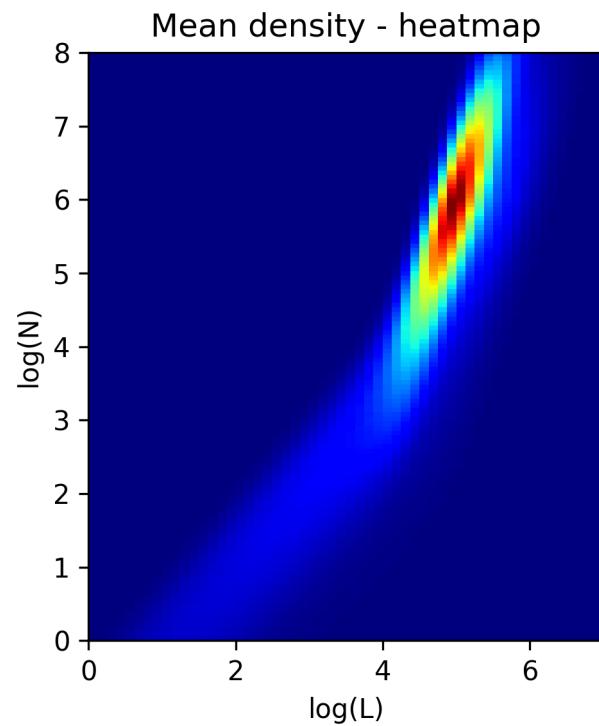
Percentage of distributions  
 $(\log(N), \log(f_p), \log(f_c))$  by (lognormal, gauss, loglinear)  
 coloured by cluster

