International Conference on Pervasive Computing, Bierritz (France), March 13th, 2024

Climate Smart Computing: A Perspective

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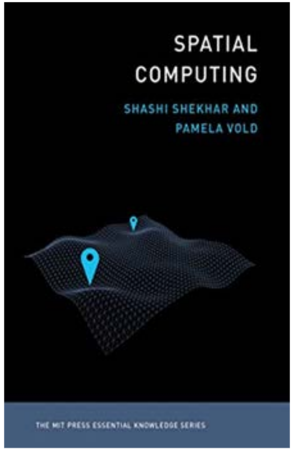
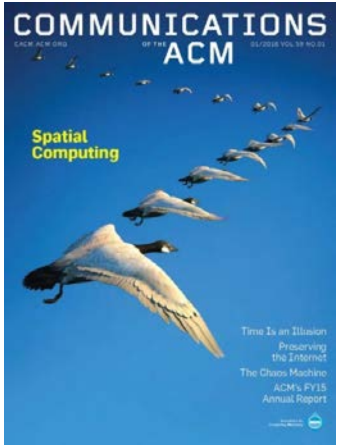
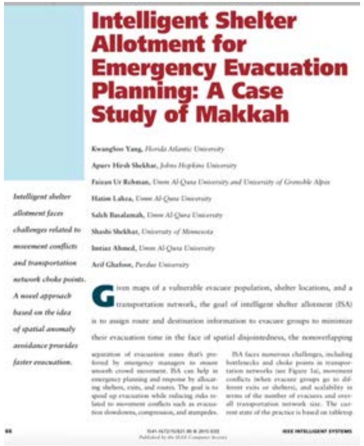
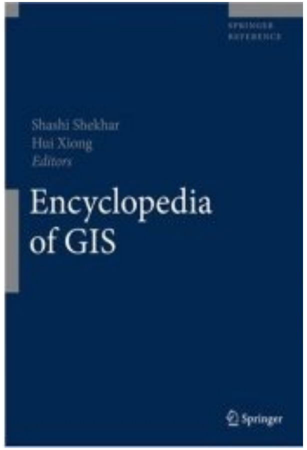
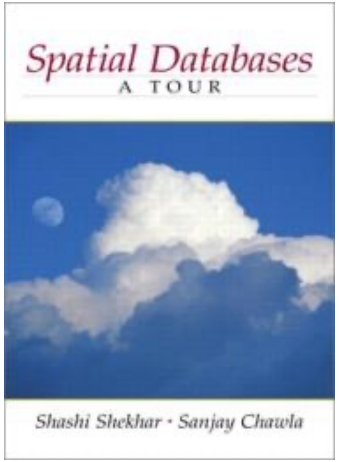










Growing Computing Engagement with Climate

- NSF Workshop on Sustainable Computing for Sustainability, April 16th-17th, 2024.
- Communications of the ACM (CACM)
  - upcoming Special issue on Special Issue on Sustainability and Computing
  - NSF on Chien's Grand Challenge for Sustainability, CACM May 2023
  - Editorial: Computing Grand Challenge for Sustainability, CACM, Oct. 2022

- Fall 2023-onwards: CRA Workgroup on Socially Responsible Computing
- 2022 CRA Snowbird Panel on Climate Smart Computing, July 2022
- Computing and Climate, Guest Editor's Introduction to the Special Issue of IEEE Computing in Sc. & Eng., 17(6):6-8, Nov.-Dec. 2015. 10.1109/MCSE.2015.114.

What is Climate-Smart Computing?

- [NSF on Chien's Grand Challenge for Sustainability, Comm. of the ACM May 2023]

… advances in computing technology to understand and analyze the climate ecosystem, build resilience to climate-driven extreme events, and mitigate and adapt to climate change.

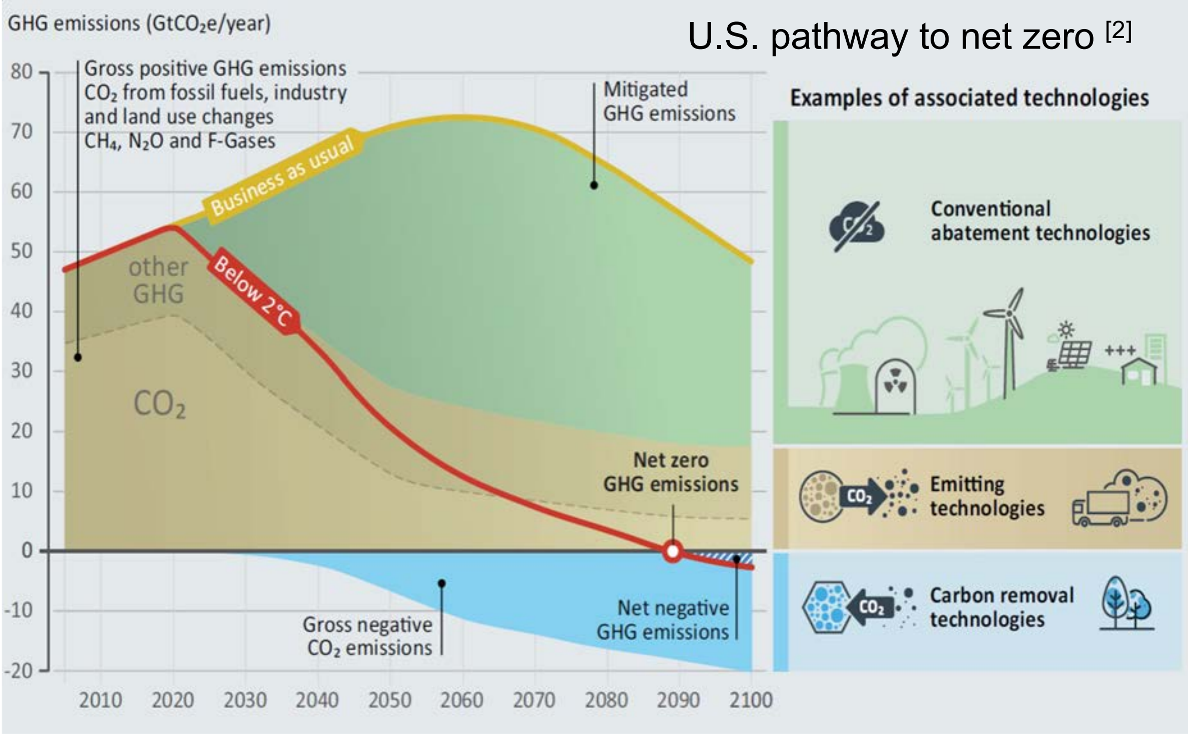
These techniques include:

- Smart sensor-based networks or self-adaptive robots for collecting valuable data in real time and in extreme conditions;
- Communication networks resilient to natural disasters;
- Advanced computing infrastructure for efficient storage and aggregation of the data, and high-speed, heterogeneous computing resources that can handle enormous volumes of climate-related data and large complex climate models;
- State-of-the-art, data-driven computational modeling and high-precision simulation for enabling deeper understanding and new discoveries;
- New climate informatics (including AI) techniques to provide more advanced analysis and prediction capabilities; and
- Human-centered computing approaches for understanding and visualizing key challenges, impacts, and solutions.

Global Engagement with Climate

- To avert worst impacts of climate change
- Paris Agreement
  - ***Net zero emissions by 2050***
- 70 countries
  - China, EU, U.S.
  - [Short video]

U.S. pathway to net zero [2]



[1] Climate Change 2022: Mitigation of Climate Change, IPCC 6th Assessment Report, 2022. Short video
. [2] U.S. Executive Office of the President, The long-term strategy of the united states: Pathways to net-zero greenhouse gas emissions by 2050., (2021).

Climate Smart Computing Activities

Service

- Co-chair: CRA Workgroup on Socially Responsible Computing, Fall 2023 onwards
- Co-chair, 2022 CRA Snowbird Panel on Climate Smart Computing, July 2022
- Co-Editor, Computing and Climate, Guest Editor's Introduction to the Special Issue of IEEE Computing in Sc. & Eng., 17(6):6-8, Nov.-Dec. 2015. 10.1109/MCSE.2015.114.

