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Applications of Fuzzy Cognitive Mapping in climate change impact and adaptation research
-
Approaches, experiences, and methodological issues

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My background

Specialization: interface of climate change and urban research

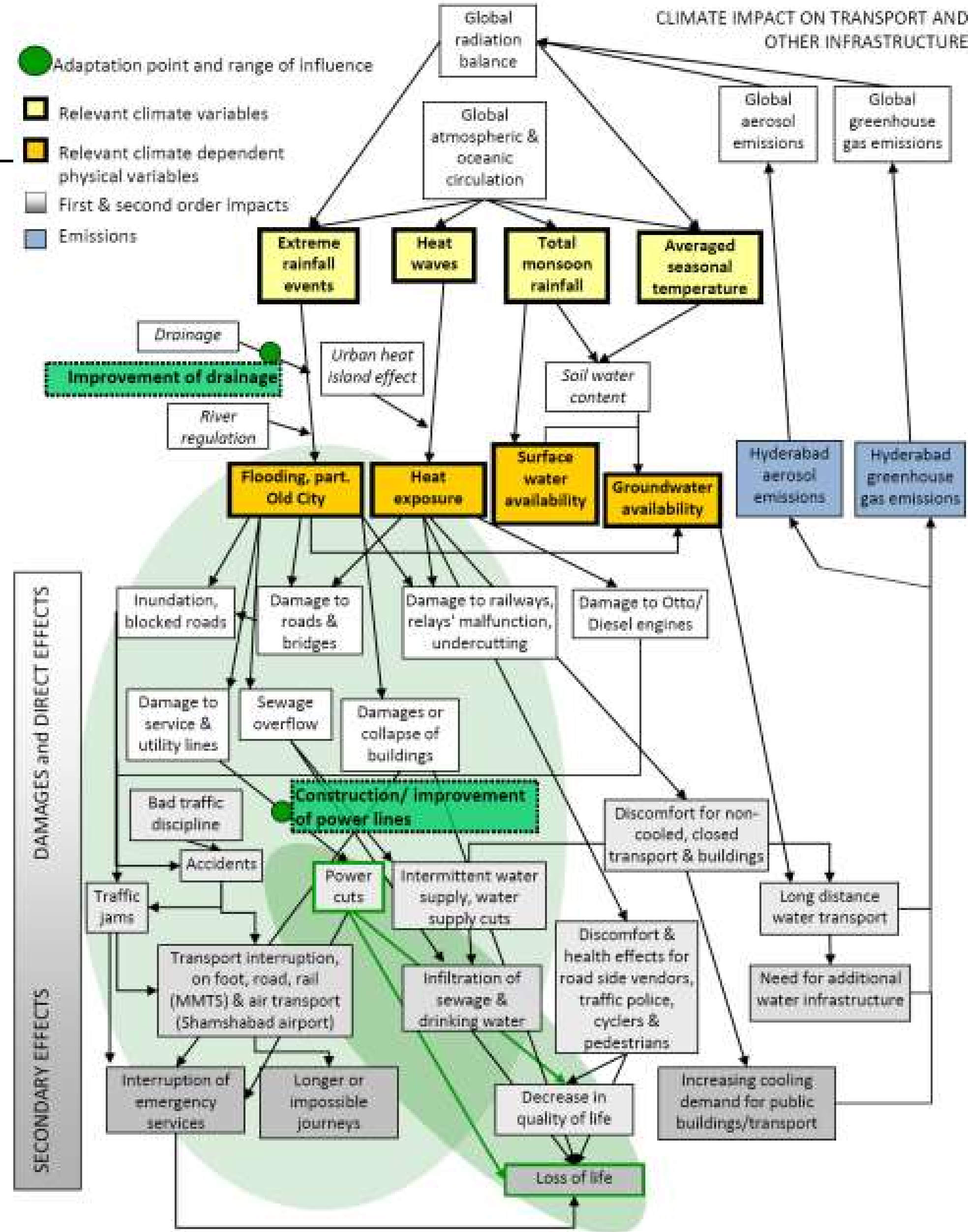
- Climate change impacts, social vulnerability, adaptation across socio-economic groups, climate change gaming, climate change migration, and climate change policy and practice
- … in large urban areas in Europe, India and the US
- … particularly concerned about equity and equality aspects
- Often combined with methods development for applications in climate change policy and planning

Selected Methods

- Qualitative Differential Equations; Fuzzy Cognitive Mapping, Statistics; Text analysis and coding, Interview techniques, Questionnaire surveys, Scenario techniques

Previous approaches/ FCM precursors

- Qualitative differential equations (QDEs) , Kuipers 1992
  - Similar to cause-effect-networks with increase/decrease/no influence interconnections
- Impact pathway approaches with „adaptation influence ranges“:
  - First-order, second-order, third-order impacts
- FCMs: Introduction by Wildenberg/ Bachhofer, who developed the FCMappers software (xls-based)



Outline

1. Case study 1: Assessing **differential impacts of climate change and adaptation** options in **Delhi**, India
2. Case study 2: Assessing **differential climate change impacts and socially sensible adaptation** options in **Hyderabad**, India
3. Case study 3: **Climate change impacts across New York City and Chicago**
4. Comparative study 1: **Generating FCM with different interview methods**
5. Other **aspects/ issues/ problems**

References

Reckien D, Wildenberg M, Deb K (2011): Understanding Climate Change Impacts and Adaptation Options in Indian Megacities. In Otto-Zimmermann K (Ed): Resilient Cities - Cities and Adaptation to Climate Change, Proceedings of the Global Forum 2010, Dordrecht: Springer, ISBN 978-94-007-0784-9, pp 15-34.

Reckien D, Wildenberg M, Bachhofer M (2013): Subjective realities of climate change: how mental maps of impacts deliver socially sensible adaptation options. Sustainability Science, 8 (2): 159-172. DOI: 10.1007/s11625-012-0179-z.

Reckien D (2014): Weather extremes and street life in India – Implications of Fuzzy Cognitive Mapping as a new tool for semi-quantitative impact assessment and ranking of adaptation measures. Global Environmental Change, 26: 1-13, http://dx.doi.org/10.1016/j.gloenvcha.2014.03.005.

Reckien D (2016): Comparison of stakeholder-generated FCMs across generation methods and metrics. IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), Vancouver/ Canada, forthcoming August 2016.

Reckien D (2016): Identifying most feasible adaptation options to heatwaves and heavy rain events in New York City: Fuzzy Cognitive Mapping as a versatile tool to investigate how to prepare for climate change. IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), Vancouver/ Canada, forthcoming August 2016.

1. Assessing differential impacts of climate change and adaptation options in Delhi, India

Methods:

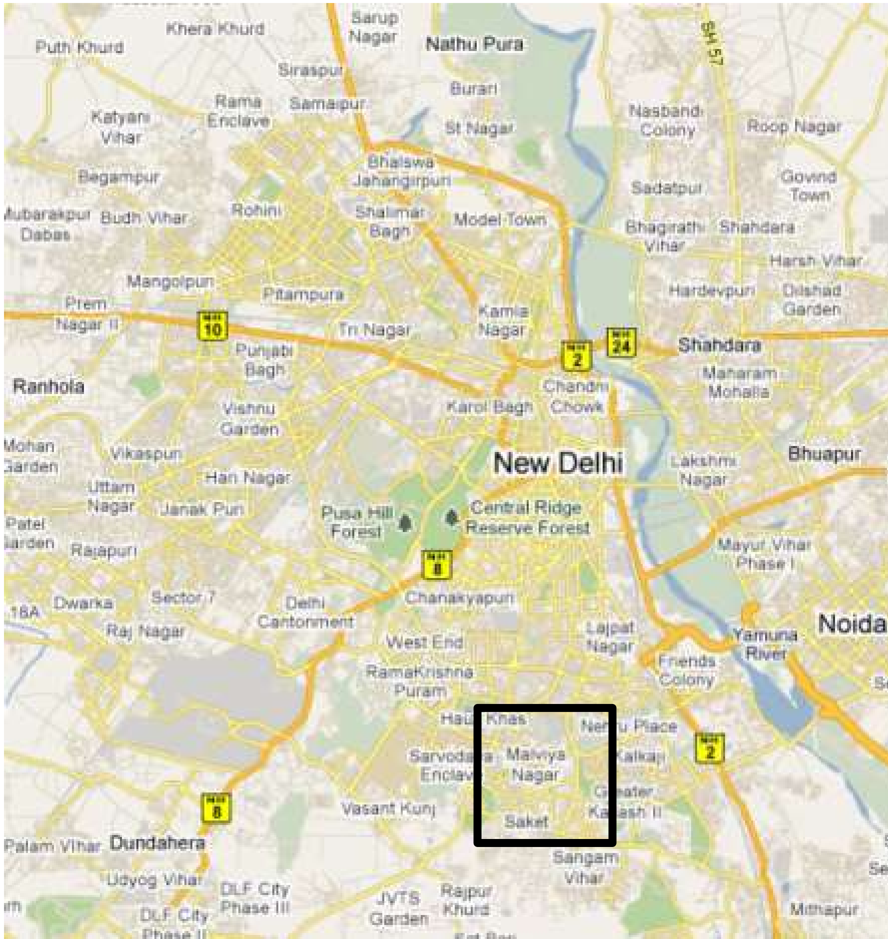
- Fuzzy Cognitive Mapping: Network statistics and scenarios

Data:

- Oral, single, face-to-face interviews to impacts of either 1) strong rain and 2) heat waves (N=131)
- 5 stakeholder groups,
  - Random selection of street scenes near the University
- Interviewers: Native speakers
- Time of year: February/ March (no heat, not a lot of rain)
- Time of day: not recorded

Objective:

- **Explorative**: impacts and effects of adaptation options



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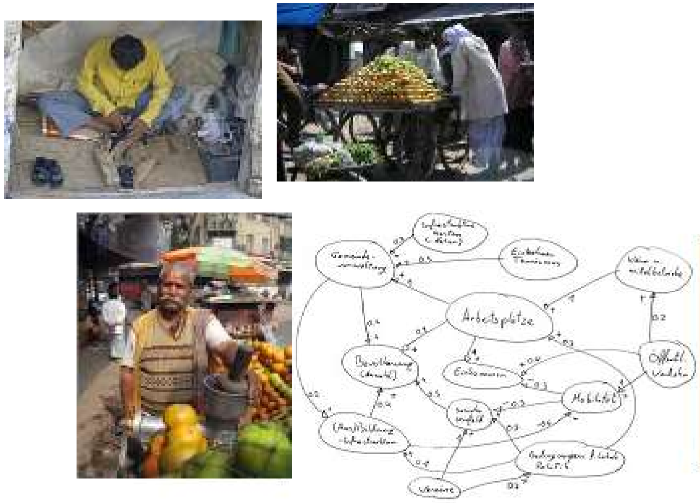
Data

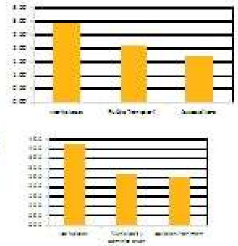
- **Planners (Pl)/ City managers**: NDMA, CWC, DDA, independent contractor
- **Wallahs/ Street Vendors/ Small entrepreneurs (SE)**: vegetable w., icecream w., tea stall w., guards, housekeepers, auto rickshaw drivers, …
- **Professionals**: Teachers, IT service, architect, civil servants, government officials, HR manager, bank employee
- **Researchers**: TERI, IMD
- **Students**: TERI Univ.

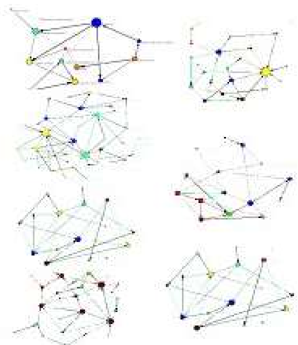
Frequency distribution				
DELHI		Strong rain	Heat wave	Total
	PLANNERS	7	4	**11**
	WALLAHS	26	23	**49**
	PROFESSIONALS	13	13	**26**
	RESEARCHERS	7	8	**15**
	STUDENTS	14	11	**25**
				131

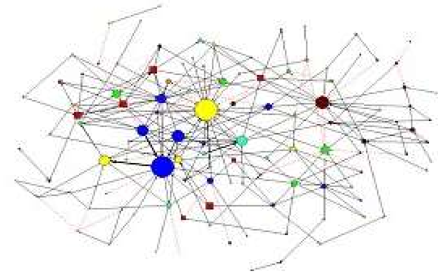
→ Different group size demands (form of) "normalization"



	A	B	C
A	0	0.2	0
B	0	0	0.5
C	0	0.8	0







1.) Participative Mapping

2.) Analyses & Visualization with FCMapper

3.) Aggregation of Maps
Simulation & Scenarios

- **“What happens under strong rain events/ heat waves & how does this affect you?”**
- Stakeholder names issues, indicates relations, directions, and weights
- Interviewer writes down

- Network statistics (receiver, transmitter, outdegree, indegree, centrality)

- Aggregation (.xls-based own, self-written tool)
- Scenario analysis with www.FCMappers.net (developed by Bachhofer and Wildenberg, Uni Klagenfurt):
    - Kosko’s inference and sigmoid squashing function

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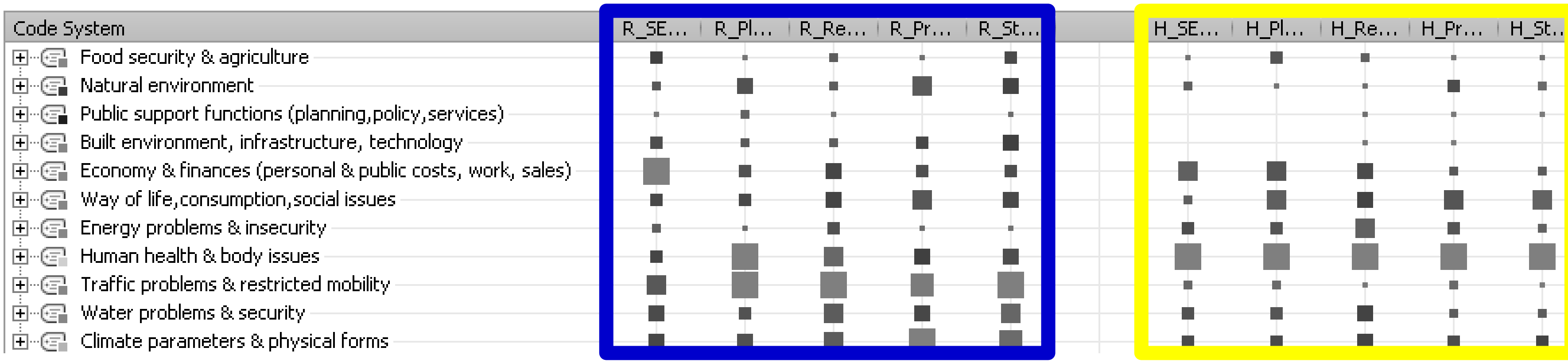
What are most numerous impacts per sector?

Aggregated maps: Concepts grouped to sectors (Column sum)



→Impacts of strong rain differs ALSO across social groups (as in Hyde.)

→Heat waves affect people in similar ways

Strong rain	Wallahs/ Small entrepreneurs	City managers (Planners & Researchers)
Causes = high out-degree	Rain	Rain
	Local flooding	Local flooding
	Contamination of/dirty water	Traffic jams
	Electricity shortcuts	Bad drainage
	Bad drainage	Water borne diseases
Consequence = high in-degree	Working problems/affected	Time to reach destination
	Income	Irritation=routine disruption
	Diseases, health impacts	Work productivity
	Discomfort	Diseases, health impacts
	Affected mobility	Local flooding

How to compare data/ normalize it for different *n*? ….Aggregated INTENSITY maps (w_{ij} > 0.8)

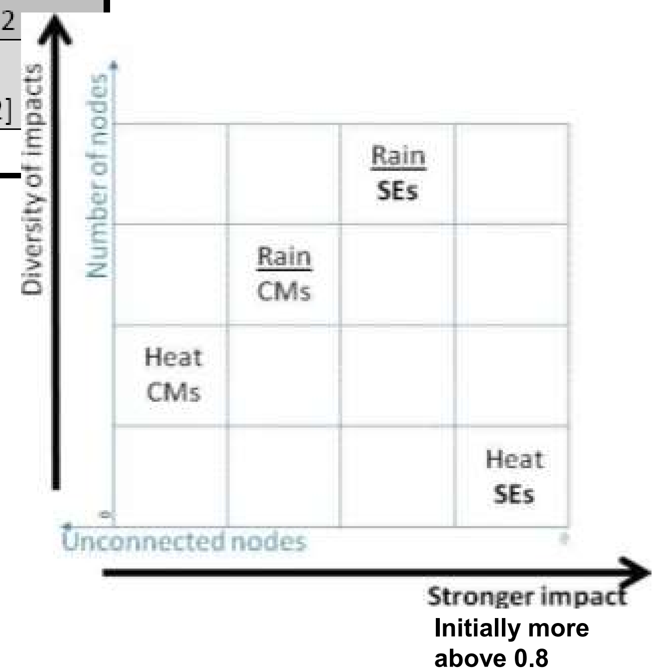
Network statistics of "Intensity Maps" I (0.8)			
Socio-economic group	Indices	Weather event	
		Strong rain event	**Heat wave**
Small local entrepreneurs & service providers	Density of map	0.008129	0.019376
	Total number of nodes,	83	46
	Unconnected nodes, nr [%]	36 [43.4]	13 [28.3]
	Arcs	56	41
City managers (planners, researchers)	Density of map	0.007340	0.005792
	Total number of nodes,	71	67
	Unconnected nodes, nr [%]	35 [49.3]	39 [58.2]
	Arcs	37	26

… one form of normalization, or..

