

## Introduction

### Global Impact of Natural Disasters (2022) Catastrophic Events

380+

↑ Increasing frequency trend

Natural catastrophic events recorded worldwide, including Extreme weather events, Hydrometeorological disasters, Geological events, Climate-related catastrophes

### Human Impact

30,000+

↑ Significant increase in casualties

Deaths recorded from climate and hydrometeorological events: Heatwaves, Floods, Storms, Other weather-related disasters

### Economic Impact

\$223B

↑ Rising economic costs

Total economic damages from: Infrastructure damage, Business interruption, Recovery operations, Long-term economic effects

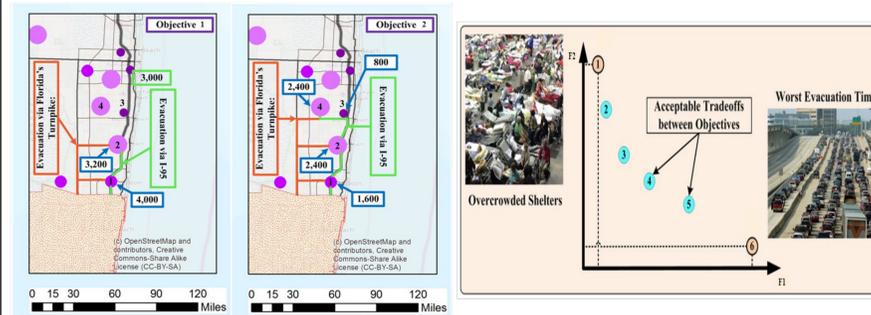
### Key Implications for Emergency Planning

- Growing need for robust evacuation strategies due to increasing disaster frequency
- Necessity for scalable solutions to handle large-scale evacuations
- Critical importance of protecting vulnerable populations
- Need for cost-effective and efficient evacuation planning methods
- Importance of region-specific adaptation strategies

### Emergency Evacuation Challenges

- Complex multi-factor decision making
- Real-time response requirements
- Resource allocation constraints
- Coordination of multiple agencies

- A bi-objective optimization model for emergency evacuation planning under pandemic settings is developed to minimize both virus transmission risk and total evacuation time.
- Minimize shelter utilization deviation and evacuation time, considering virus risks, capacity, vulnerable populations, and accurate travel time estimation.
- A Pareto-based solution approach is developed to effectively analyze trade-offs between the conflicting objectives.
- A decomposition algorithm (DECON) inspired by the  $\epsilon$ -constraint algorithm (ECON) is developed.



Comparison of Evacuation Strategies and Trade-offs Between Shelter Utilization and Evacuation Time.

### Algorithm: $\epsilon$ -Constraint Method (ECON)

$ECON(InputData, PF^{size}, \epsilon_1, \epsilon_2)$

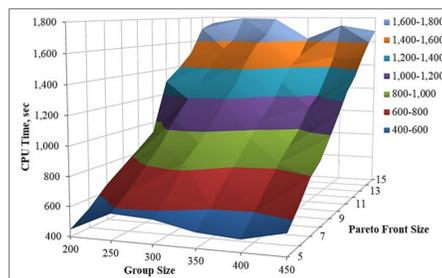
in:  $InputData$  - the EEPPS input data;  $PF^{size}$  - PF size;  $\epsilon_1$  - upper bound on  $F_1$ ;  $\epsilon_2$  - upper bound on  $F_2$

out:  $PF$  - PF for the EEPPS model

- 0:  $|PF| \leftarrow PF^{size}$   $\triangleleft$  Initialization
- 1:  $[F_1^*; F_2(F_1^*)] \leftarrow EEPPS-1(InputData, \epsilon_2)$   $\triangleleft$  Determine the  $F_1^*$  corner point
- 2:  $[F_1(F_2^*); F_2^*] \leftarrow EEPPS-2(InputData, \epsilon_1)$   $\triangleleft$  Determine the  $F_2^*$  corner point
- 3:  $\epsilon \leftarrow (F_1(F_2^*) - F_1^*) / (PF^{size} - 1)$   $\triangleleft$  Calculate the upper bound interval for  $F_1$
- 4:  $iter \leftarrow 1$   $\triangleleft$  Start the iteration counter
- 5:  $\epsilon_1(iter) \leftarrow F_1^*$   $\triangleleft$  Set the first upper bound on  $F_1$
- 6:  $PF \leftarrow PF \cup [F_1^*; F_2(F_1^*)]$   $\triangleleft$  Append the  $F_1^*$  corner point
- 7: **while**  $iter \leq (PF^{size} - 2)$  **do**
- 8:  $iter \leftarrow iter + 1$   $\triangleleft$  Update the iteration counter
- 9:  $\epsilon_1(iter) \leftarrow \epsilon_1(iter-1) + \epsilon$   $\triangleleft$  Update the upper bound on  $F_1$
- 10:  $[F_1(F_2(iter)^*); F_2(iter)^*] \leftarrow EEPPS-2(InputData, \epsilon_1(iter))$
- 11:  $PF \leftarrow PF \cup [F_1(F_2(iter)^*); F_2(iter)^*]$   $\triangleleft$  Append the newly generated PF point to the PF
- 12: **end while**
- 13:  $PF \leftarrow PF \cup [F_1(F_2^*); F_2^*]$   $\triangleleft$  Append the  $F_2^*$  corner point
- 14: **return**  $PF$

## Results

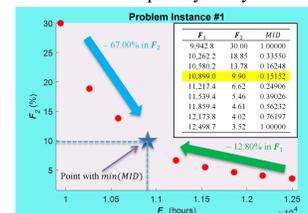
- Assess the computational performance of the DECON algorithm.
- ✓ Influencing factors include PF size (number of points in the Pareto Front) and group size (maximum number of evacuees per group).