Projects

- NSF 2118285: HDR Institute: HARP- Harnessing Data and Model Revolution in the Polar Regions
  1901099 : Spatio-temporal Informatics for Transportation Science
  1916518: Midwest Big Data Hub: Building Communities to Harness the Data Revolution
- NIFA 2023-67021-39829: AI-CLIMATE (AI Institute for Climate-Land Interactions, Mitigation, Adaptation, Tradeoffs and Economy)
  2021-51181-35861: Winterturf: A holistic approach to understanding the mechanisms and mitigating the effects of winter stress on turfgrasses in northern climates
- USDOE EERE CX-020456: Improving the Freight Productivity of a Heavy-Duty, Battery Electric Truck, (FOA DE-FOA-0002044 via Volvo Technology of America LLC), (with W. Northop)

Key Messages

- Climate change
  - A key societal challenge of our generation
  - And a major opportunity for computing

- **Ask for computing community**
  - Researcher: Engage with climate topics
  - Educator: Include climate topics in courses and curricula
  - Sponsors: Nurture approaches to overcome challenges

- Rest of the presentation
  - Share personal stories (primarily climate informatics)
    - Climate is not just an application of Computer Sc.
    - It provides rich opportunities to advance and transform Computer Sc.
  - Learn about pervasive computing challenges and opportunities from you

Outline

1. Motivation
2. Share personal stories
    a. Climate Resilience Projects
        i. **Evacuation Route Planning**
        ii. **Shelter allocation**
    b. Climate Understanding, Mitigation, Adaptation Projects
3. Conclusions and Asks

Climate-Smart Computing Problem: Large Scale Evacuation

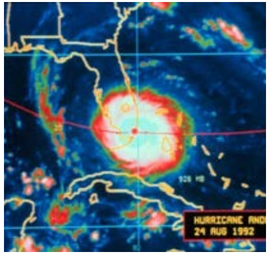
Climate change is increasing frequency and severity of extreme events, e.g., Hurricanes

Hurricane: Andrews, Rita

- Traffic congestions on all highways
- e.g. 100-mile congestion (TX)
- Great confusions and chaos

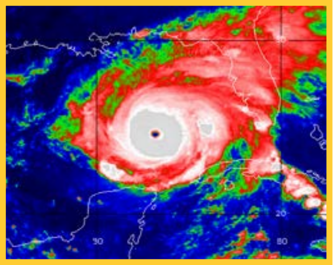
"We packed up Morgan City residents to evacuate in the a.m. on the day that Andrew hit coastal Louisiana, but in early afternoon the majority came back home. The **traffic was so bad** that they couldn't get through Lafayette."
Mayor Tim Mott, Morgan City, Louisiana
(http://i49south.com/hurricane.htm)

Florida, Lousiana (Andrew, 1992)



(National Weather Services)

Houston (Rita, 2005)



(National Weather Services)

(www.washingtonpost.com)

I-45 out of Houston
(FEMA.gov)

Evacuation Route Selection: Problem Statement

Given

- A transportation network, a directed graph $G = (N, E)$ with
  - Capacity constraint for each edge and node
  - Travel time for each edge
- Number of evacuees and their initial locations
- Evacuation destinations

Output: Evacuation plan consisting of a set of origin-destination routes
  - and a scheduling of evacuees on each route.

Objective: Minimize evacuation egress time
  - time from start of evacuation to last evacuee reaching a destination

Constraints

- Route scheduling should observe **capacity constraints** of network
- Reasonable computation time despite limited computer memory
- Capacity constraints and travel times are non-negative integers
- Evacuees start from and end up at nodes

Why is this problem hard computationally?

Intuition:

- Spread people over space and time
- Multiple paths + pipelining over those

A. Flow Networks

OR = Population / (Bottleneck Capacity of Transport Network)

If (OR <=1) { shortest path algorithms, e.g. A* }

Else if (OR → infinity) { Min-cut max-flow problem }

Else { Computationally hard problem ! }

B. Spatio-temporal Networks

- Violate stationary assumption
  - behind shortest path algorithms, e.g. A*, Dijktra's
  - Optimal sub-structure and dynamic programming

Summary of Related Works & Limitations

A. Capacity-ignorant Approach

- Simple shortest path computation, e.g. A*, Dijkstra's, EXIT89 (Natl. Fire Prot. Asso.)

Limitation: Poor solution quality as evacuee population grows

B. Operations Research: Time-Expanded Graph + Linear Programming

- Optimal solution, e.g. EVACNET (U. FL), Hoppe and Tardos (Cornell U).

Limitation: - High computational complexity => Does not scale to large problems

- Users need to guess an upper bound on evacuation time

Number of Nodes	50	500	5,000	50,000
EVACNET Running Time	0.1 min	2.5 min	108 min	> 5 days

C. Transportation Science: Dynamic Traffic Assignment

- Game Theory: Wardrop Equilibrium, e.g. DYNASMART (FHWA), DYNAMIT(MIT)

Limitation: Extremely high compute time; Also evacuation not an equilibrium phenomena

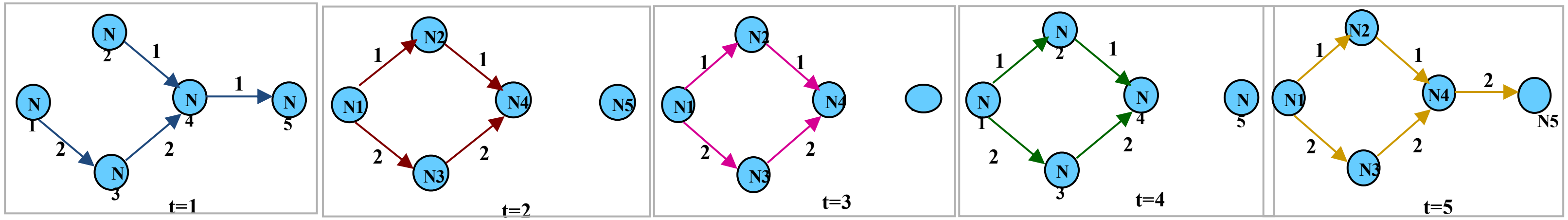
Proposed Approach

- Key Ideas
  A. Time Aggregated Graph (TAG) to reduce data size
  B. Precompute Earliest arrival time-series
  C. Capacity Constraint Route Planner to pull ideas together

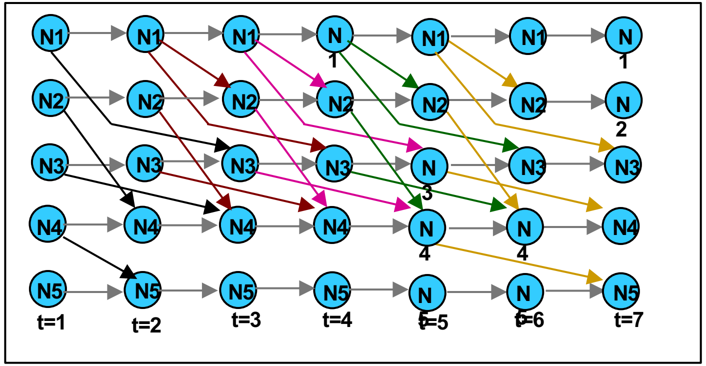
A. Time Aggregated Graph (TAG) to reduce data size

(1) Snapshot Model [Guting 04]

Node: N..   Edge: Travel time



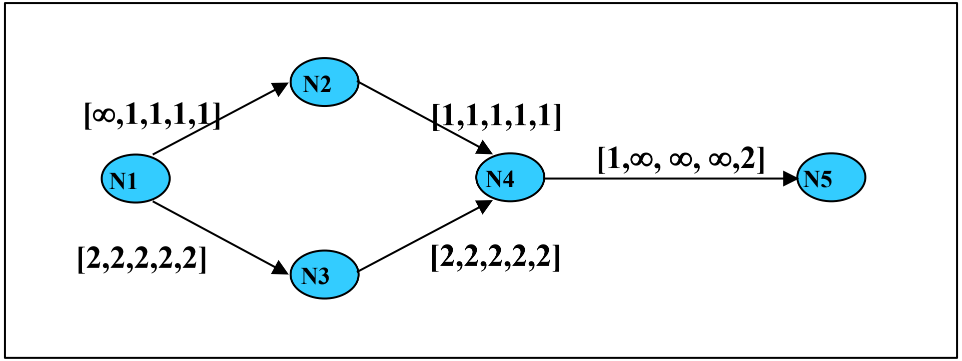
(2) Time Expanded Graph (TEG) [Ford 65]