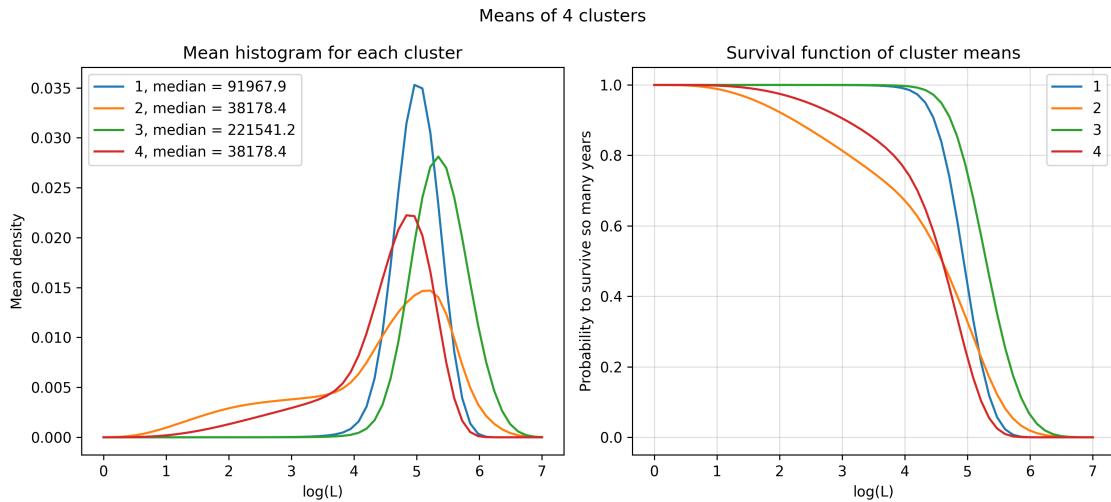


# Model III

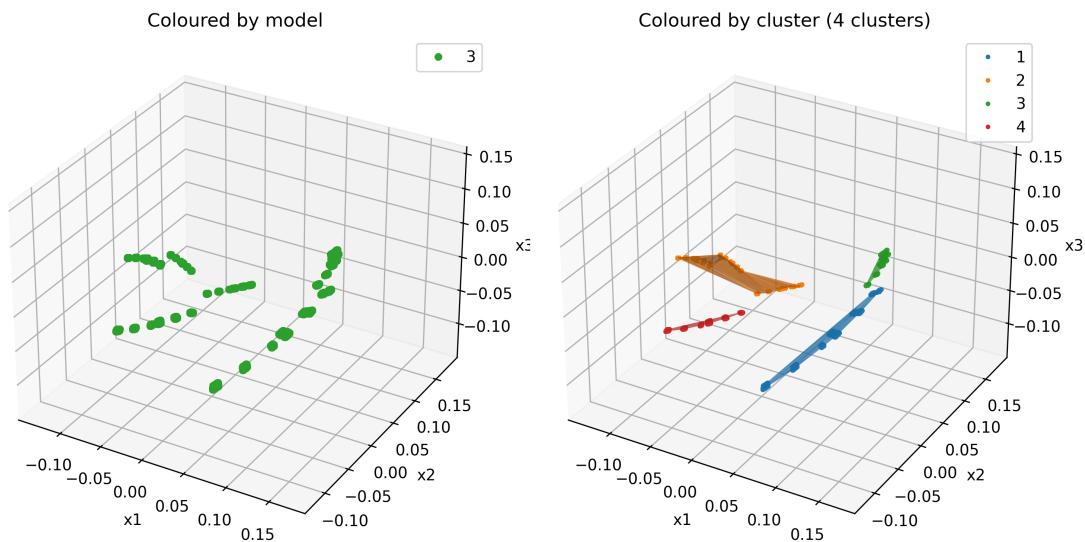
Mean density







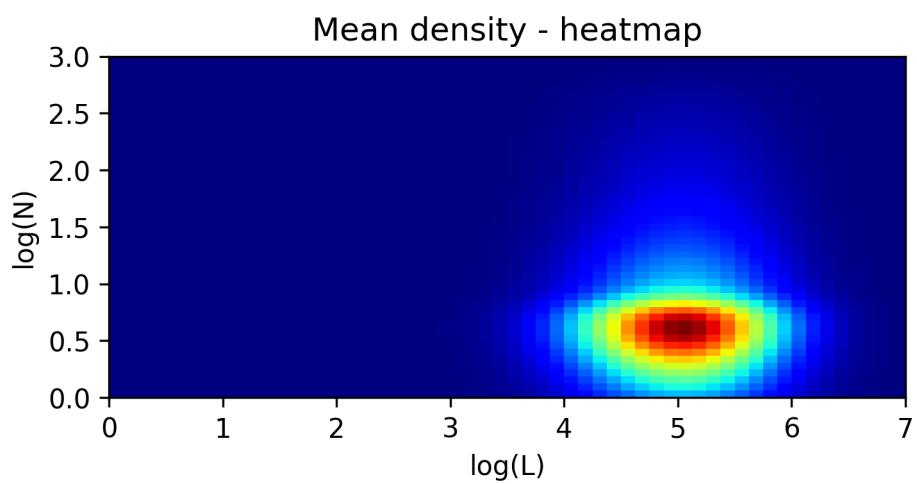
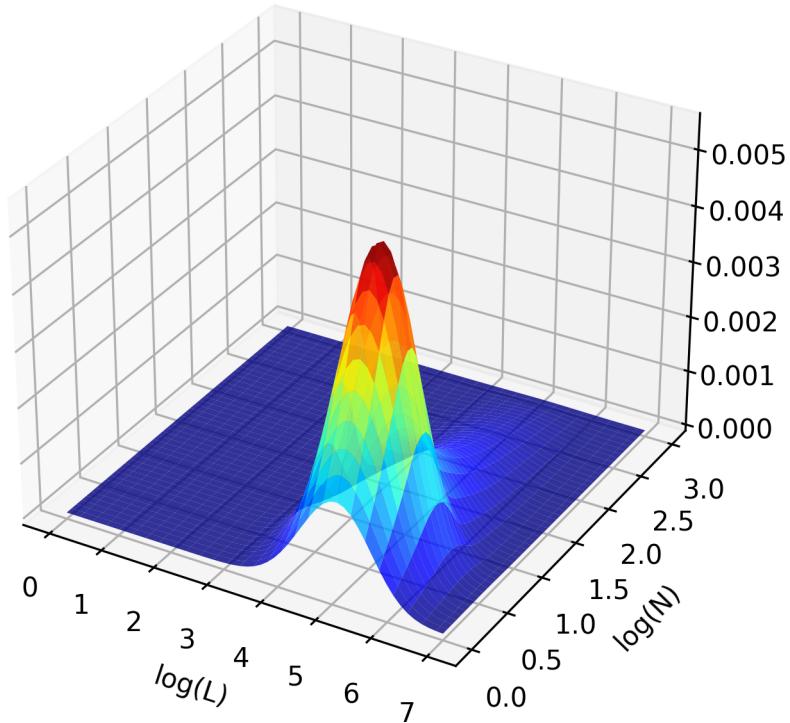
Model III after Principal component analysis (PCA)

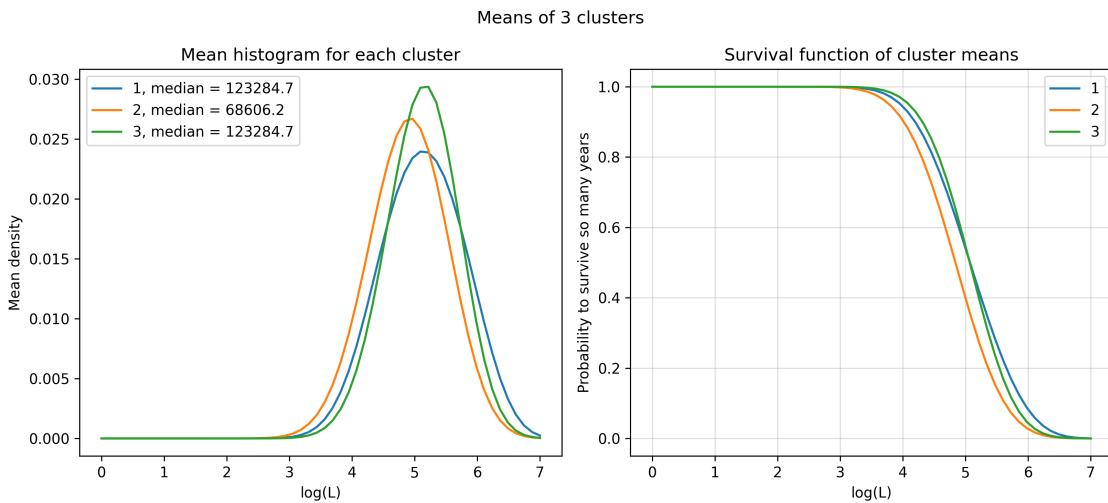
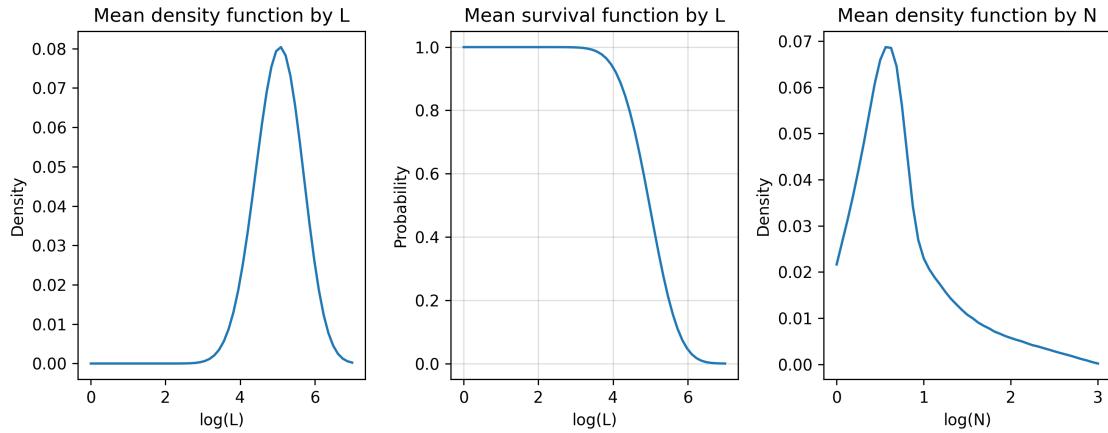


```
[6]: cluster(model=4, ks=[3]) # model 4
```