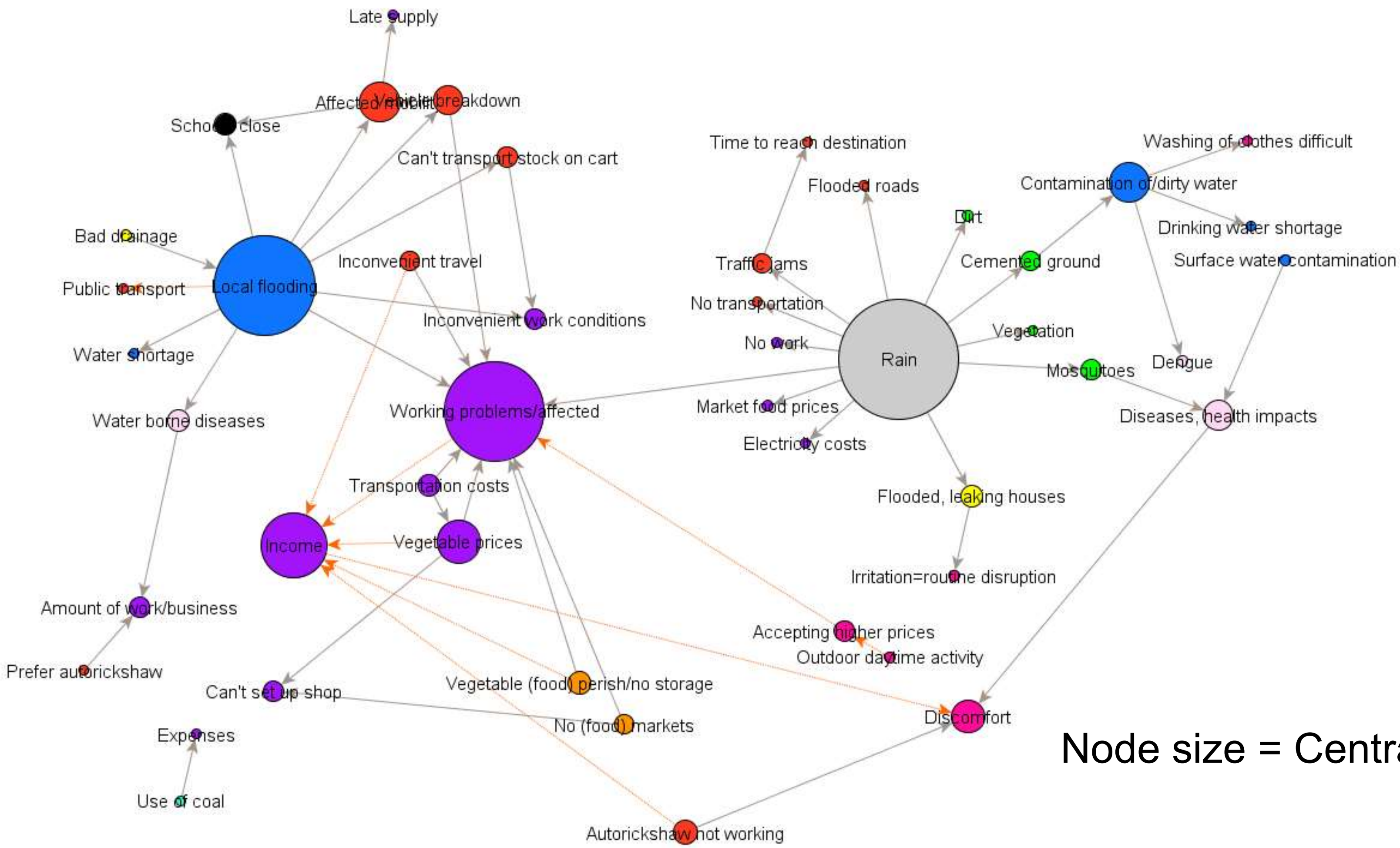
Increasing certainty: 2+ and 3+ networks (see further down)

→ Heat has strong and equal impacts for SEs; and small and rel. equal impacts for CMs

→ Rain has medium strong and diverse impacts for both groups

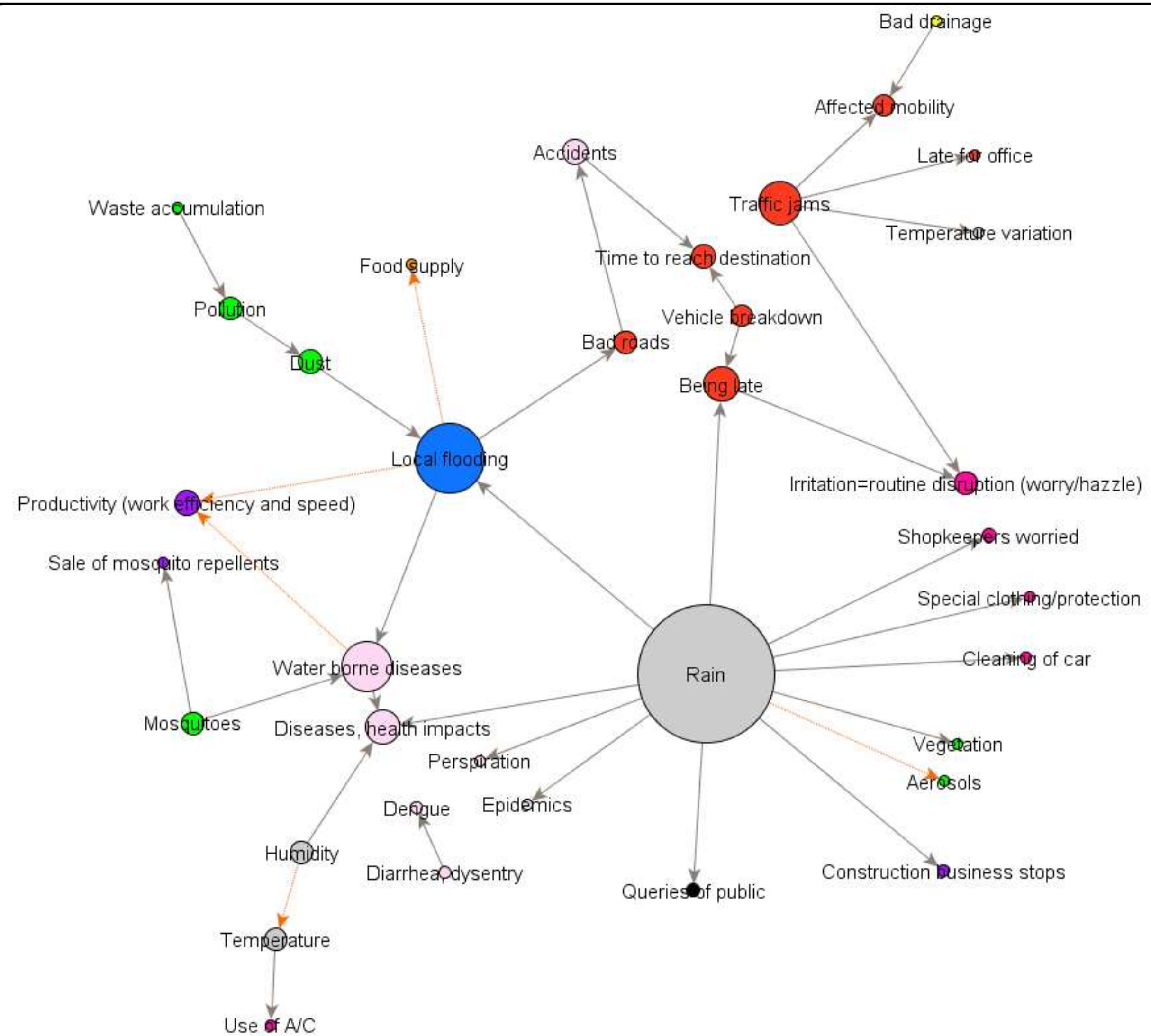


Results: Small Entrepreneurs during strong rain



Node size = Centrality

Results: City Managers during strong rain



Node size = Centrality

Results: Adaptation scenarios

0) **Base** run

1) **CC** run (more T & Tvar increase; more strong rain)

2) **CC & Adaptation** run (CC + certain adaptation options)

(i) Improving the water and sewage infrastructure (all related concepts fixed throughout iterations to 1)

(ii) Self-help solutions for street vendors (all 1)

(iii) Increasing the ease of mobility and increasing public transport (all 1)

(iv) Investment in the electricity infrastructure (all 1)

(v) As in (iv) but with “illegal access”, i.e. electricity tapping (all 1)

(vi) Investment in the health infrastructure (all 1)

Case 1: More CC impacts → Where to place adaptation?

Case 2: More CC impacts + Adaptation → How CC affects adaptation efforts?

Results: Adaptation scenarios

- CASE 1 – DELHI: … effects on “Quality of life”

Adaptation strategies: Investment in …		1) Water and sewage infra-structure	2) Ease of mobility	3) Health infra-structure	4) Electricity infra-structure		5) Self-help solutions	Total structural measures
					Current costs	No costs		
Strong rain	Street vendors	**2.87**	**5.52**	1.07	1.56	*2.11*	*2.28*	11.01
	City managers	**1.58**	**2.66**	1.03	0.92	*n.a.*	*n.a.*	6.19
Heat waves	Street vendors	**3.70**	1.11	**2.33**	1.87	*2.49*	*2.60*	7.9
	City managers	**3.47**	n.a.	0.67	**3.16**	*3.61*	*n.a.*	7.3
		11.62	**9.29**					

- CASE 2 – DELHI

RAIN	Adaptation	Adaptation & CC
	8,840217	-6,495086

→ CC renders adaptation useless, reduces perceived situation relative to today

→ CC increases burden substantially

2. Assessing differential climate change impacts and socially sensible adaptation options in Hyderabad, India

Methods:

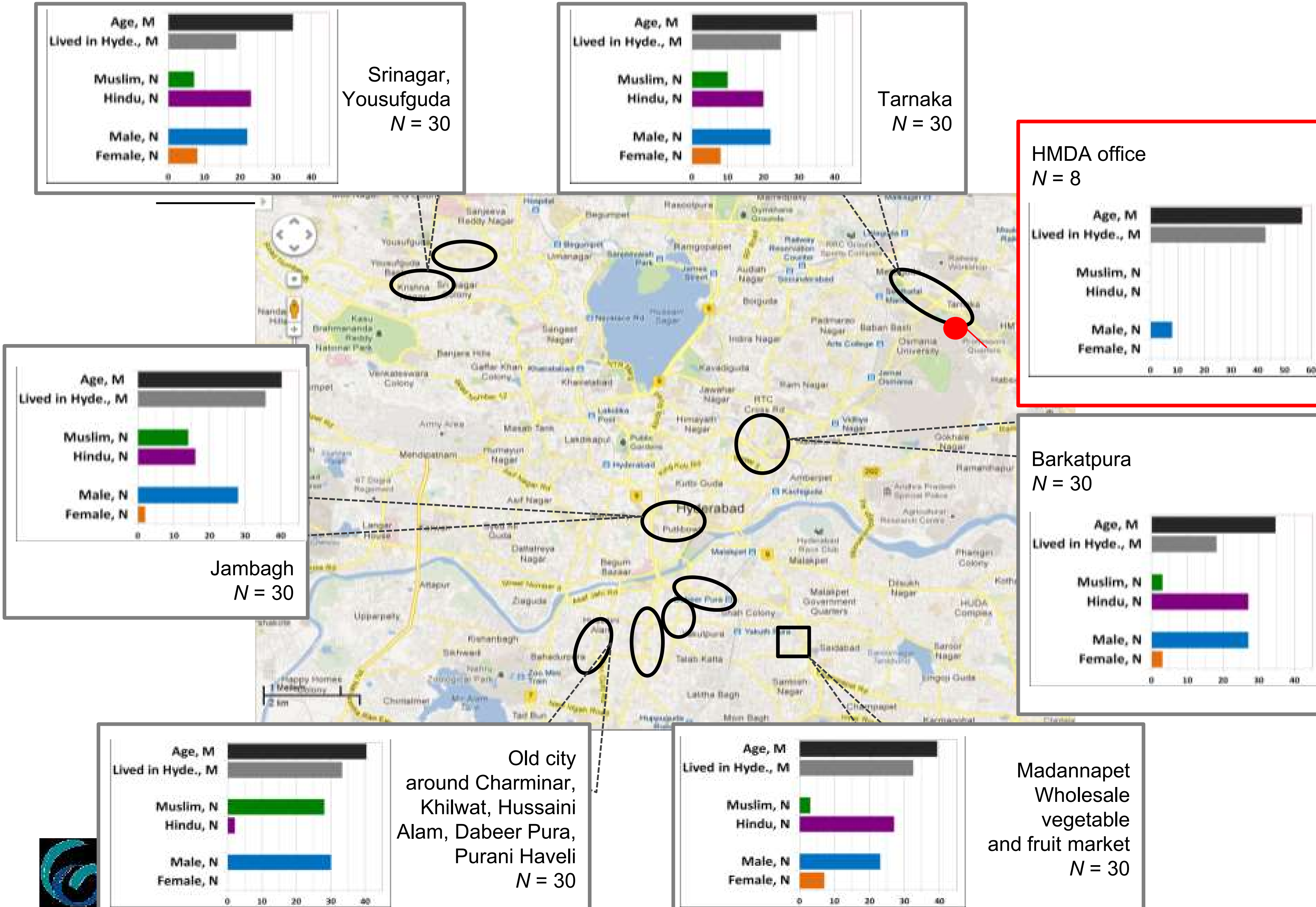
- Fuzzy Cognitive Mapping: Network statistics and scenarios