Holdover Edge

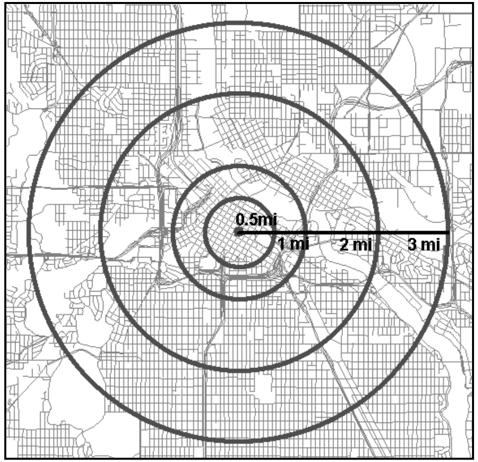
Transfer Edges

(3) Time Aggregated Graph (TAG) **[Our Approach]**



Edge $\xrightarrow{[m_1,\ldots,m_T]}$ m_i- travel time at t=i

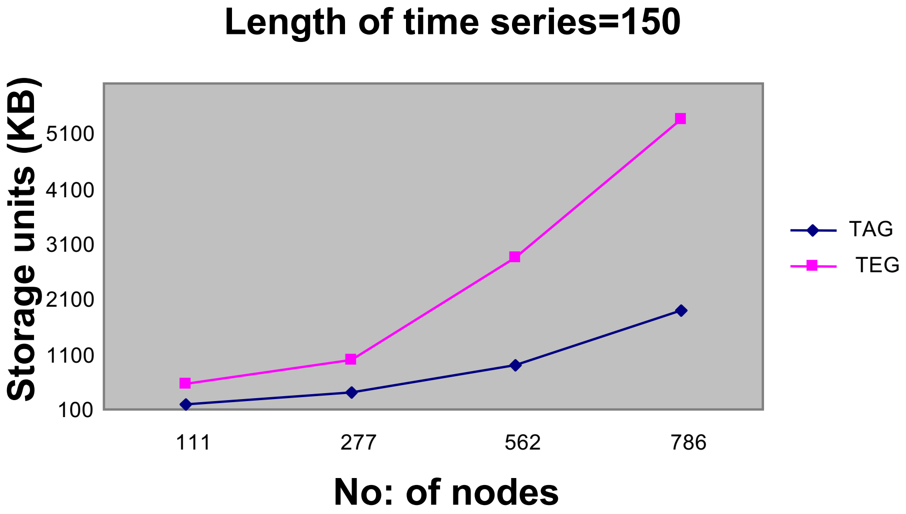
Storage Cost Comparison



Benchmark Maps: Minneapolis
[1/2, 1, 2, 3 miles radii]

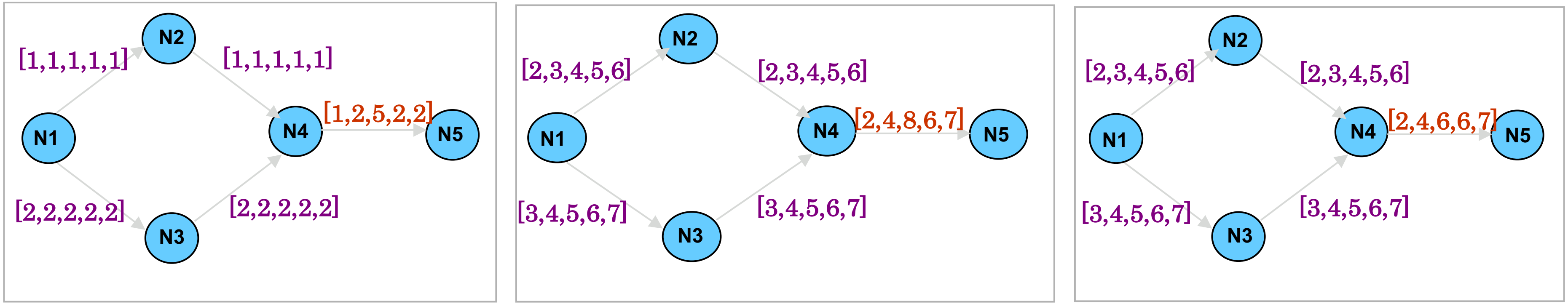
Dataset	# Nodes	# Edges
(MPLS -1/2 mi)	111	287
(MPLS -1 mi)	277	674
(MPLS - 2 mi)	562	1443
(MPLS - 3 mi)	786	2106

Trend: Proposed approach (TAG) better than alternatives (e.g.,TEG) on storage overhead!



B. Precompute Earliest arrival time-series

Challenge: To wait or not to wait? Ex. N4 to N5 with start time 3 in leftmost graph
Approach: Pre-compute earliest arrival time-series



travel times → arrival times at end node → Min. arrival time series

C. Capacity Constraint Route Planner to pull ideas together

- Time-series attributes

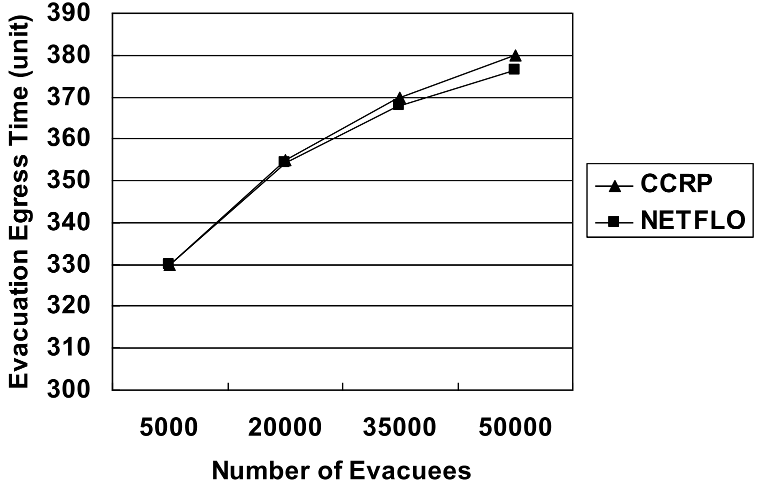
  Available_Node_Capacity (*Ni* , *t*) = *#additional evacuees that can stay at* node *Ni* at time *t*

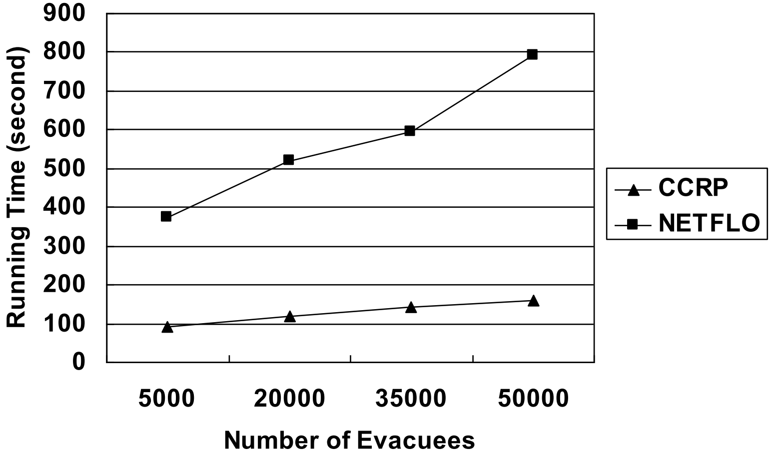
  Available_Edge_Capacity (*Ni* -*Nj* , *t*) = #additional evacuees that may travel via edge *Ni* -*Nj* at time *t*
- Generalize shortest path algorithms to honor capacity constraints
- Each iteration
  - Generates route and schedule for a group of evacuee closest to destination
  - Make reservations by updating node/edge capacities

Comparative Evaluation of SOTA (NETFLO) and Proposed Method (CCRP)

Experiment 1: Effect of Number of Evacuees

Setup: fixed network size = 5000 nodes, fixed number of source nodes = 2000 nodes, vary number of evacuees





- CCRP produces high quality solution, solution quality drops slightly as number of evacuees grows.
- Run-time of CCRP is less than 1/3 that of NETFLO.
- CCRP is scalable to the number of evacuees.