Assessing the effects of the PF size and evacuee group size on the DECON computational time.

$ PF _{PF^{size}}$	200	250	300	350	400	450	Average
5	488.6	577.5	561.8	502.2	583.2	547.5	520.1
6	534.6	677.2	676.4	610.2	601.4	661.7	627.0
7	651.5	791.1	842.0	732.6	707.1	792.4	752.8
8	740.5	905.6	938.2	840.5	824.8	861.3	851.8
9	829.9	1,064.7	1,046.7	955.5	913.9	988.3	966.5
10	922.6	1,191.9	1,186.9	1,064.6	1,000.8	1,122.1	1,081.5
11	1,299.0	1,295.5	1,298.8	1,149.2	1,129.4	1,263.3	1,239.2
12	1,390.9	1,424.6	1,465.9	1,290.9	1,195.9	1,354.9	1,353.9
13	1,501.1	1,545.1	1,592.1	1,419.2	1,327.3	1,487.5	1,478.7
14	1,702.4	1,614.8	1,655.9	1,478.8	1,473.2	1,601.3	1,587.8
15	1,746.6	1,792.2	1,786.4	1,618.7	1,734.7	1,688.8	1,727.9
Average:	1,069.8	1,170.9	1,186.5	1,060.3	1,035.6	1,124.5	

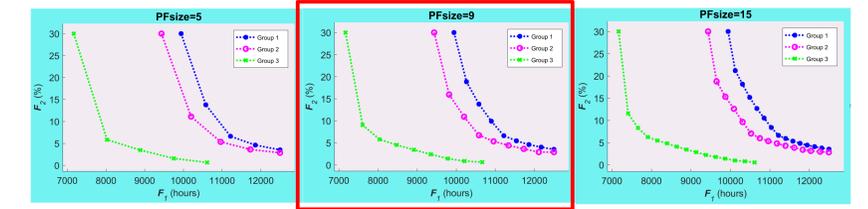
### DECON time complexity analysis results



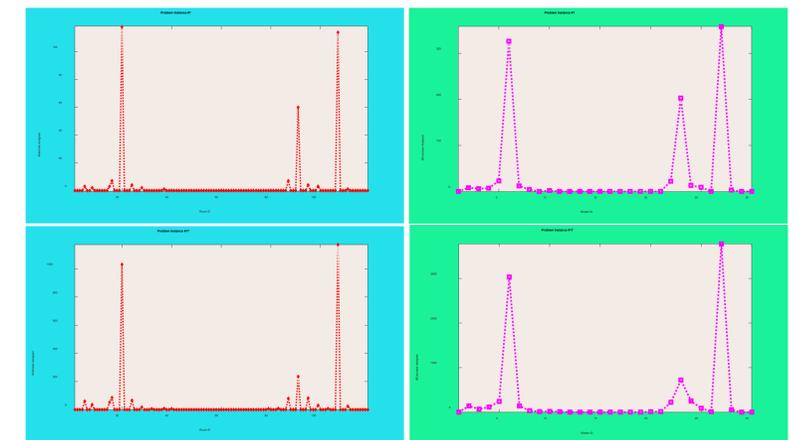
Identification of the PF point with the minimum mean ideal distance.

- Analysis of PF Corner Points and Mean Ideal Distance:
- ✓ Solutions with minimum MID yield better trade-offs between conflicting objectives.

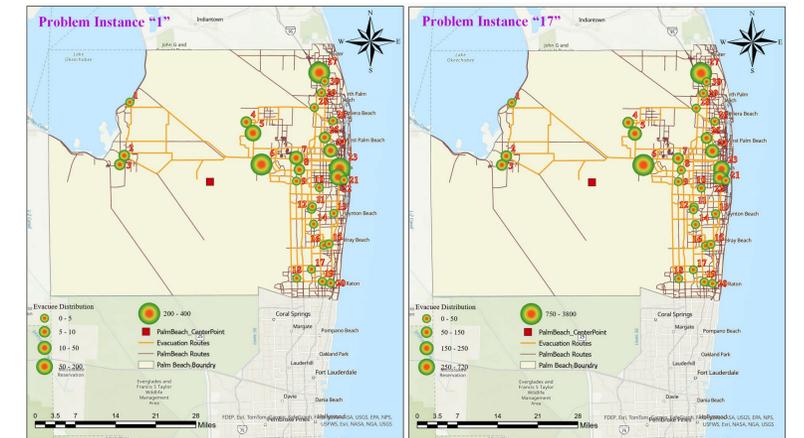
- ✓ PF size set to 9 points and evacuee group size set to 350 for a balance of computational time and solution density.



Assessing the effects of the PF size on solution density.



Assignment of evacuees to evacuation routes and emergency shelters for problem instances "1" and "17".



Spatial distribution of evacuees between the available emergency shelters for problem instances "1" and "17".

## Conclusion

- DECON computational time is more sensitive to PF size than evacuee group size.
- Minimum mean ideal distance (MID) solutions provide a reasonable trade-off between evacuation time and shelter utilization.
- DECON algorithm effectively solves large problem instances within reasonable computational times.
- DECON can be viewed as a custom multi-objective optimization algorithm to solve the proposed bi-objective optimization model and assist with decision-making in a timely manner.