Data:

- Oral, single, face-to-face interviews to impacts of 1) strong rain and 2) heat waves (N=376); Order effects were accounted for
- Interviewees: mostly small entrepreneurs on Hyderabad streets (N=188)
- 6 stakeholder groups, unified by “flooding hotspot” (via flood modelling & media analysis) and socio-economic/ income level, divided by income and affectedness (entrepreneurs on streets) versus influence (planners)
- Two interviewers: One native speaker (Muslim; male), one (international/ white) English speaking note-taker (female)
- Time of year: February (no heat, not a lot of rain); we selected days without rain and without exceptional heat
- Time of day: during ‘normal’ business hours (from 10-4pm)

Objective: **Representative study to differential impacts between street sellers (impacted) and planners (could influence it)**


City area: Srinagar, Yousufguda
N = 30
City area Tarnaka
N = 30
HMDA planning office
N = 8
City area: Barkatpura
N = 30
City area: Jambagh
N = 30
City area: Old city around Charminar, Khilwat, Hussaini Alam, Dabeer Pura, Purani Haveli
N = 30
City area: Madannapet Wholesale vegetable and fruit market
N = 30
Hyderabad


Srinagar, Yousufguda
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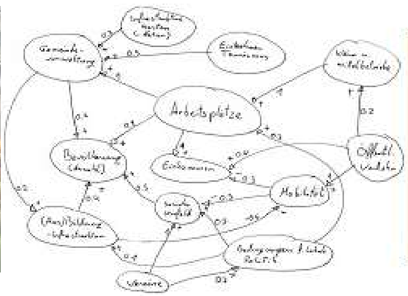
N = 30
Jambagh
N = 30
Old city around Charminar, Khilwat, Hussaini Alam, Dabeer Pura, Purani Haveli
N = 30
Madannapet Wholesale vegetable and fruit market
N = 30
Age, M
Lived in Hyde., M
Muslim, N
Hindu, N
Male, N
Female, N
0 10 20 30 40
Hyderabad

Same approach & process



1.) Participative Mapping

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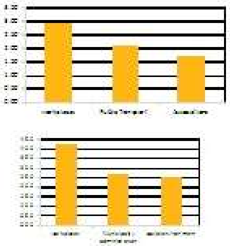

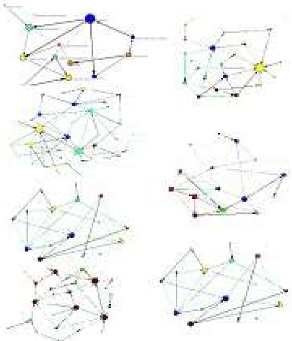

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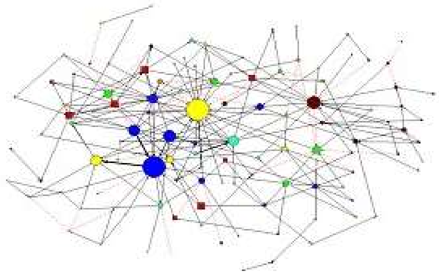

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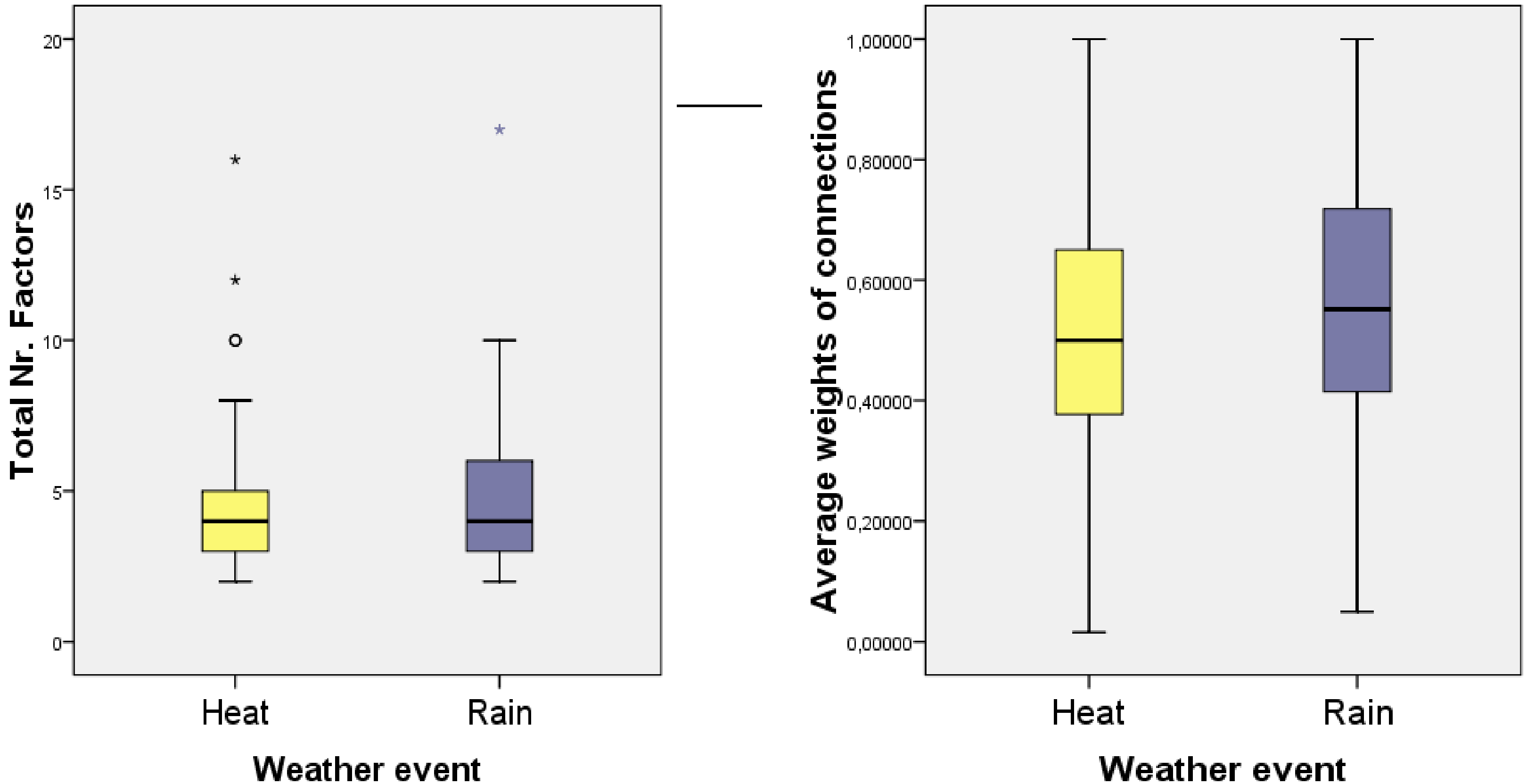
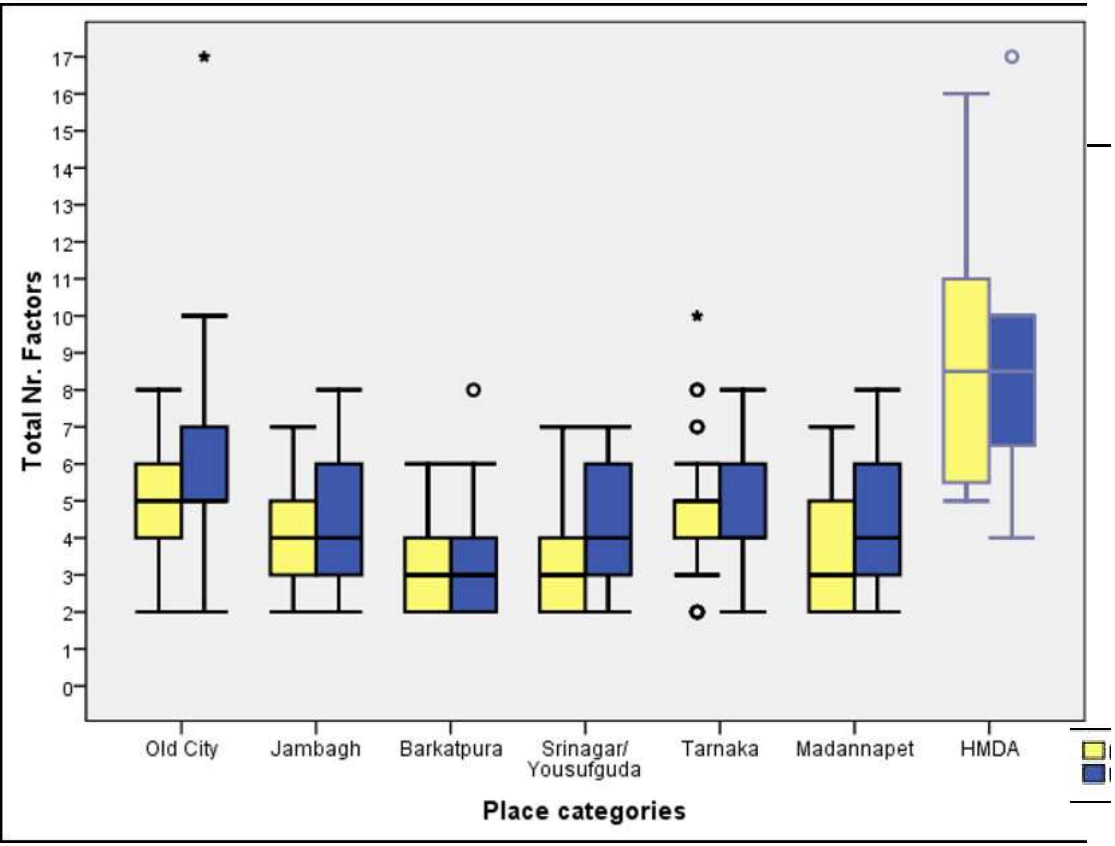
Does the impacts of rain and heat differ?