FoxTV newsclip (5-minutes), Disaster Area Evacuation Analytics Project

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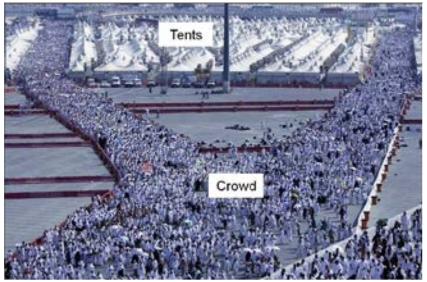
Makkah Hajj Shelter Allocation

Context: Flash floods require evacuation of Tent city on to the Jamarat bridge

Jamarat Complex



Crowd walking from tent city to Jamarat complex

Problem Formulation:

Given: Graph *G = (nodes, edges)*

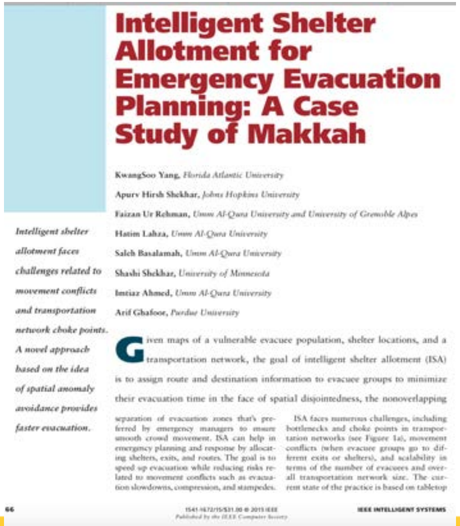
Edge travel-time and Capacity/unit-time

Evacuee map, Shelters with capacities

Find: Allot shelters to evacuees

Objective: Minimize evacuation time

Constraints: avoid movement conflicts (Stampede risk)



Intelligent Shelter Allotment for Emergency Evacuation Planning: A Case Study of Makkah

KwangSoo Yang, *Florida Atlantic University*

Apurv Hirsh Shekhar, *Johns Hopkins University*

Faizan Ur Rehman, *Umm Al-Qura University and University of Grenoble Alpes*

Hatim Lahza, *Umm Al-Qura University*

Saleh Basalamah, *Umm Al-Qura University*

Shashi Shekhar, *University of Minnesota*

Imtiaz Ahmed, *Umm Al-Qura University*

Arif Ghafoor, *Purdue University*

Intelligent shelter allotment faces challenges related to movement conflicts and transportation network choke points. A novel approach based on the idea of spatial anomaly avoidance provides faster evacuation.

Given maps of a vulnerable evacuee population, shelter locations, and a transportation network, the goal of intelligent shelter allotment (ISA) is to assign route and destination information to evacuee groups to minimize their evacuation time in the face of spatial disjointedness, the nonoverlapping separation of evacuation zones that's preferred by emergency managers to ensure smooth crowd movement. ISA can help in emergency planning and response by allocating shelters, exits, and routes. The goal is to speed up evacuation while reducing risks related to movement conflicts such as evacuation slowdowns, compression, and stampedes.

ISA faces numerous challenges, including bottlenecks and choke points in transportation networks (see Figure 1a), movement conflicts (when evacuee groups go to different exits or shelters), and scalability in terms of the number of evacuees and overall transportation network size. The current state of the practice is based on tabletop

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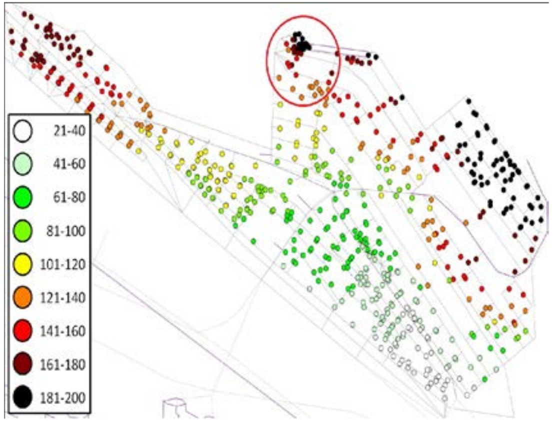
Note: NP-hard.

Details: Intelligent Shelter Allotment for Emergency Evacuation Planning: A Case Study of Makkah, Intelligent Systems, IEEE, 30(5):66-76, Sept.-Oct., 2015.

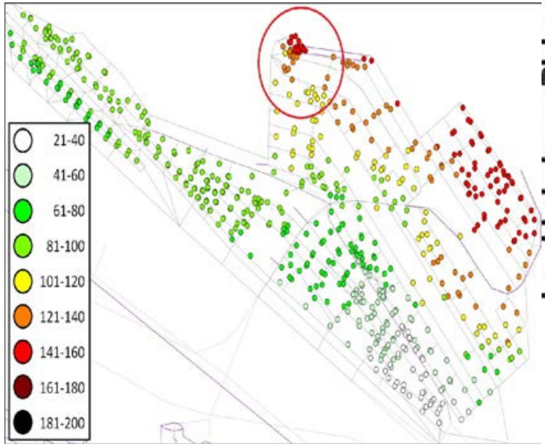
Comparative Evaluation

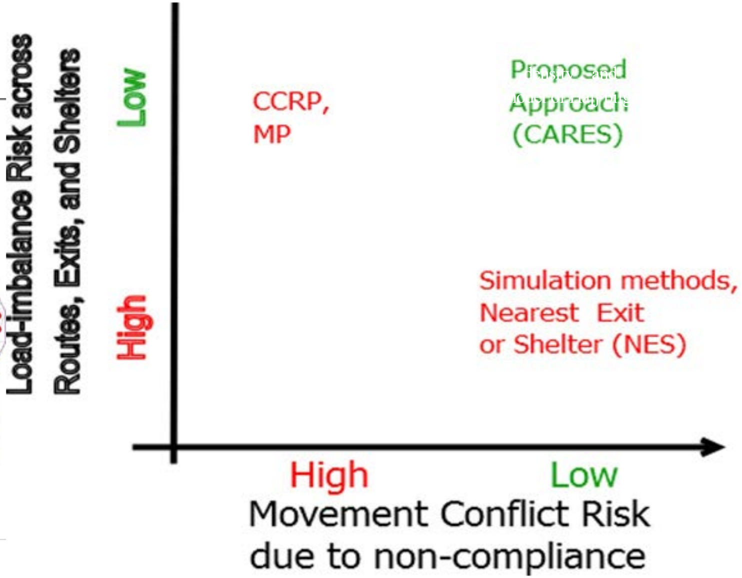
Trend: Proposed approach (CARES) gets evacuees to shelter faster than SOTA (NES)

SOTA(NES) arrival time



Proposed Method (CARES) arrival time





Details: K. Yang et al.. "Intelligent shelter allotment for emergency evacuation planning: A case study of makkah." *IEEE Intelligent Systems* 30, no. 5 (2015): 66-76.

Future Directions

- Data Availability
  - Estimating evacuee population, available transport capacity
  - Pedestrian data: walkway maps, link capacities based on width
- Traffic Eng.
  - Link capacity depends on traffic density
  - Modeling traffic control signals, ramp meters, contra-flow, …
- Evacuee Behavior
  - Unit of evacuation: Individual or Household
  - Heterogeneity: by physical ability, age, vehicle ownership, language, …
- Policy Decisions
  - How to gain public's trust in plans? Will they comply?
  - When to evacuate? Which routes? Modes? Shelters? Phased evacuation?
  - Common good with awareness of winners and losers due to a decision
- Science
  - How does one evaluate an evacuation planning system ?

Outline

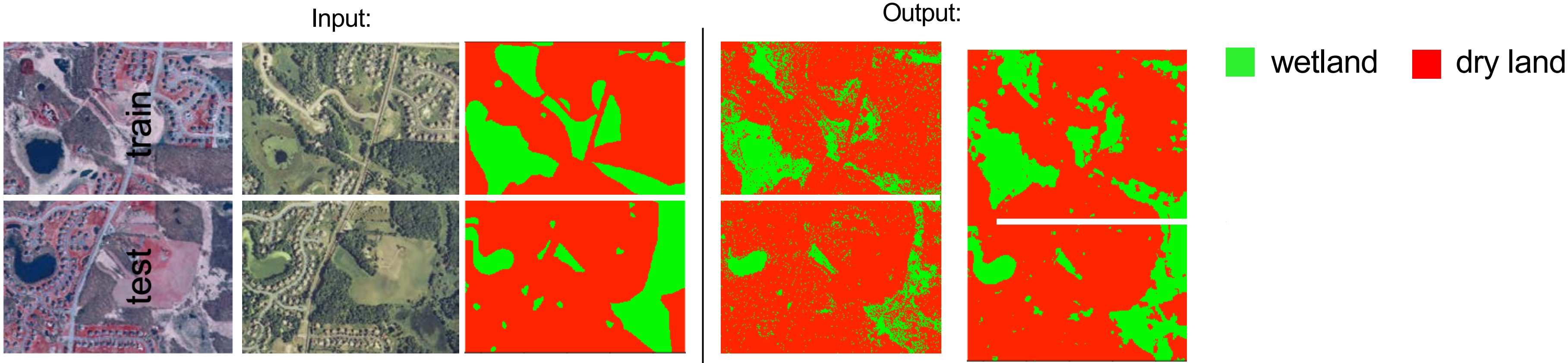
1. Key Messages
2. Share personal stories
    a. Climate Resilience Projects
    b. Climate Understanding, Mitigation, Adaptation Projects
        i. **NSF Expedition: Data Driven Understanding of Climate Change**
        ii. NSF INFEWS Data Science Workshop
        iii. AI-CLIMATE
3. List opportunities
4. Conclusions