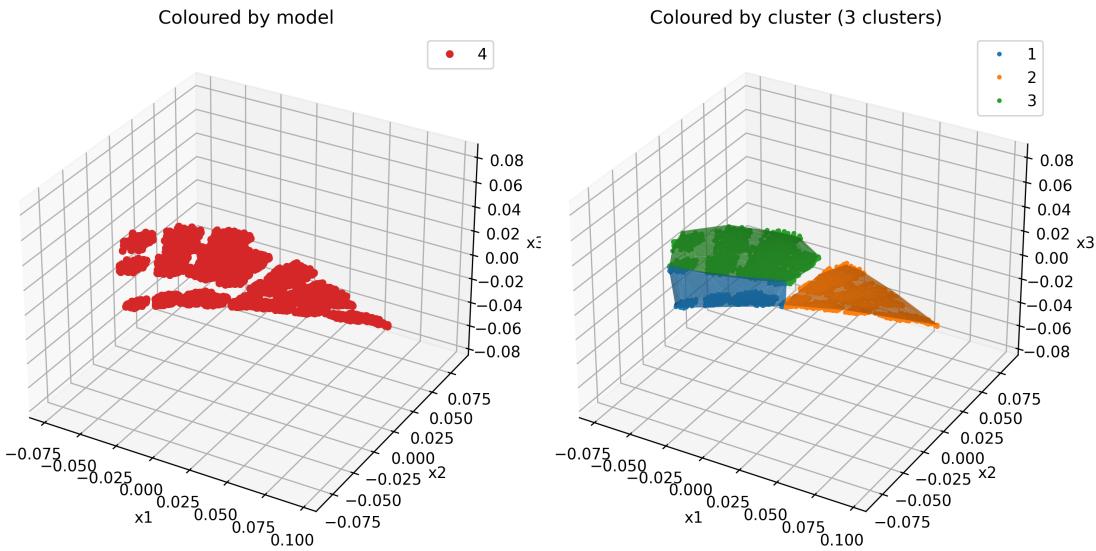
# Model IV

Mean density

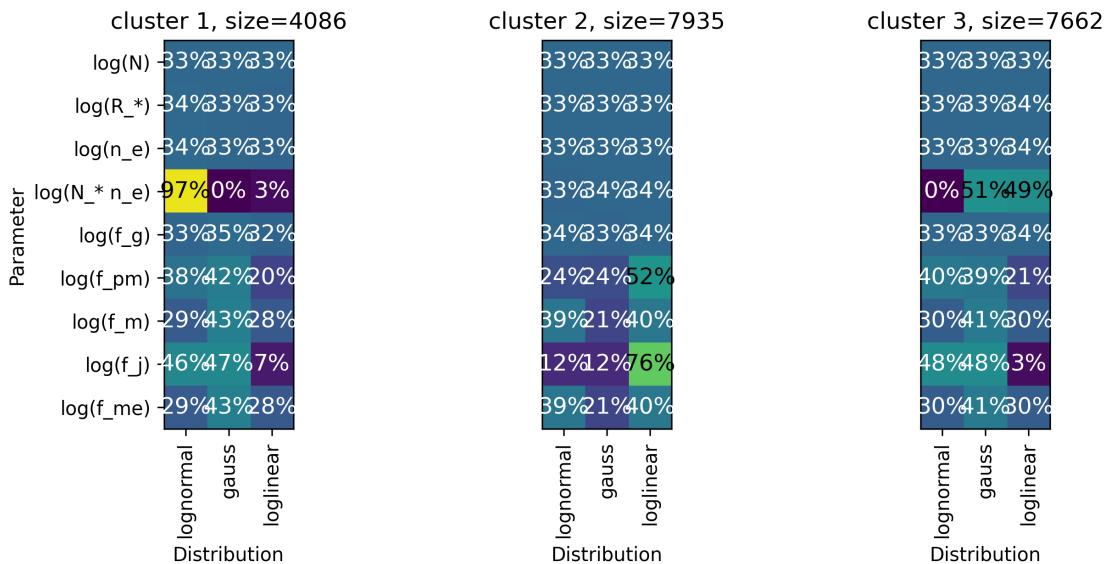




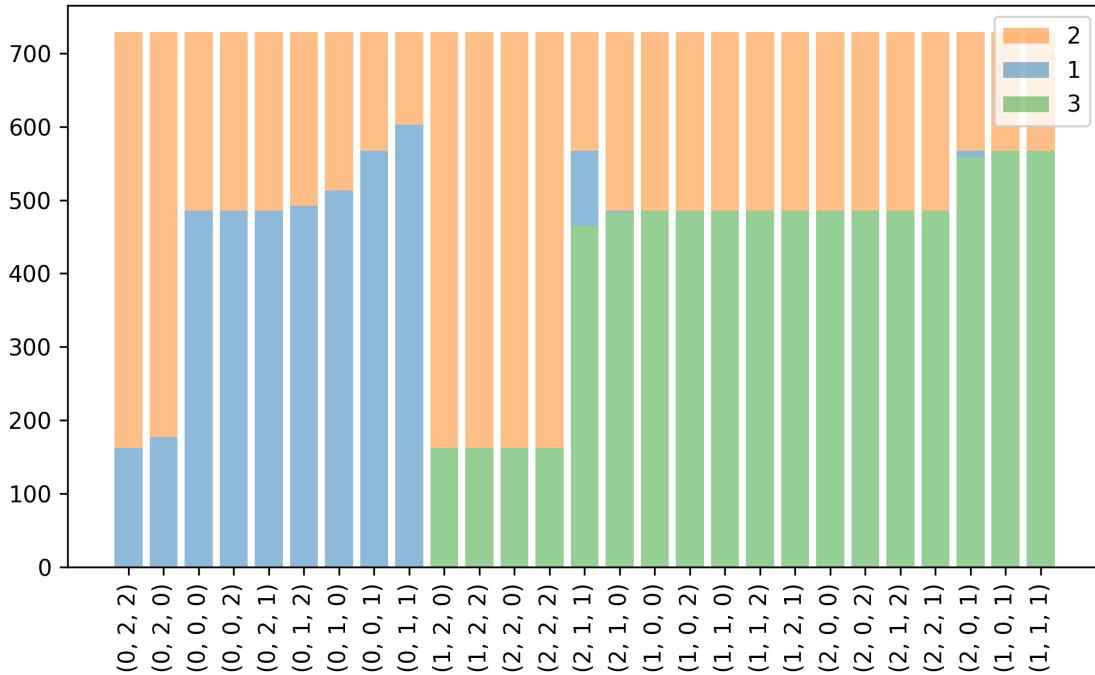
Model IV after Principal component analysis (PCA)