Yes. Strong rain causes more factors (M=4.72, SE=.165) than heat waves (M=4.19, SE=.150), t(182)=-3.724, p<.001, r=.27) and has stronger impact relations (M=.56, SE=.02) than heat (M=.52, SE=.01), t(182)=-2.583, p<.05, r=.19).

Does impacts differ across locality?



Single networks	Interviews	Multitude of impacts				Severity of impacts	
Location * Weather event		Number of factors in networks				Average weights on arcs	
HEAT	*N*	*N*	$\bar{x}$	*Min - Max*	*SD*	$\bar{x}$	*SD*
Barkatpura	30	101	3.48	2-6	1.35	0.50	0.16
Jambagh	30	116	3.87	2-7	1.28	0.56	0.19
Old City	30	141	4.70	2-8	1.64	0.52	0.20
Srinagar	30	93	3.32	2-7	1.42	0.57	0.24
Tarnaka	30	136	4.69	2-10	1.93	0.55	0.20
Madannapet	30	113	3.76	2-7	1.68	0.45	0.21
HMDA	8	71	8.88	5-16	3.87	0.39	0.10
"Expert Project Partners"	5	54	10.80	4-17	4.97	0.52	0.22
TOTAL	193	825	5.44		2.27	0.51	0.19
RAIN	*N*	*N*	$\bar{x}$	*Min - Max*	*SD*	$\bar{x}$	*SD*
Barkatpura	30	101	3.37	2-8	1.45	0.64	0.22
Jambagh	30	132	4.40	2-8	2.52	0.57	0.21
Old City	30	175	5.87	2-17	2.70	0.58	0.19
Srinagar	30	126	4.20	2-7	1.47	0.58	0.21
Tarnaka	30	146	4.87	2-8	1.76	0.57	0.18
Madannapet	30	135	4.50	2-8	1.61	0.45	0.19
HMDA	8	71	8.88	4-17	3.87	0.48	0.19
"Expert Project Partners"	5	50	10.00	7-16	3.94	0.57	0.23
TOTAL	193	936	5.76		2.42	0.56	0.20

- YES. ANOVA reveals locations to be significantly different (F(5,349)=9.16, p<.001)(all locations).
- Differences remain when testing for heat and rain independently, heat: (F(5,169)=4.18, p<.01); rain: (5,174)=6.16, p<.001).

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Rain is a significant larger burden than heat on average & for low-income people.

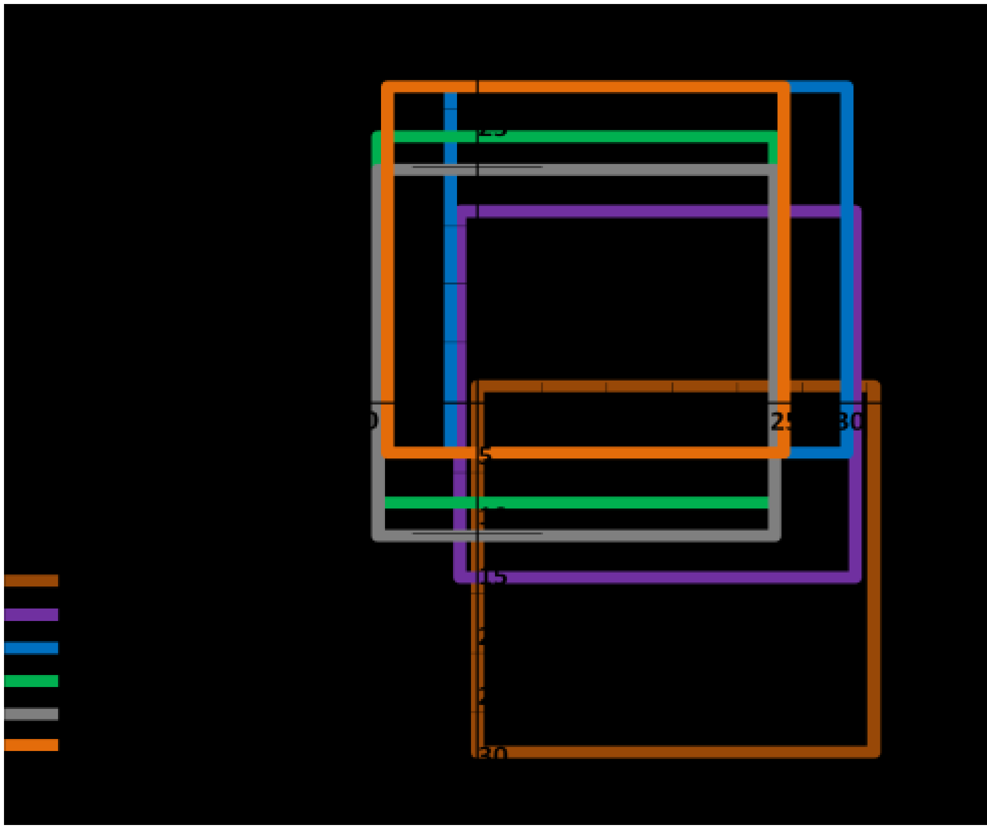
Does religion, age, gender matter?

- Religion is a significant covariate ($F(1,352) = 20.44$, $p<.001$, $r=.23$) of weather events ($F(1,352 = 9.25$, $p<.01$, $r = 0.16$) with regards to the number of impacts mentioned. Muslims report higher number of concepts.

- Age is a significant covariate of weather events with regard to the weights. Older people state relations to be **<u>less</u> strong** ($F(1,360=5.51$, $p<.05$, $r =.12$).

- Gender: small but insignificant differences (too small *N*)

Is locality important?



Most Muslims live in the Old City, which is run down and of poor infrastructure.

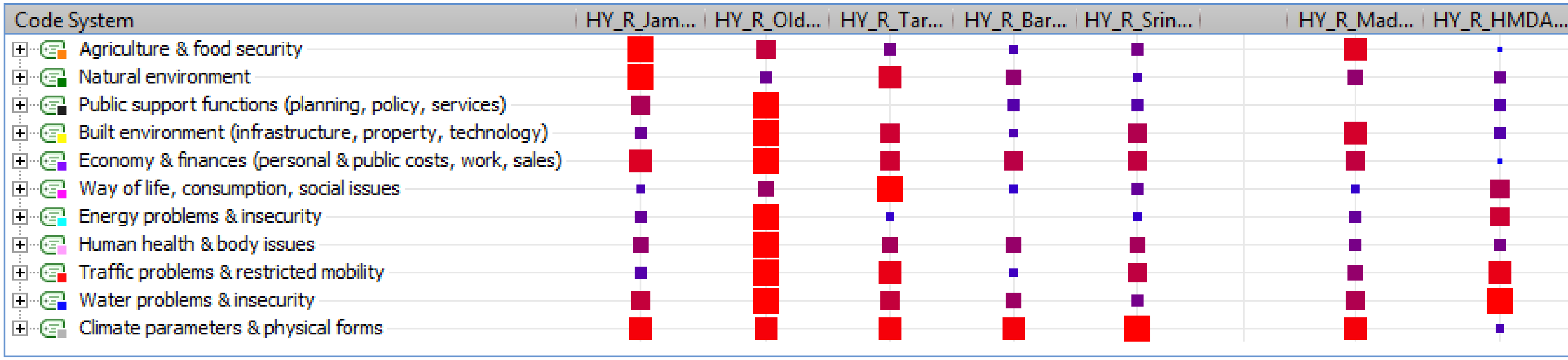
Excluding data of the Old city, religion remains as a significant covariate ($F(1,292) = 6.10$, $p < 0.05$, $r = 0.14$) of weather event ($F(1,292) = 5.63$, $p < 0.05$, $r = 0.14$).

However, testing a more equally distributed sample (i.e. Jambagh) reveals that differences cannot be attributed to religion per se.