NSF Climate Expedition

- NSF Expedition: Understanding Climate Change: A Data-Driven Approach (2010-2016)
- Aims: Data-driven approach to complement physics-based models to improve understanding of climate change and its impacts
- Partners: U Minnesota (lead), NASA, NCAT, NCSU, ORNL, U Tennessee
- **Challenges**
  - Spatial Auto-correlation and variability
  - Temporal non-stationarity and lags,
  - Physics-constraints, …
- **Research**
  - Spatial Classification and Prediction Models
  - Relationship Mining
  - Complex Networks
  - High Performance Computing

Classification Models and Spatial Auto-correlation

Challenge: Climate data violates ubiquitous i.i.d. assumption
Symptom: Salt and Pepper noise



(a) aerial photo (b) aerial photo (c) true classes (d) DT prediction (Salt n Pepper Noise) (e) SDT prediction

Training samples: upper half
Test samples: lower half
Spatial neighborhood: maximum 11 pixels by11 pixels

DT: decision tree
SDT: spatial decision tree

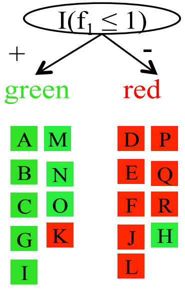
Details: Focal-Test-Based Spatial Decision Tree Learning. [IEEE Trans. Knowl. Data Eng. 27(6):](#) 1547-1559, 2015 (A summary in Proc. IEEE Intl. Conf. on Data Mining, 2013).(w/ Z. Jiang et al.

Proposed Approach: Spatial Decision Tree

Traditional decision tree

Inputs: table of records

ID	f_1	f_2	Γ_1	class
A	1	1	1	green
B	1	1	0.3	green
C	1	3	0.3	green
G	1	1	0.3	green
I	1	3	0	green
K	1	2	-1	red
M	1	1	1	green
N	1	1	0.3	green
O	1	3	0.3	green
D	3	2	0.3	red
E	3	2	0.3	red
F	3	2	1	red
H	3	1	-1	green
J	3	2	0	red
L	3	2	0.3	red
P	3	2	0.3	red
Q	3	2	0.3	red
R	3	2	1	red



Predicted map

A	B	C	D	E	F
G	H	I	J	K	L
M	N	O	P	Q	R

feature test	information gain
$f_1 \leq 1$	0.50
$f_2 \leq 1$	0.46
$f_2 \leq 2$	0.19

Spatial decision tree

Inputs:

- feature maps, class map
- Rook neighborhood

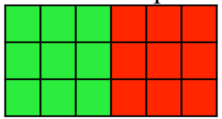
Feature f_1

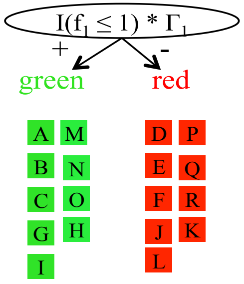
1	1	1	3	3	3
1	3	1	3	1	3
1	1	1	3	3	3

Feature f_2

1	1	3	2	2	2
1	1	3	2	2	2
1	1	3	2	2	2

Class map





Focal function Γ_1

1	.3	.3	.3	.3	1
.3	-1	0	0	-1	.3
1	.3	.3	.3	.3	1

Predicted map

A	B	C	D	E	F
G	H	I	J	K	L
M	N	O	P	Q	R

Modeling Spatial Auto-correlation

- Traditional, e.g., Linear Regression (LP) with Logit or Probit, Bayes Classifier, …
- Semi-Spatial: LR with auto-corr. Regularizer $\varepsilon = \|y - \beta X\|^2 + \|\beta X - \beta X_{neighbor}\|^2$
- Spatial
  - Spatial autoregressive model (SAR)
  - Markov random field (MRF) based Bayesian Classifier

Traditional	Spatial
$y = X\beta + \varepsilon$	$y = \rho W y + X\beta + \varepsilon$
$\Pr(C_i \mid X) = \frac{\Pr(X \mid C_i)\Pr(C_i)}{\Pr(X)}$	$\Pr(c_i \mid X, C_N) = \frac{\Pr(C_i)\Pr(X, C_N \mid c_i)}{\Pr(X, C_N)}$
Neural Networks	Convolutional Neural Networks
Decision Trees	Spatial Decision Trees

Computational Problem: Parameter Estimation

Name	Model
Classical Linear Regression	$\boxed{\mathbf{y} = \mathbf{x}\boldsymbol{\beta} + \boldsymbol{\varepsilon}}$
Spatial Auto-Regression	$\boxed{\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{x}\boldsymbol{\beta} + \boldsymbol{\varepsilon}}$

ρ : the spatial auto-regression (auto-correlation) parameter

$\mathbf{W}$: n-by-n neighborhood matrix over spatial framework

- **<u>Maximum Likelihood Estimation</u>**

- Computing determinant of large matrix is a hard (open) problem!

– size(W) is quadratic in number of locations/pixels.

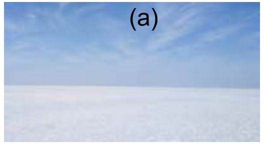
– Typical raster image has Millions of pixels

– W is sparse but not banded.

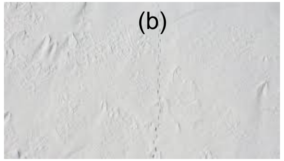
Details: A parallel formulation of the spatial auto-regression model for mining large geo-spatial datasets, SIAM Intl. Workshop on High Perf. and Distr. Data Mining, 2004. (with B. Kazar)

Spatial Heterogeneity

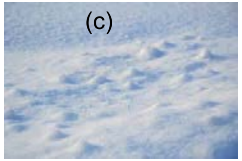
- Knowledge of location can improve land-cover and object recognition
  - Q? Which pictures show snow?



Salt Marsh
(Runn of Kutch, Gujarat, India)



Snow



Snow

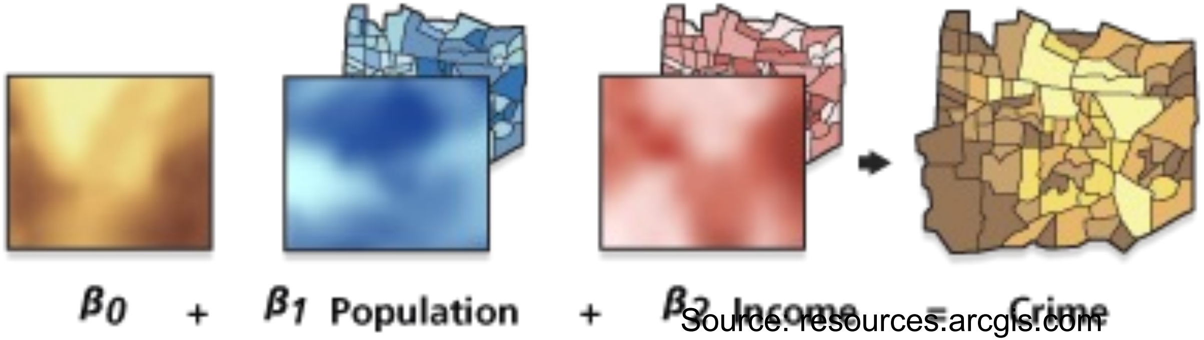
- Coarse Satellite Imagery (e.g., 30m pixels)
  - More effective for large mono-crop farms the small mixed-crop plots

- However, Convolutional Neural Networks does not model geographic heterogeneity.

Modeling Spatial Heterogeneity: GWR

- Geographically Weighted Regression (GWR)
    - Goal: Model spatially varying relationships
    - Example: $y = X\beta' + \varepsilon'$

      Where β' and ε' are location dependent

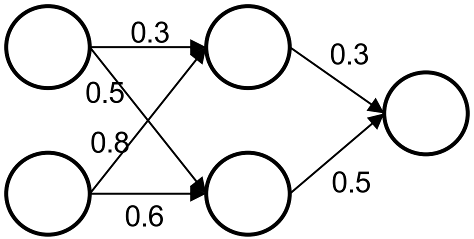


Source: resources.arcgis.com

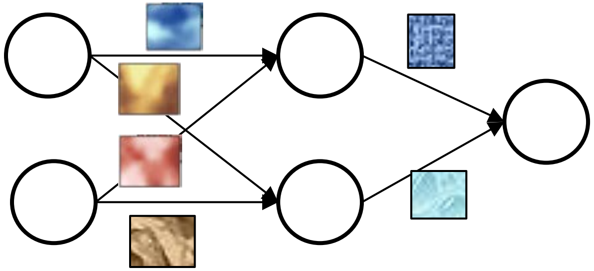
Spatial Variability Aware Neural Networks (SVANN)

- Each NN parameter is a map i.e., a function of location
  - Similar to Geographically Weighted Regression

A Neural Network (NN)



SVANN



- Evaluation:
  - Urban Garden Detection across Hennepin County, MN and Fulton County, GA.
  - SVANN outperformed OSFA by 14.34% on F1-scores.