Percent of submodels in model 4 distributed with particular distribution on particular parameter in each of 3 clusters



Percentage of distributions  
 $(\log(N \cdot n_e), \log(f_p m), \log(f_m))$  by (lognormal, gauss, loglinear)  
 coloured by cluster



```
[7]: def polyDeltaL(logL1):
    minP, meanP, maxP = -2, np.log10(1.8), np.log10(5)
    L1 = 10 ** logL1
    a1 = 10 ** (9 - np.array([minP, meanP, maxP]) - np.log10(np.pi * 4))
    a1 = [np.roots([1, 3 * L1, 3 * L1 ** 2 + a, L1 ** 3]) for a in a1]
    return [- min(a, key=lambda x: np.abs(x.imag)).real for a in a1]

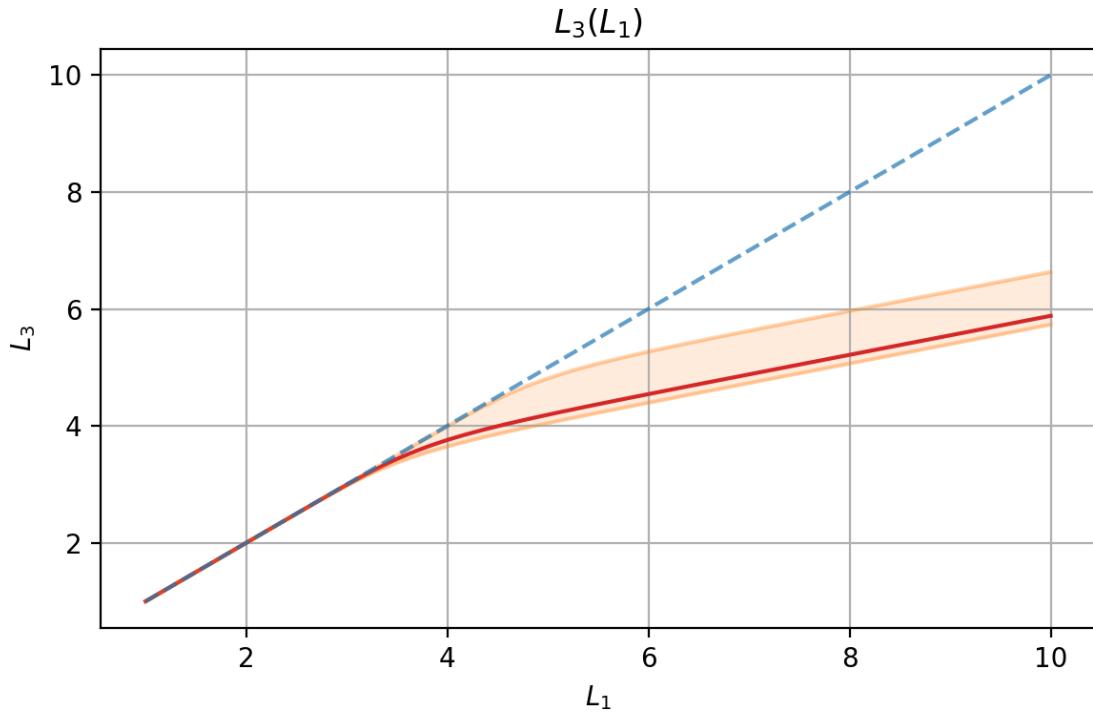
xi = np.linspace(1, 10, 100)
xi3 = np.array([xi, xi, xi]).T
h = np.array([polyDeltaL(x) for x in xi])
ca = [("tab:orange", 0.3), ("tab:red", 1), ("tab:orange", 0.3)]

for ylab, ydat in [("$L_3$", np.log10(np.abs(10 ** xi3 - h)))]:
    plt.figure(figsize=(6, 4), dpi=200, tight_layout=True)
    plt.fill_between(xi, ydat[:, 0], ydat[:, 2],
                     color=ca[0][0], alpha=ca[0][1] / 2)
    for i in range(3):
        plt.plot(xi, ydat[:, i], color=ca[i][0], alpha=ca[i][1])
        if "L_1" not in ylab:
            plt.plot(xi, xi, "--", alpha=0.7)
    plt.title(f"${ylab}({L_1}$")
```

```

plt.xlabel("$L_1$")
plt.ylabel(f"${ylab}$")
plt.grid()
# plt.savefig(f"slice/model3-model1.png")
plt.show()