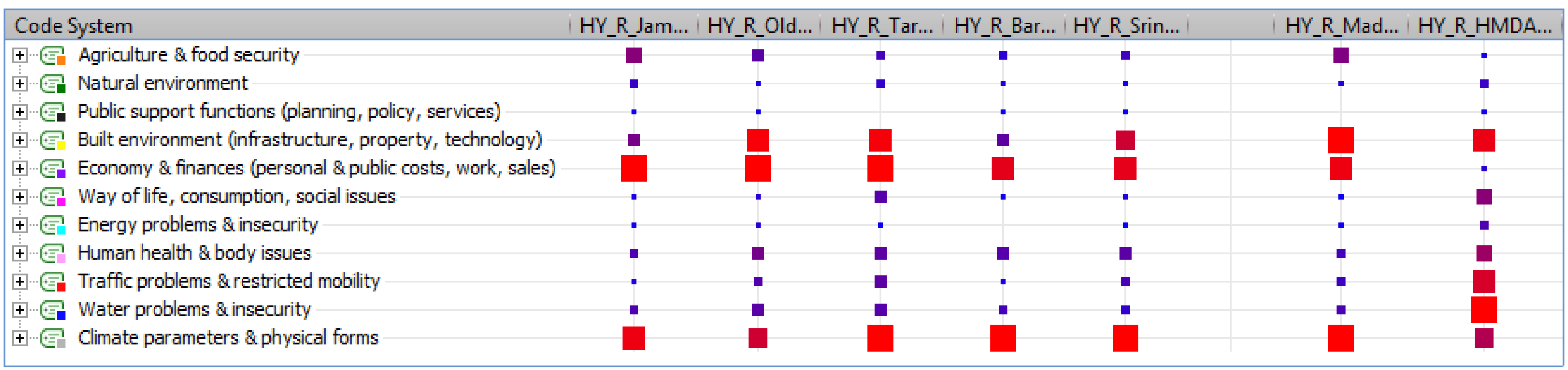
→Religion acts as a proxy for location.
→Muslims live in places more affected or they are less adapted to it.

Is locality important?

Row sum: Example Rain

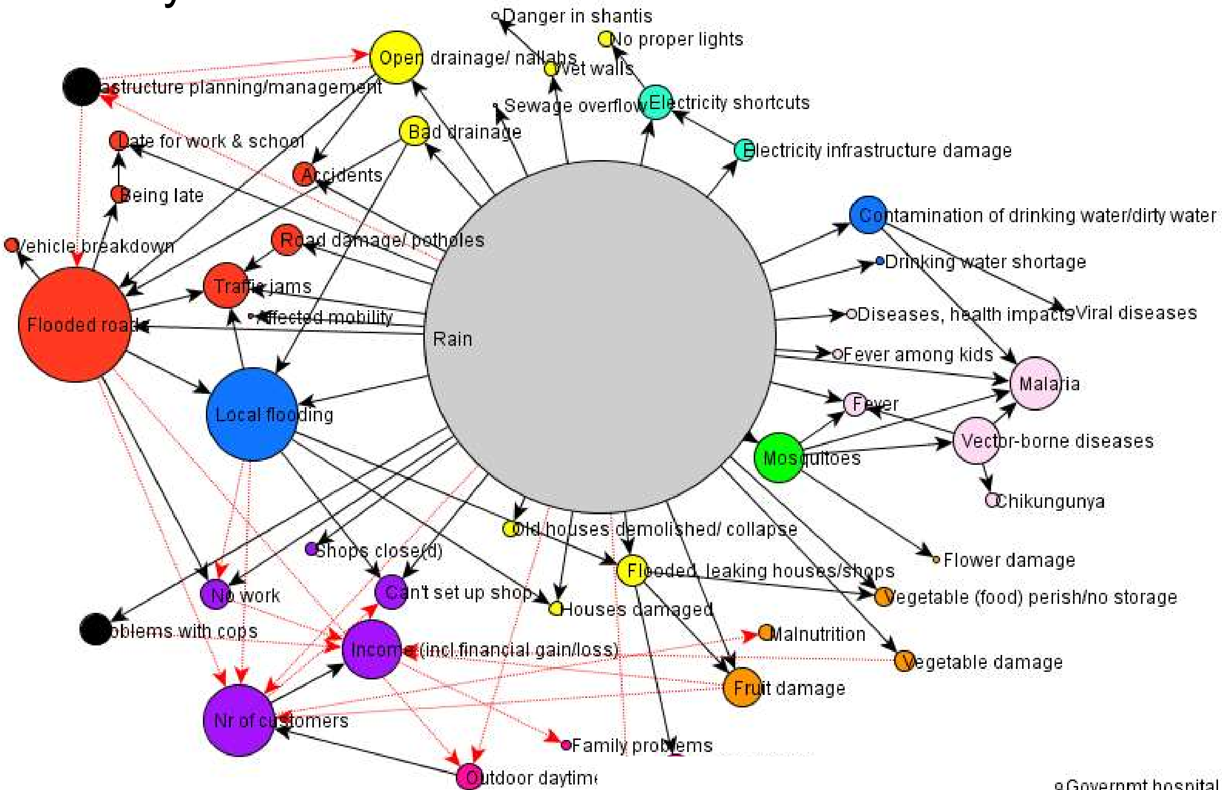


Column sum: Example Rain

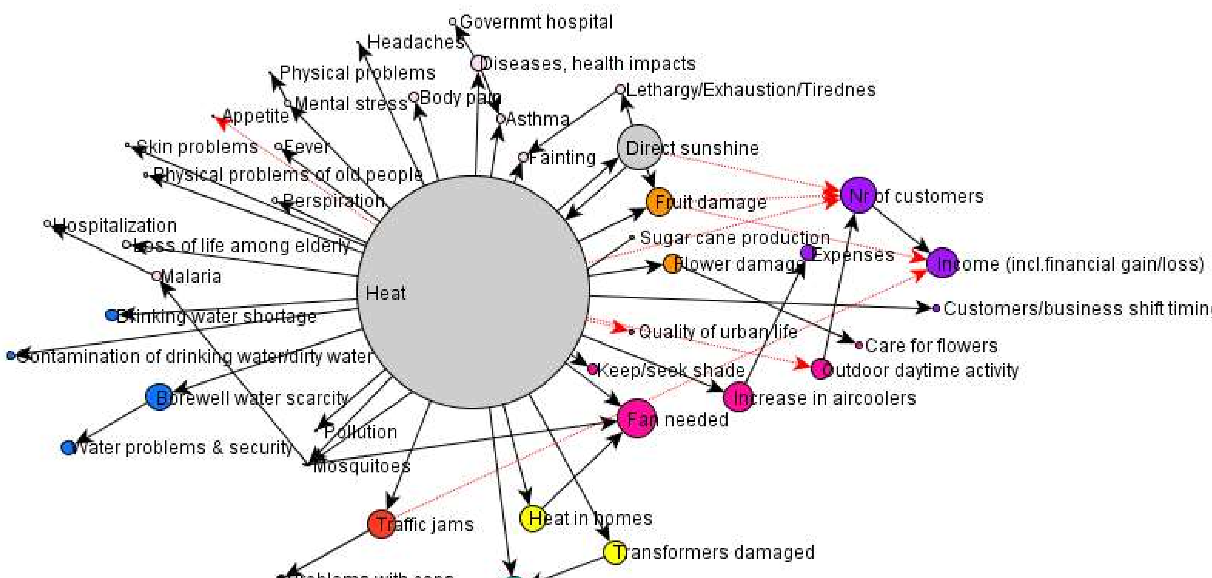


→ Sectors Economy/ Finances and Built environment see most impacts

Old City: RAIN



HEAT



What are best adaptation options?

Two scenarios tested:

0) **Base** run/ Current/ Steady state:

- Initial state vector set to 1
- Kosko's inference rule; sigmoid squashing function

1) Increasing extreme weather events vs. current state:

- T & Tvar = 1;
- Strong rain = 1 throughout all iterations

2) Comparison of adaptation options with and w/o CC

- Traffic management; water management; health management; electricity management; self-help ……………>>>>