Details: Towards Spatial Variability Aware Deep Neural Networks (SVANN), ACM Transactions on Intelligent Systems and Technology, 12(6):1-21, Dec. 2021. (A Summary in ACM SIGKDD Workshop on Deep Learning for Spatiotemporal Data, Applications, and Systems, 2020. (Best Paper Award)

Outline

1. Motivation
2. Share personal stories
   a. Climate Resilience Projects
   b. Climate Understanding, Mitigation, Adaptation Projects
      i. **NSF Expedition: Data Driven Understanding of Climate Change**
      ii. **Congressional Reception, NSF INFEWS Data Science Workshop**
      iii. AI-CLIMATE
3. Conclusions and Asks

Deconstructing Precision Agriculture

#AgInnovates2015

Wednesday, March 4, 2015
Reception | 5:00 to 7:00 pm

House Agriculture Committee Room,
1300 Longworth House Office Building,
Washington, DC

Think Moon landing.

Think Internet.

Think iPhone and Google.

Think bigger.

Come hear U.S. farmers, leading agriculture technology companies, and scientists tell how they work together to fuel U.S. innovation and the economy to solve this global challenge.

The event will exhibit three essential technologies of precision agriculture that originated from a broad spectrum of federally funded science: Guidance Systems and GPS, Data & Mapping with GIS, and Sensors & Robotics.

Moderator

Raj Khosla, Professor of Precision Agriculture at Colorado State Univ.

Farmers

David Hula, of Renwood Farms in Jamestown, Virginia

Rod Weimer, of Fagerberg Produce in Eaton, Colorado

Del Unger, of Del Unger Farms near Carlisle, Indiana

Speakers

Mark Harrington, Vice President of Trimble

Carl J. Williams, Chief of the Quantum Measurement Division at NIST

Bill Raun, Professor at Oklahoma State Univ.

Marvin Stone, Emeritus Professor at Oklahoma State Univ.

J. Alex Thomasson, Professor at Texas A&M Univ.

Dave Gebhardt, Director of Data and Technology at Land O'Lakes/WinField

Shashi Shekhar, Professor at the Univ. of Minnesota

RSVP

http://bit.ly/1CoOYoa

Hosted by
the Congressional Soils Caucus

In partnership with

Agricultural Retailers Association
American Society of Plant Biologists
American Physical Society
American Society of Agronomy
Association of Equipment Manufacturers
Coalition for the Advancement of Precision Agriculture
Computing Research Association
CropLife America
Crop Science Society of America
PrecisionAg Institute
Soil Science Society of America
Task Force on American Innovation
Texas A&M AgriLife
Trimble
WinField

This is about feeding the world.

NSF INFEWS Data Science Workshop (Oct. 2015)

- **Goals**
  - —Develop visions, Identify gaps
  - —Develop a research agenda
- **At** USDA NIFA, Oct. 5th-6th, 2015
- **Co-organizers:** Shekhar, Mulla, Schmoldt
- **URL:** www.spatial.cs.umn.edu/few

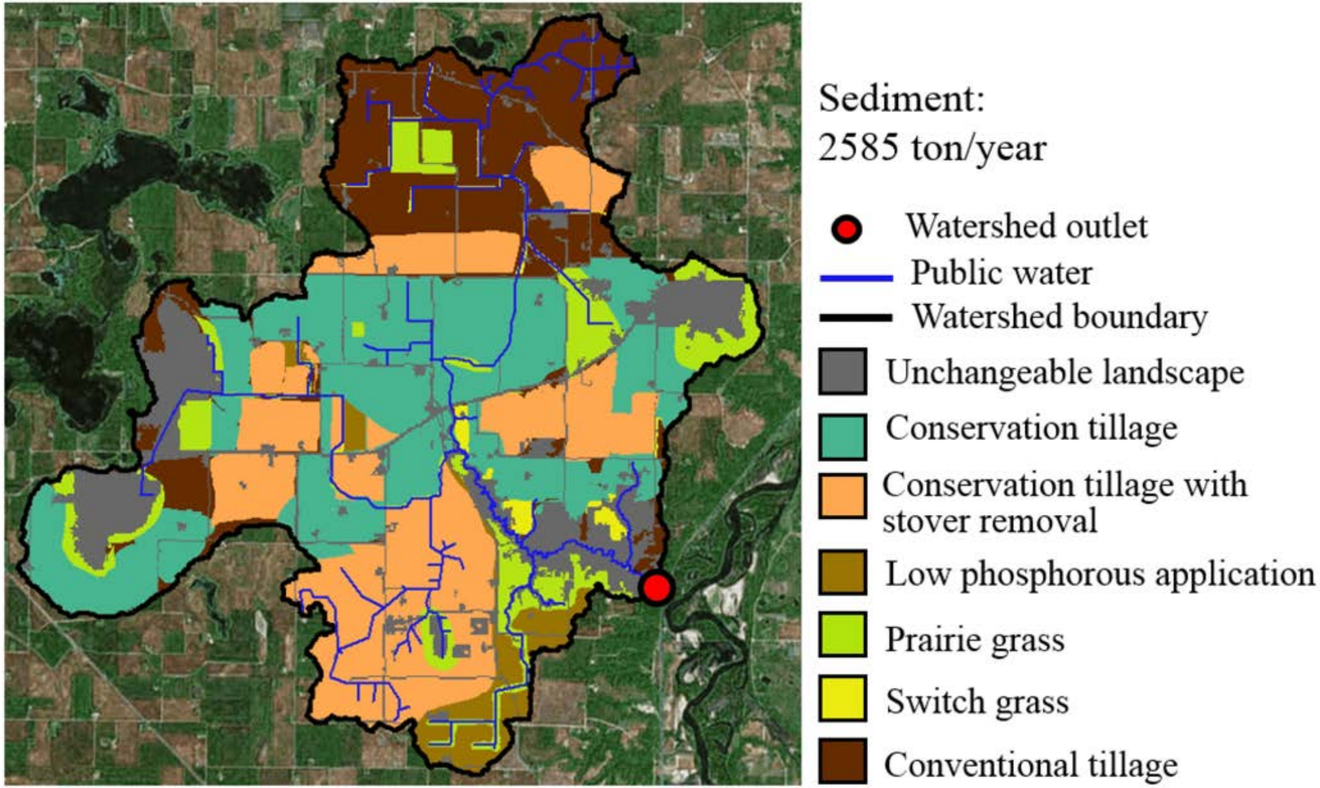
- **55 Participants**

Gov.	Aca.	Industry
26	24	5

Food	Energy	Water	DataSc.
14	10	11	20

- **Details:** NSF Workshop to Identify Interdisciplinary Data Science Approaches and Challenges to Enhance Understanding of Interactions of Food Systems with Energy and Water Systems , *Computing Research News* (ISSN 1069-384X), Computing Research Asso., 27(10), Nov. 2015.