```

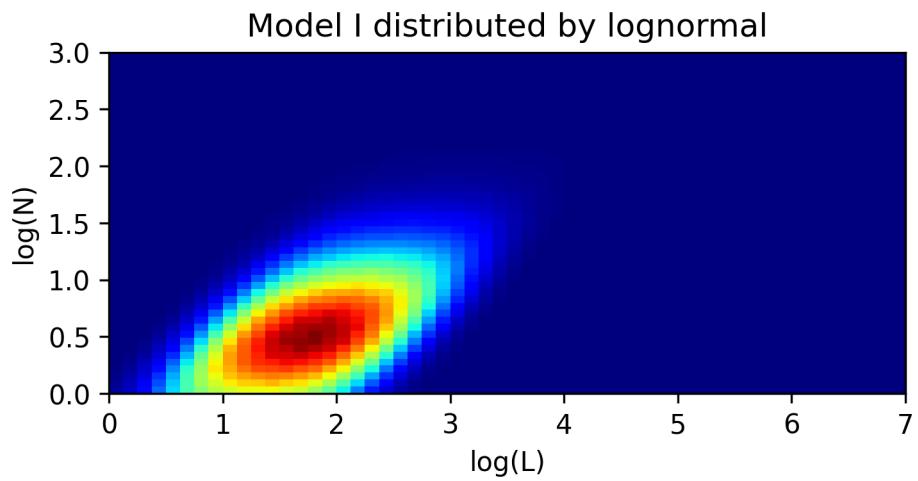
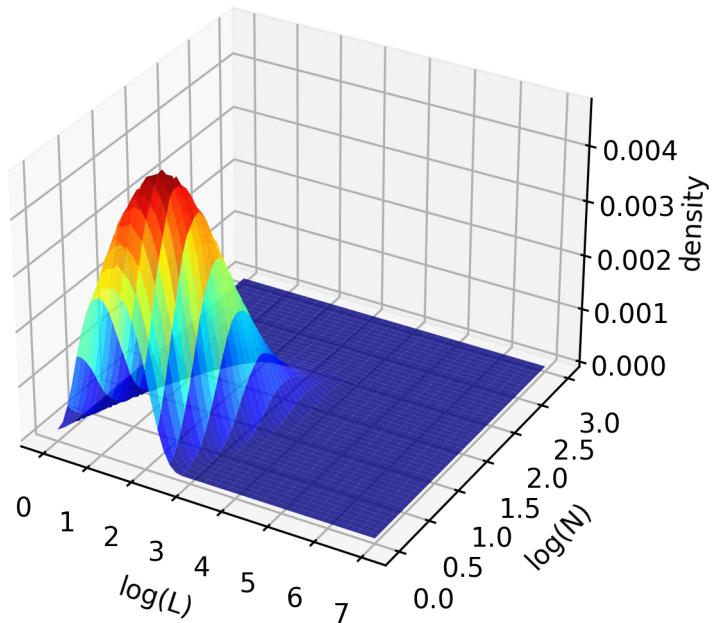


```

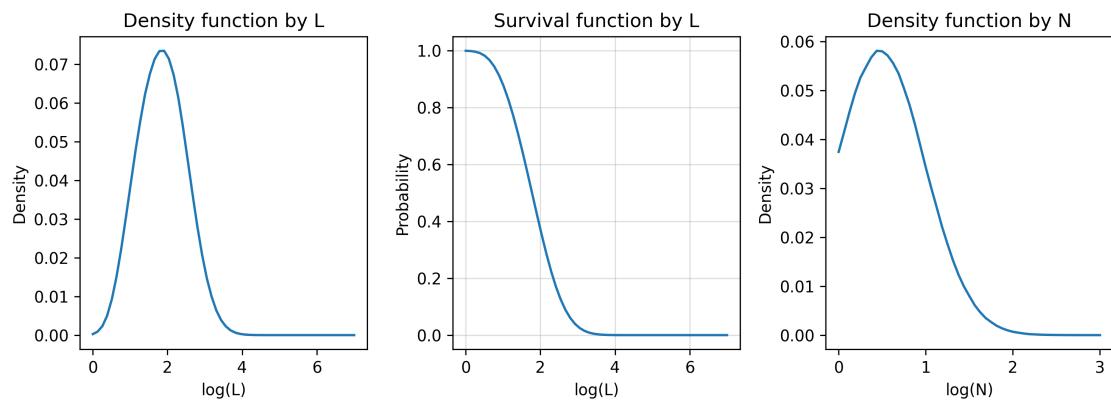
[8]: from plot3D_L import *
draw_histograms3D(model=1, distribution=tuple(0 for _ in range(6)), ↴
                  supermodel=1)
draw_histograms3D(model=2, distribution=tuple(0 for _ in range(2)), ↴
                  supermodel=1)
draw_histograms3D(model=3, distribution=tuple(1 for _ in range(6)), ↴
                  supermodel=1)
draw_histograms3D(model=4, distribution=tuple(0 for _ in range(8)), ↴
                  supermodel=1)
draw_histograms_N3D()
plt.show()