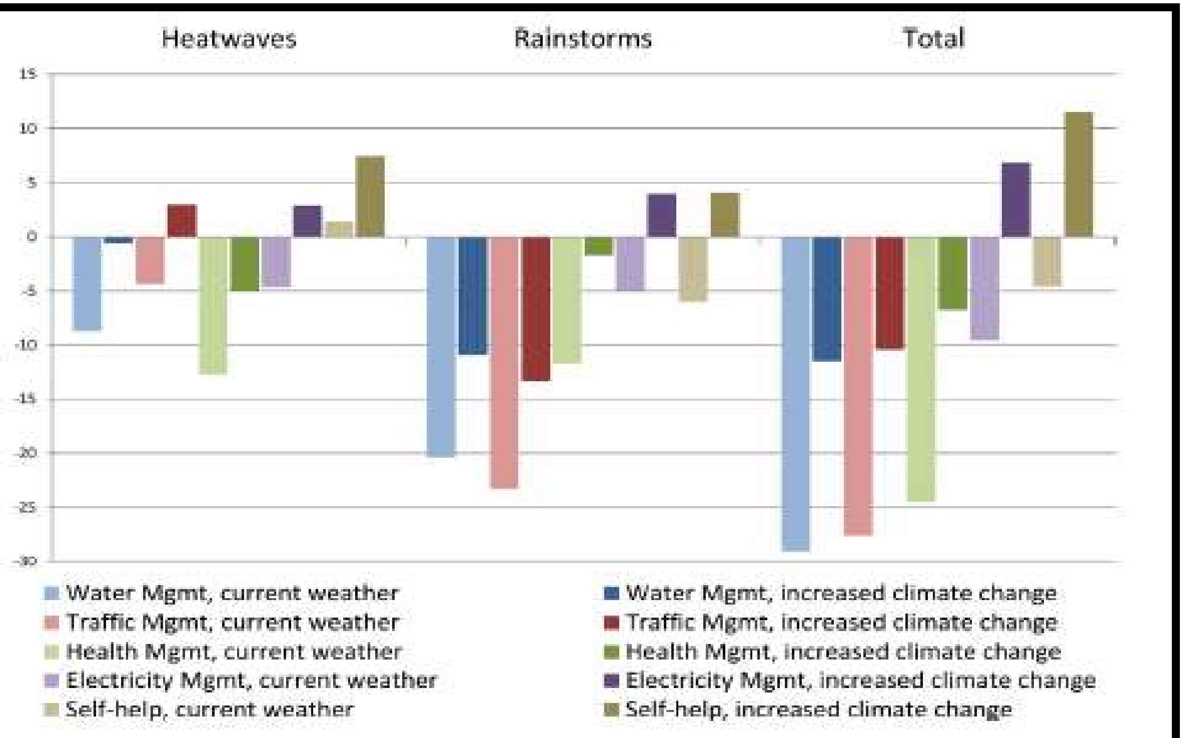
Water management		Traffic management		Health management		Electricity management		Self help	
Bad drainage	0	Affected mobility	0	Medical expenses	0	Electricity costs	0.1	Flooded, leaking houses/ shops	0
Contamination of drinking water/ dirty water	0	Bad roads	0	Water borne diseases	0	Electricity infrastructure damage	0	Houses damaged	0
Drinking water shortage	0	Buses late	0	Chikungunya	0.2	Electricity shortcuts	0	Buy drinking water	1
Local flooding	0	Flooded roads	0	Cholera in slums	0.2	Precautionary power shutdown	0	Care for flowers	1
Nallahs [open drain]	0	Road damage/ potholes	0	Dengue	0.2	Transformers damaged	0	Carry drinking water	1
Sewage overflow	0	Stranded vehicles	0	Diarrhoea, dysentery	0.2	Efficiency of cooling appliances	1	Fortify roofs	1
Water problems	0	Traffic jams	0	Diseases among kids	0.2	Hydro energy production	1	Go to village	1
Water shortage	0	Accidents	0.2	Diseases, health impacts	0.2			Increase in air coolers	1
Drinking water tankers	1	Auto-rickshaw not working	0.2	Doctors' attendance	0.2			Keep shade for customers	1
Groundwater recharge/ table	1	Engine failure	0.2	Epidemics	0.2			Keep/seek shade	1
Water management	1	Speed	1	Fever	0.2			Leave Andhra Pradesh	1
Water saving	1	Vehicle breakdown	0.2	Fever among kids	0.2			Manual drainage	1
		Infrastructure planning/ management	1	Gastroenteritis in slums	0.2			Number of bore wells	1
		Mobility	1	Gov. hospital attendance	0.2			Sleep on roof	1
		Traffic discipline	1	Hospitalization	0.2			Special clothing/ protection	1
		Traffic management	1	Infectious diseases	0.2			Take private loans	1
				Malaria	0.2			Private power generation	1
				Nausea/ Vomiting	0.2			Use of A/C	1
				Shivering	0.2				
				Smallpox in slums	0.2				
				Vector-borne diseases	0.2				
				Viral diseases	0.2				
				Health	1				

What are best adaptation options?

Scenario output on: Quality of life

1) Increasing extreme weather events vs. current state:

Quality of life	Barkat-pura	Jam-bagh	Old City	Srina-gar	Tar-naka	Madan-napet	HMDA	Expert Partners
HEAT WAVE + CC	-1.61	-1.42	-1.06	-1.33	-1.21	-1.34	-1.08	-0.61
STRONG RAIN + CC	-1.78	-1.68	-2.68	-1.40	-1.78	-1.22	-0.64	-0.20



2) Comparison of adaptation options with and w/o CC

→ Investment in **water and sewage infrastructure** most important, despite current impact experience

3. Climate change impacts in New York City & Chicago

Methods:

- Fuzzy Cognitive Mapping: Network statistics and scenarios

Data:

- **Online** interviews to impacts of 1) heavy rainstorm and 2) heat waves
- Qualtrics Survey Software
- Sample: Random selected via MTURK community
- Place: wherever, but (probably) mostly at home
- Date: 02.02.-13.03.2013
- Time: any time during the day

Objective:

- Try to 'ease' gathering of FCM interviews + comparison across conduction methods (also related to Carvalho, 2013: what are people actually giving you? Probability, Certainty …????)

Data

	NYC	Chicago
Sample	**N = 168**	**N = 176**
Females	92	66
Males	76	110
Number of people in the household	M = 2.49 +/- 0.12	M = 3.02 +/- 0.14
Residence in NYC	M = 13.87 +/- 0.92	M=15.65 +/- 0.91
Age	29.10 +/- 0.60	27.92 +/- 0.62

Aim: 105 participants = 35 responses from NYC and Chicago each

- 3 surveys, differing in the way the connections and weights were elicited:
  - **0.1-1 Strength** (asking for the “strength” of relation when assigning weights, ranging from 0.1 to 1),
  - **1-100 Strength** (asking for the “strength” of relation when assigning weights, ranging from 1 to 100), and
  - **1-100%** (asking for the “percentage” of occurrence as a measure to assign the weights, ranging from 1 to 100).
- Qualtrics Survey software; MTurk participant panel.

Do weights differ across weighting methods?

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16
		Maps	# of Nodes/ map				# Edges	# of Edges/ map			Weights/ map	# of Nodes/ map		Density		
		N	N	$\bar{x}$	Range	SD	N	$\bar{x}$	Range	SD	$\bar{x}$	Range	SD	$\bar{x}$	Range	SD
NY, line by line	01strength	44	229	5.20	2-9	1.91	407	9.25	1-37	7.23	.72	.27-1	.18	.39	.17-.6	.11
	0100strength	44	290	5.00	2-9	1.74	493	8.50	1-32	6.01	.62	.25-1	.18	.40	.17-.7	.12
	0100percent	44	311	4.71	2-9	2.25	527	8.11	1-38	7.80	.60	.10-1	.22	.44	.10-1	.19
	Sum	168	830	4.94	2-9	2.00	1427	8.54	1-38	7.05	.64	.10-1	.20	.41	.10-1	.15
CH, line by line	01strength	62	314	5.06	2-9	2,38	656	10.93	1-61	12.53	.80	.33-1	.18	.44	.14-1	.19
	0100strength	62	325	5.24	2-9	1.78	668	10.77	1-40	7.92	.70	.29-1	.18	.45	.18-.8	.15
	0100percent	52	227	4.37	2-9	1.76	365	7.02	1-27	5.79	.61	.15-1	.19	.46	.17-1	.18
	Sum	176	866	4.92	2-9	2.03	1689	9.71	1-61	9.41	.71	.15-1	.20	.45	.14-1	.17

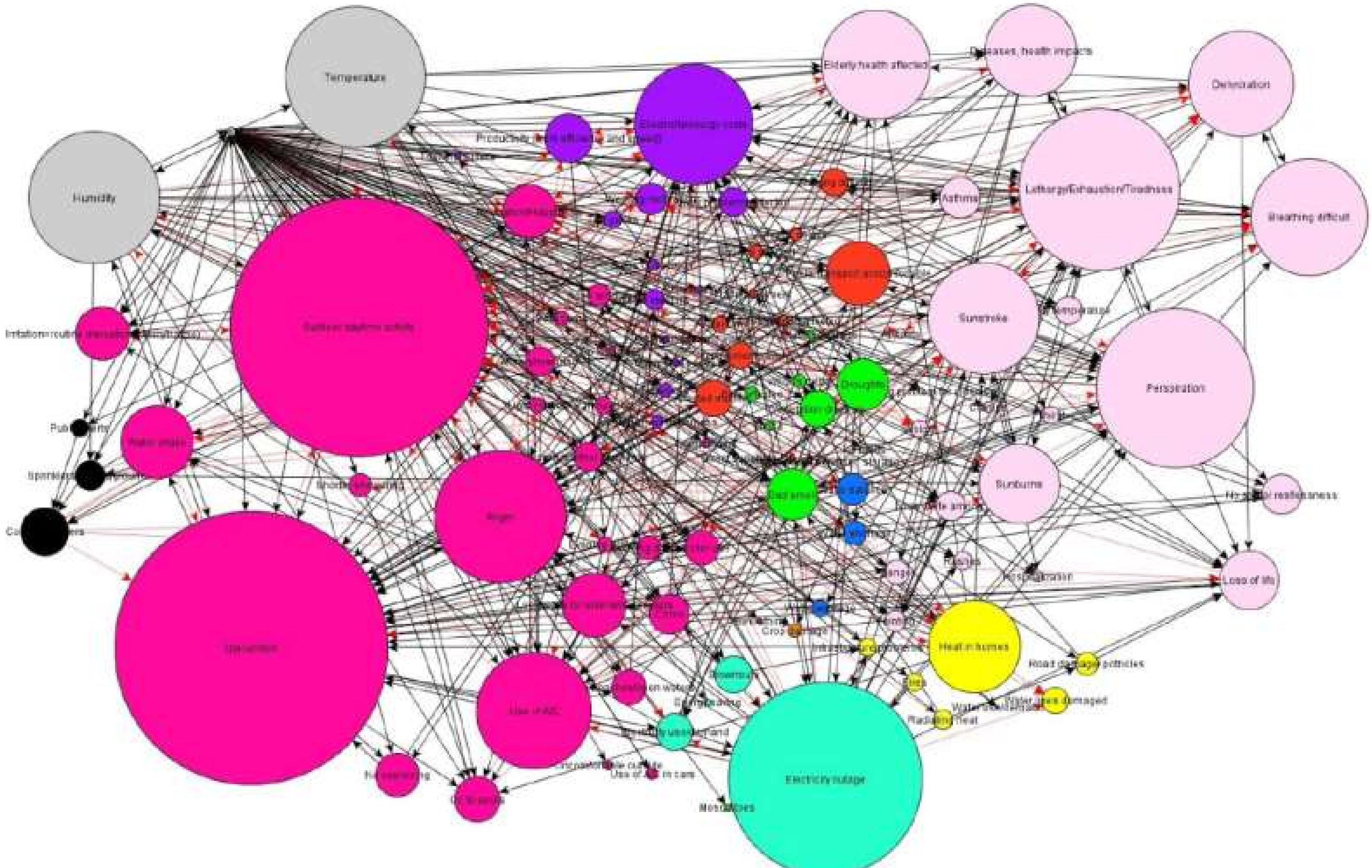
- 0-100% method had the highest completion rate, followed by the 0-100strength method and the 0.1-1strength method → “Easiness”
- Weights differs significantly across weighting methods ($F(2, 338)= 19.60$, $p<0.001$))
  - highest weights for the traditional 0.1-1 strength method; lowest weights for 0-100 methods („the fear of large numbers“)

Do weights differ? What does weights represent?