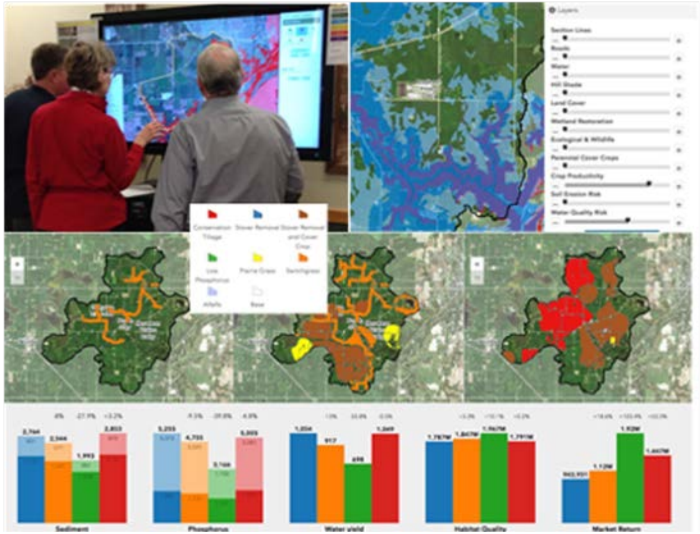
Collaborative Geo-design of a Watershed

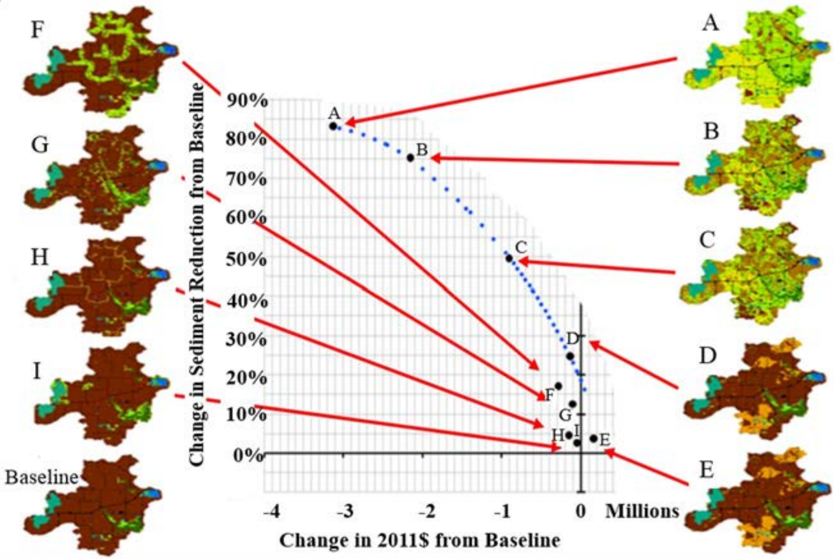


Scalable Algorithms: Ex. 7-mile Creek Watershed

Manual Geodesign

Multi-objective Optimization Algorithms



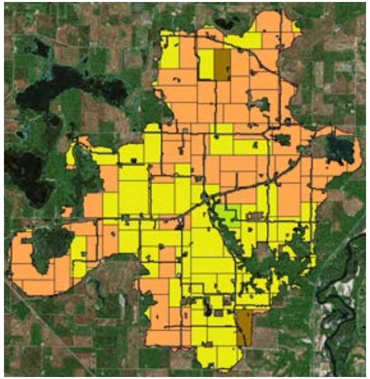


Details: Y. Xie, B. Runck, S. Shekhar, L. Kne, D. Mulla, N. Jordan, and P. Wringa, [Collaborative Geodesign and Spatial Optimization for Fragment-Free Land Allocation](), *ISPRS Int. J. Geo-Inf.* 2017, *6*(7), 226; https://doi.org/10.3390/ijgi6070226.

Computing Challenge: Fragmentation-Free Spatial Allocation

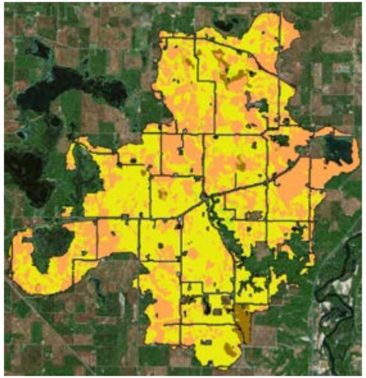
- **Inputs:** A grid partition, A set of choices
  - A profit and cost value for each (choice, grid cell)
- **Output:** A tile-partition of grid, Choice assignments on tiles
- **Objective:** maximize profit
- **Hard constraints:**
  - Total cost is smaller than budget
  - Each tile satisfies a minimum area & width

Ex. Agricultural land design



Challenge: APX-hard

SOTA (e.g., multiple-choice knapsack) limitations**:** fragmentation



[1] Y. Xie et al. Spatially-constrained Geo-design optimization for improving agricultural sustainability. AAAI-17 Workshop on AI and OR for social good. 2017.
[2] Y. Xie et al., FF-SA: Fragmentation-Free Spatial Allocation. In: Advances in Spatial and Temporal Databases, 2017.

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Curb Climate-Change with AI

AI Institute for Climate-Land Interactions, Mitigation, Adaptation, Trade-Offs, and Economy, NIFA 2023-03616, $20M, 6/23-5/28.

- Partners: U Minnesota (lead), Colorado St. U, Cornell U, Delaware St. U, NCSU, Purdue U, ISRIC
- URL: cse.umn.edu/aiclimate

DETAILS: U of M to lead new AI Institute focusing on climate-smart agriculture and forestry, UMN News Release, May 4, 2023 News and Events May 4, 2023

AI-CLIMATE

AI Institute for Climate-Land Interactions, Mitigation, Adaptation, Tradeoffs and Economy

- **Innovations:**
  - Better data (e.g., Finer-resolution soil moisture map)
  - Refined tools for climate-smart agriculture and forestry land management decisions
  - More accurate models of soil organic-matter and greenhouse gas emissions
  - Faster algorithms for multi-objective optimization and science-guided machine learning

- **Impacts:**
  - Strengthen AI for Science (e.g., honor physical laws)
  - Mitigation: Accelerate Carbon-sequestration in farms and forests
  - Adaptation: Drought resilience via healthier soil
  - Economy: Empower Carbon markets by better carbon-accounting
  - Expand and diversity AI-ready climate-smart agriculture and forestry workforce

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Conclusions and Key Messages

- Climate change
  - A key societal challenge of our generation
  - And a major opportunity for computing
- **Ask for computing community**
  - Researcher: Engage with climate topics
  - Educator: Include climate topics in courses and curricula
  - Sponsors: Nurture approaches to overcome challenges
- Rest of the presentation
  - Shared personal stories (primarily climate informatics)
    - Climate is not just an application of Computer Sc.
    - It provides rich opportunities to advance and transform Computer Sc.
  - Looking forward to learning about pervasive computing challenges and opportunities!

Climate Footprint of Computing

- **Source:** Jens Malmodin et al. ICT sector electricity consumption and greenhouse gas emissions - 2020 outcome, Telecommunications Policy, 2024, 102701, ISSN 0308-5961, https://doi.org/10.1016/j.telpol.2023.102701

- **Highlights (2020 Data)**
  - –ICT ~4% of global electricity consumption
  - –ICT 1.4% of global GHG emissions
  - –User devices: 57% of ICT GHG emissions
  - –Embodied device: 36% of ICT emissions

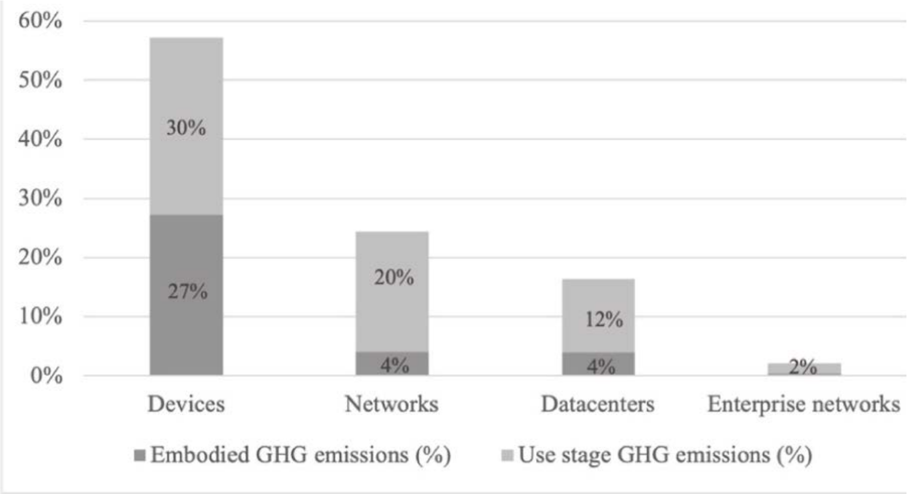
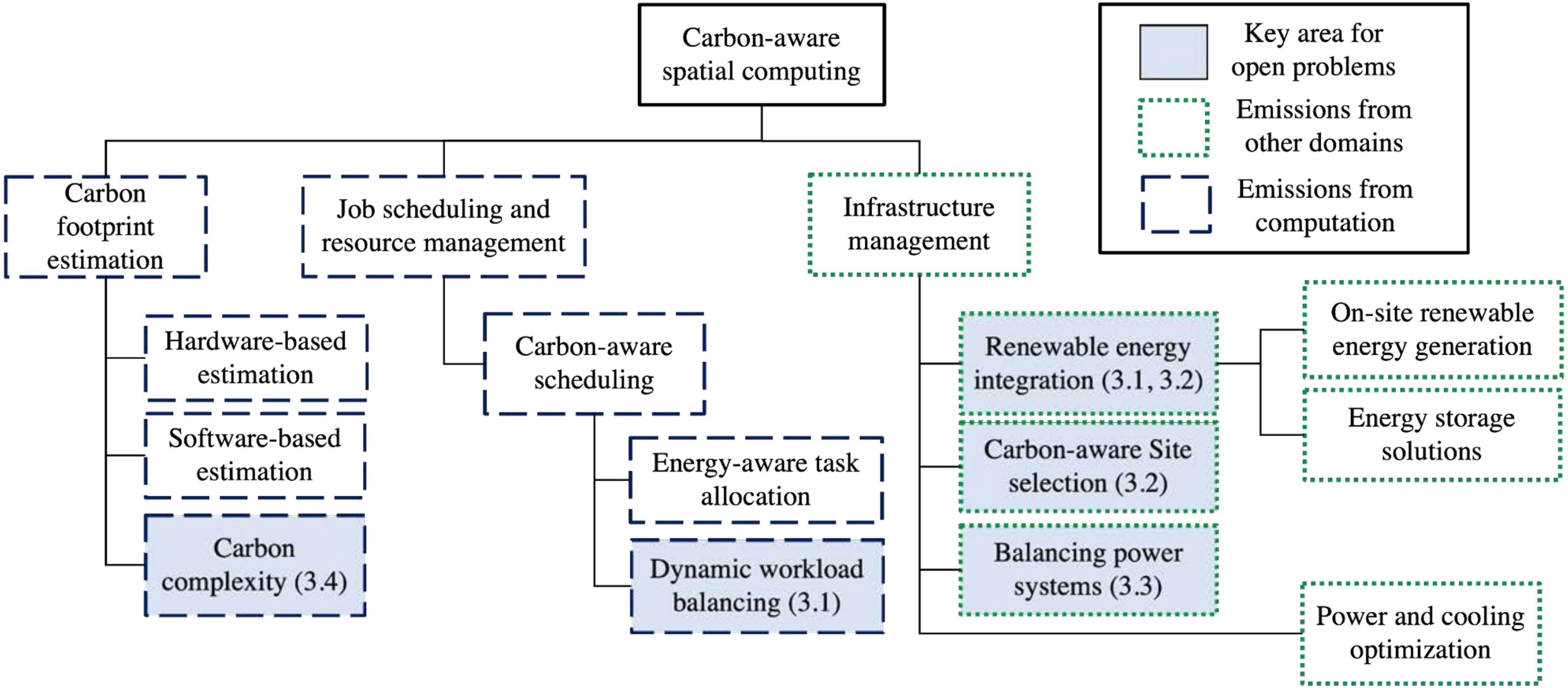