```

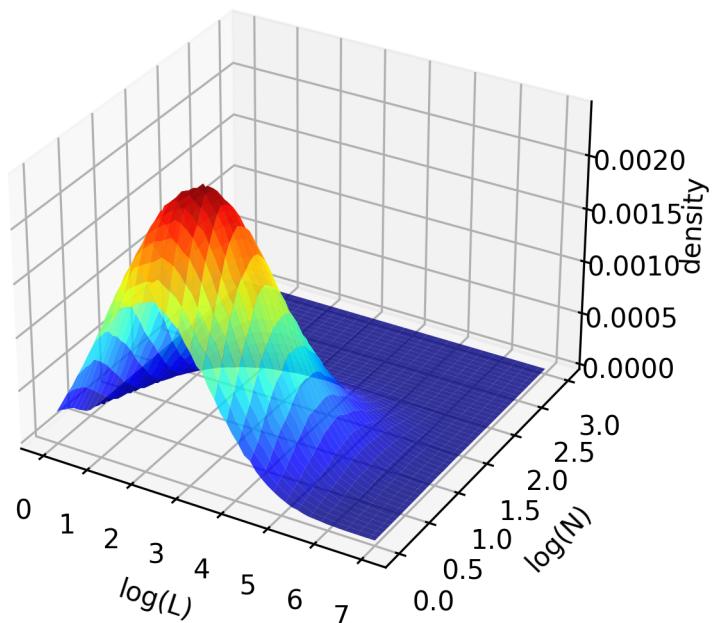
Model I distributed by lognormal



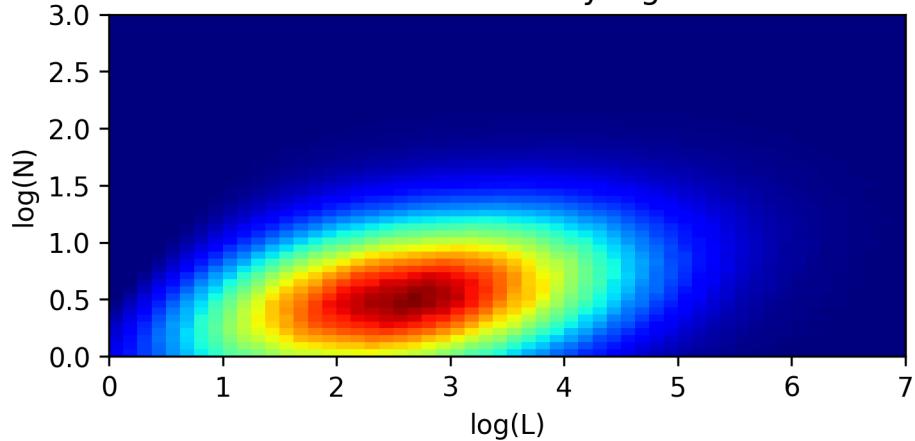
Model I distributed by lognormal



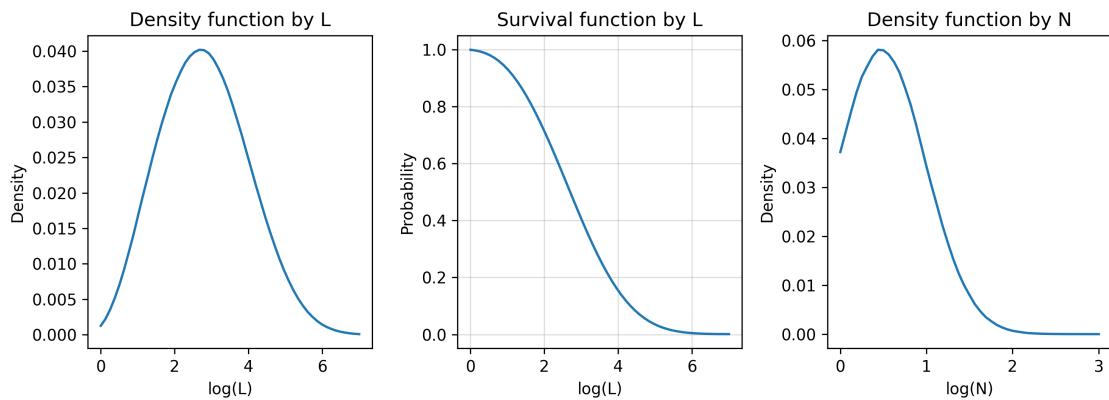
Model II distributed by lognormal



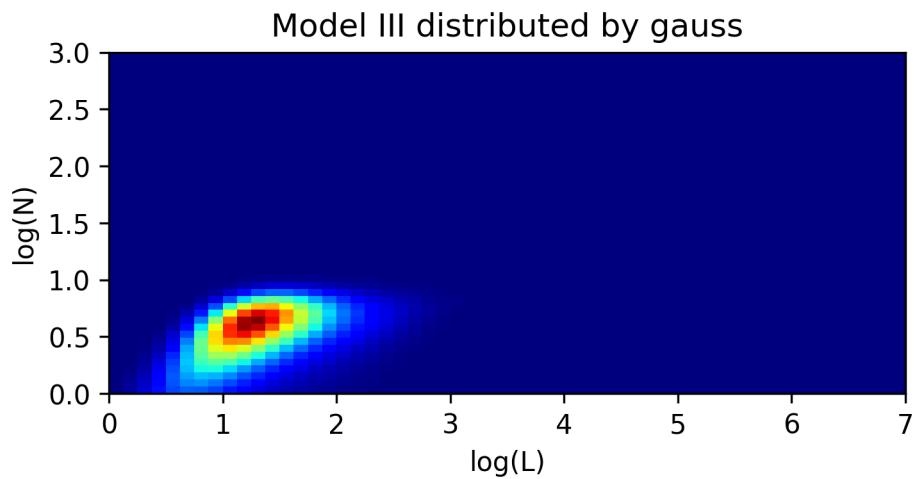
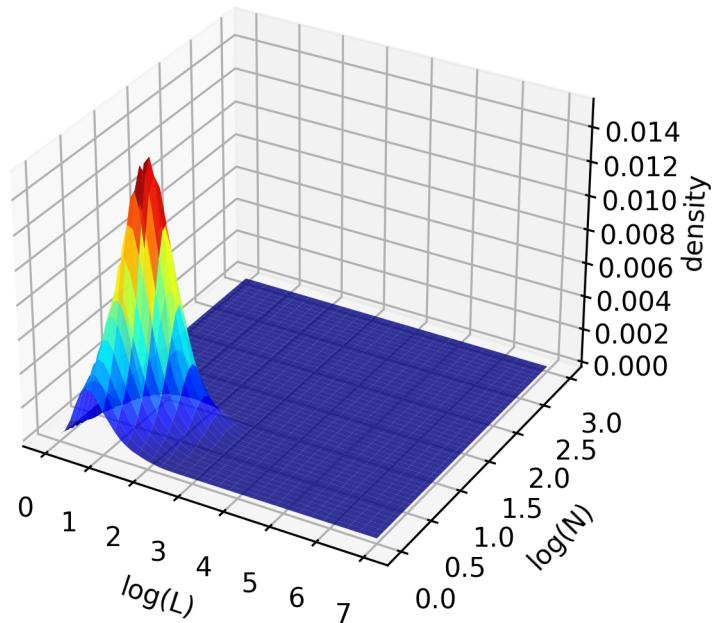
Model II distributed by lognormal



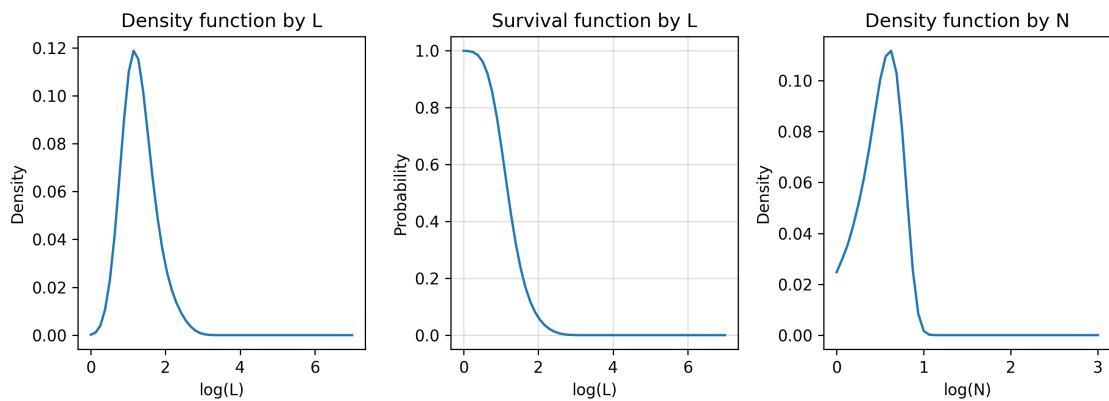
Model II distributed by lognormal



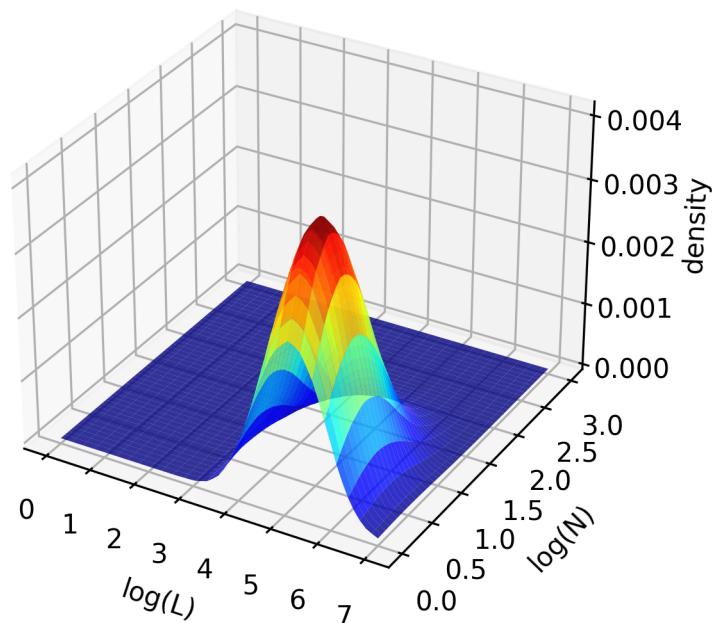
Model III distributed by gauss



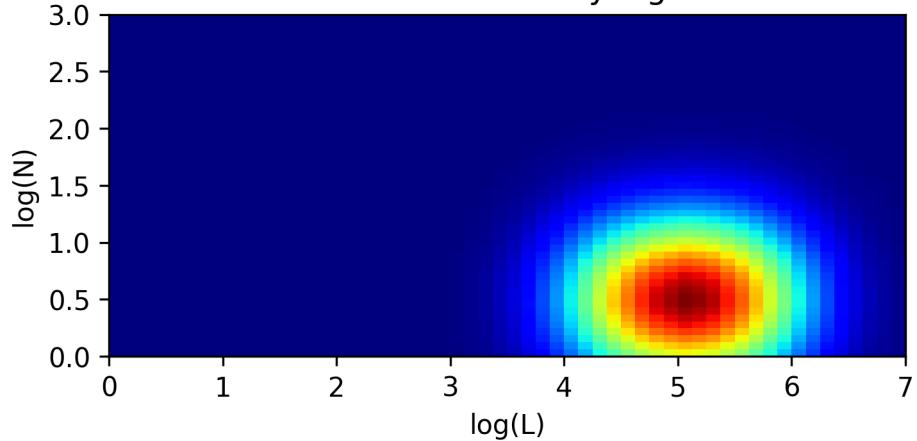
Model III distributed by gauss



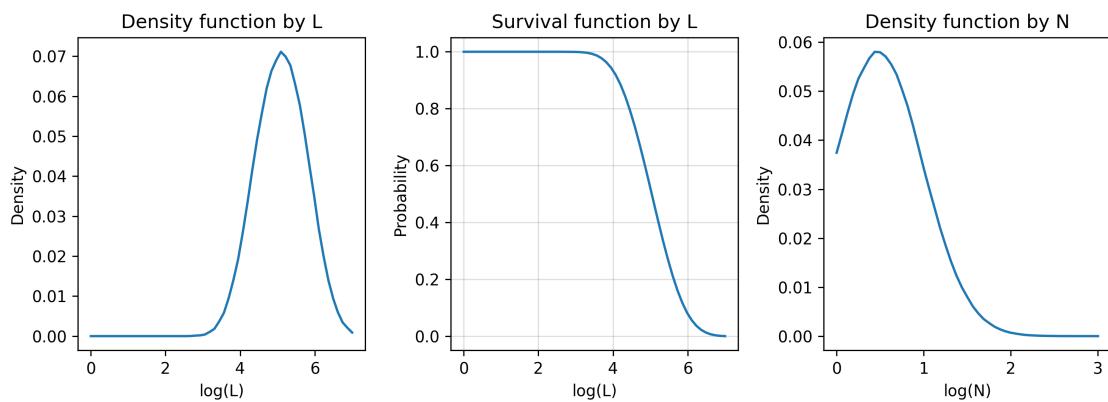
Model IV distributed by lognormal



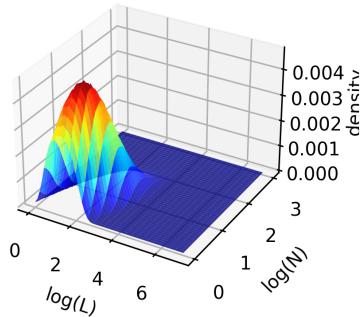
Model IV distributed by lognormal



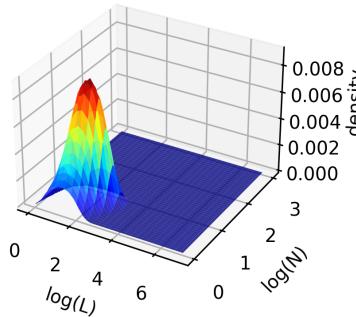
Model IV distributed by lognormal



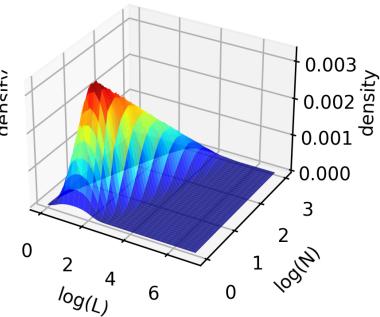
N distributed by lognormal



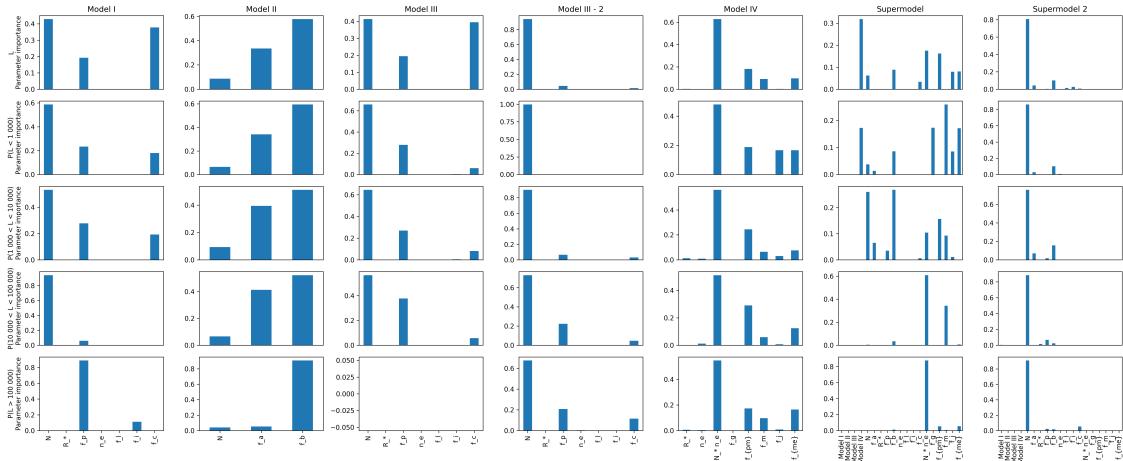
N distributed by gauss



N distributed by loglinear



```
[9]: from tabela_napake_p import modeli_napake
a = modeli_napake()
```



```
[10]: models = []
labels = []
results = {}
with open("ML_tabele.txt", "r") as f:
    lines = f.readlines()
    for i in range(len(lines) // 13 + 1):
        part_lines = lines[i * 13:(i+1) * 13 - 1]
        model = part_lines[-2][-1].replace("_", " ")
        label = part_lines[-1][-1]
        if model not in models:
            models.append(model)
        if label not in labels:
            labels.append(label)
        col_names = part_lines[0][-1].split(" ")[1:]
        row_names = [l[-1].split(" ")[0][:-13]
                     for l in part_lines[1:-2] if "error" not in l]
        part_lines = [[round(float(n), 4) for n in l[-1].split(" ")[1:]]
                      for l in part_lines[1:-2] if "error" not in l]