Fig. 3. Total ICT sector carbon footprint 2020.

(Spatial) Computing for Mitigation

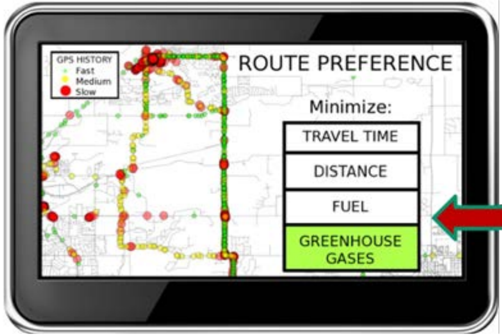


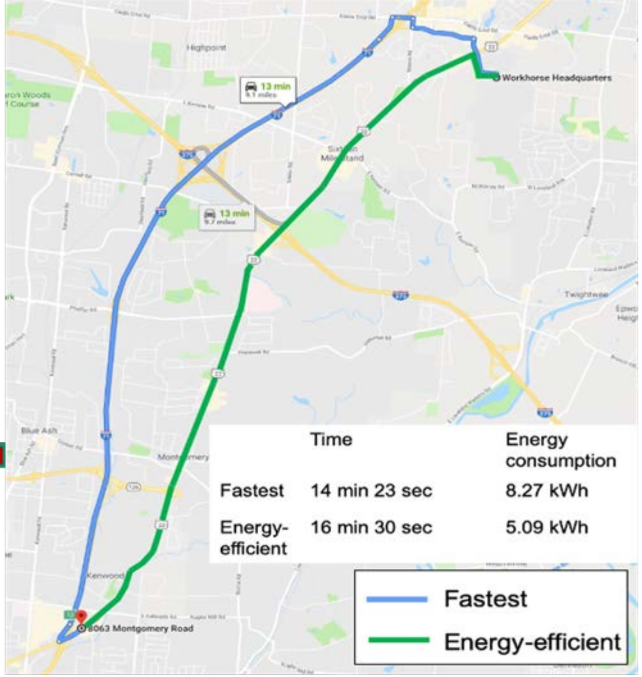
Detail: B. Jayaprakash et al., Towards Carbon-Aware Spatial Computing: Challenges and Opportunities, NSF I-GUIDE Forum, Columbia U, June 2023 10.5703/1288284317678. (youtube video presentation)

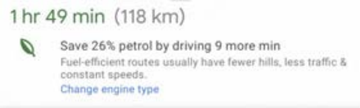
Reducing Emissions: Eco-routing

- **Goal:** Reduce emissions and energy needs
- **Big Data:** Trajectories (GPS + On Board Diagnostics)
- **Collaborators**: UPS, Workhorse, ARPA-E, NSF, …
- Oct. 2021: Google Maps supports Eco-Routing

GPS Tracks + On Board Diagnostics Data







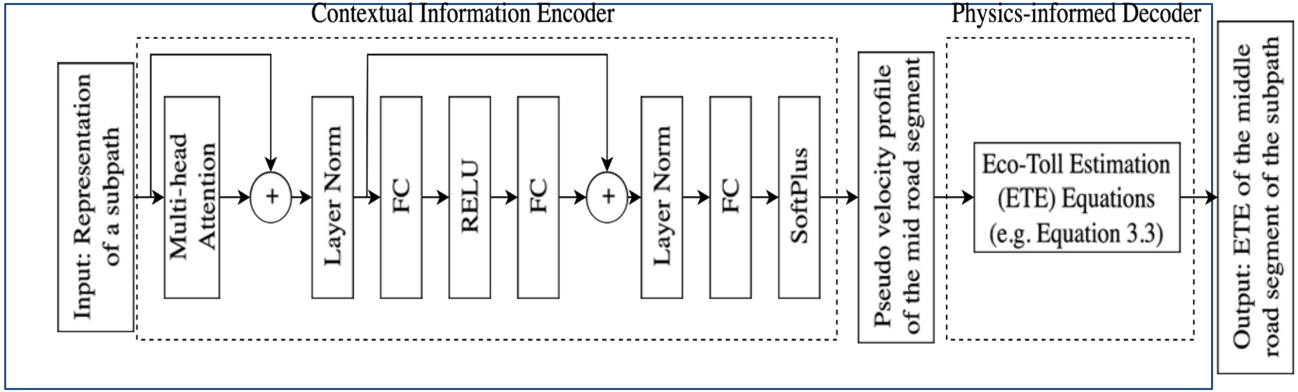
Google Ecorouting

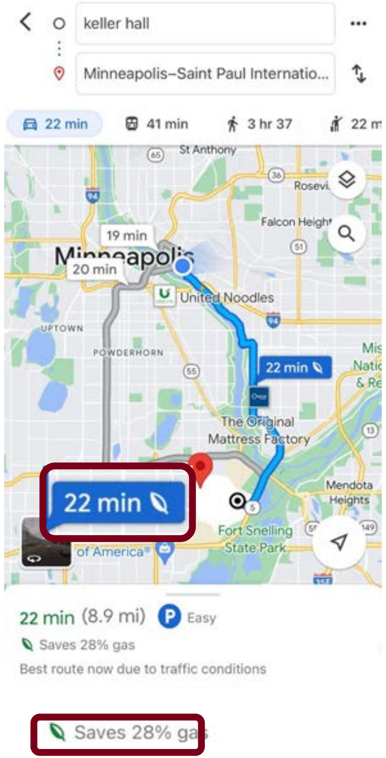
Details: *1. Yan Li, Mingzhou Yang, Matthew Eagon, Majid Farhadloo, Yiqun Xie, Shashi Shekhar, and William Northrop. "Eco-PiNN: A Physics-informed Neural Network for Eco-toll Estimation." submitted to the 2023 SIAM International Conference on Data Mining (SDM). (Under review)*
2. Y. Li, P. Kotwal, P. Wang, Y. Xie, S. Shekhar, and W. Northrop, Physics-guided Energy-efficient Path Selection Using On-board Diagnostics Data, ACM/IMS Transactions Data Science 1(3):1-28, Article 22, Oct. 2020. (Initial results appeared in Proc. ACM SIG-Spatial, 2018).

Eco-PiNN: A Physics-informed Neural Network for Eco-toll Estimation

Problem: Estimate road segment's cost for Eco-routing
Challenges: Data paucity, vehicle physics, motion context
Contributions: Eco-PiNN

- A physics-informed Neural Network
- Physics included in Decoder and Regularization





Details: Y. Li et al, "Eco-PiNN: A Physics-informed Neural Network for Eco-toll Estimation. SIAM Intl. Conf. on Data Mining 2023.

An example of Google Maps' eco-routing (From UMN to MSP Airport)