        results[(model, label)] = pd.DataFrame(part_lines,
                                                index=row_names,
                                                ↪columns=col_names)
```

```
[11]: """
pd.set_option('display.width', 82)
pd.set_option('display.max_columns', None)
for model in models:
    print("\n" + "="*60 + "\n")
    print(" "*5 + "-"*20 + " "*3 + model + " "*3 + "-"*20 + "\n")
```

```

a = pd.concat({k[1]: l for k, l in results.items() if model in k and "<" in
↪k[1]}, 1)
a.columns = a.columns.swaplevel()
a.name = label
a = a[sorted(a.columns, key=lambda x: (x[0], x[1].replace(" 0", "0")))]
print(a)
a.style.background_gradient(cmap="Blues")
# from IPython.display import display
# display(a.style.background_gradient(cmap="Oranges"))
"""
print("")

```

[12]:

```

"""
pd.set_option('display.width', 72)
pd.set_option('display.max_columns', None)

for label in labels:
    print("\n" + "="*60 + "\n")
    print(" "*5 + "-"*20 + " "*3 + label + " "*3 + "-"*20 + "\n")
    a = pd.concat({k[0].replace("Model ", ""): l for k, l in results.items() if
↪label in k}, 1)
    a.columns = a.columns.swaplevel()
    a.name = label
    a = a[sorted(a.columns)]
    if "100 " in label:
        pd.set_option('display.width', 62)
    print(a)
    a.style.background_gradient(cmap="Blues")
    # from IPython.display import display
    # display(a.style.background_gradient(cmap="Oranges"))
"""
print("")

```