- Moreover, weights on arcs correlate positively with the perceived severity of a weather event ($t = 0.12$, $p<0.01$) and all problematic after-effects ($t= 0.19$, $p<0.001$).
- The percent of mentioned impacts that are classified as being a problem is negatively related to the total number of factors ($t=-0.13$, $p<0.001$).
- → Burden/ problems from climate change are (more) related to weights.

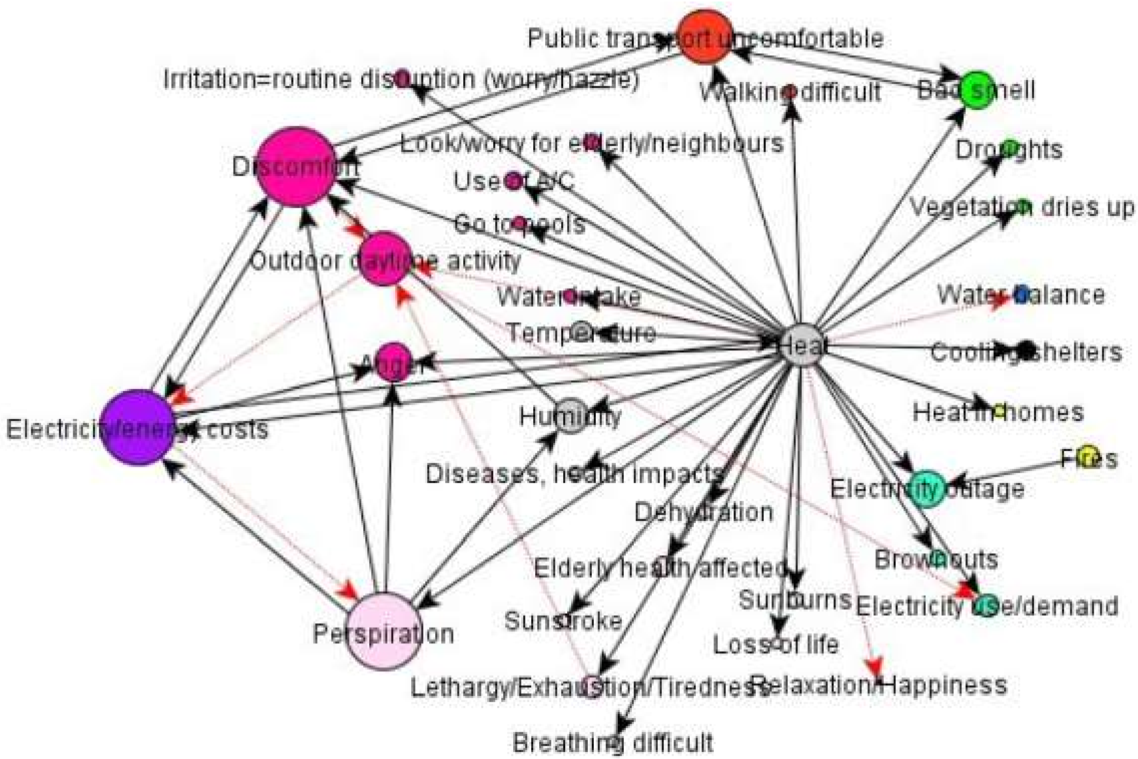
	NYC	Chicago
Sample	**N = 168**	**N = 176**
Number of impacts	M = 3.94 +/- 0.15	M = 3.92 +/- 0.15
Percent of impacts posing a problem	M = 63% +/- 2.45%	M = 63% +/- 2.60%
Weight of problems	M = 45.27 +/- 2.12	M = 50.31 +/- 2.22
Average weight on edges	M = 0.64 +/- 0.02	M = 0.69 +/- 0.02

Heat in New York City



Increasing certainty for small *N*?

- To increase certainty of answers:
  - **ALTERNATIVE/ SUGGESTION** → 3+ networks: at least 3 people gave the same concepts and connections
- Here: NYC



- Scenario analysis with 3+ networks (not shown): larger impact of heat on Chicago & larger effect of management options (electricity or traffic)

3. ADD ON: Climate change impacts in New York City

Methods:

- Fuzzy Cognitive Mapping: Network statistics and scenarios (**ANALYSIS NOT YET FINALIZED**)

Data:

- **Online** interviews to impacts of 1) heavy rainstorm and 2) heat waves (N=762); Order effects were accounted for
- Interviewees: representative sample across NYC, with population-relative distribution per borough
- Qualtrics Survey Software; Qualtrics Survey Sample

Objective:

- Large, representative sample of online-generated FCMs, including order effecs (etc.); testing online methods

Confidence level: 95%
Population: 8,336,697

Confidence Interval: 3.55%

ADD ON: Data

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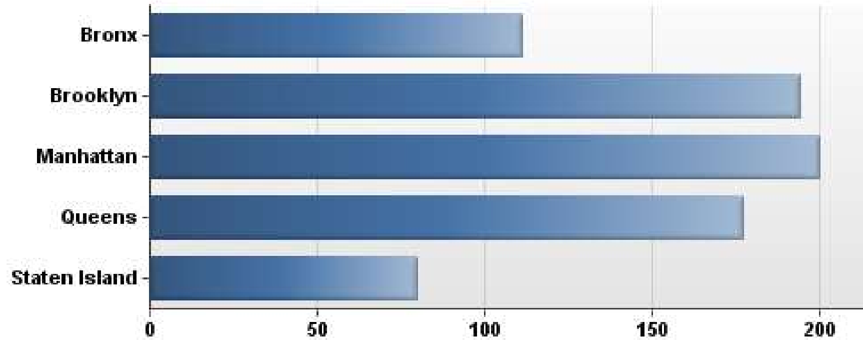
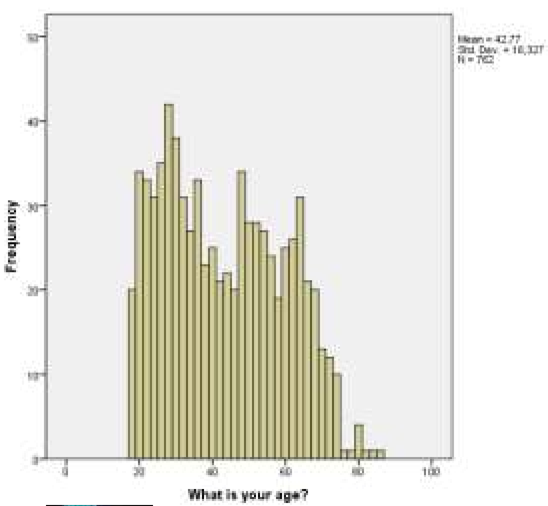
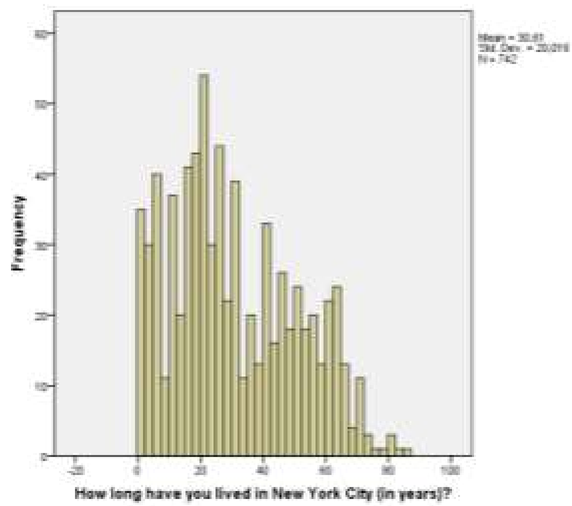


Borough	Responses N	% of total respondents	Total population (July 2012)	% of total population
Bronx	111	15%	1,619,090	0.007%
Brooklyn	194	25%	1,408,473	0.014%
Manhattan	200	26%	2,565,635	0.008%
Queens	177	23%	2,272,771	0.008%
Staten Island	80	10%	470,728	0.017%
NYC	**762**	100%	8,336,697	**0.009%**

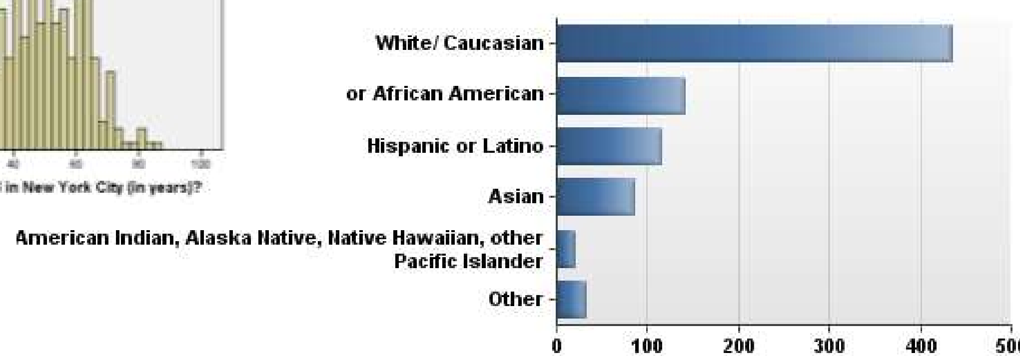
What is your age?



How have you lived in NYC (in years)?



Are you male or **female?**



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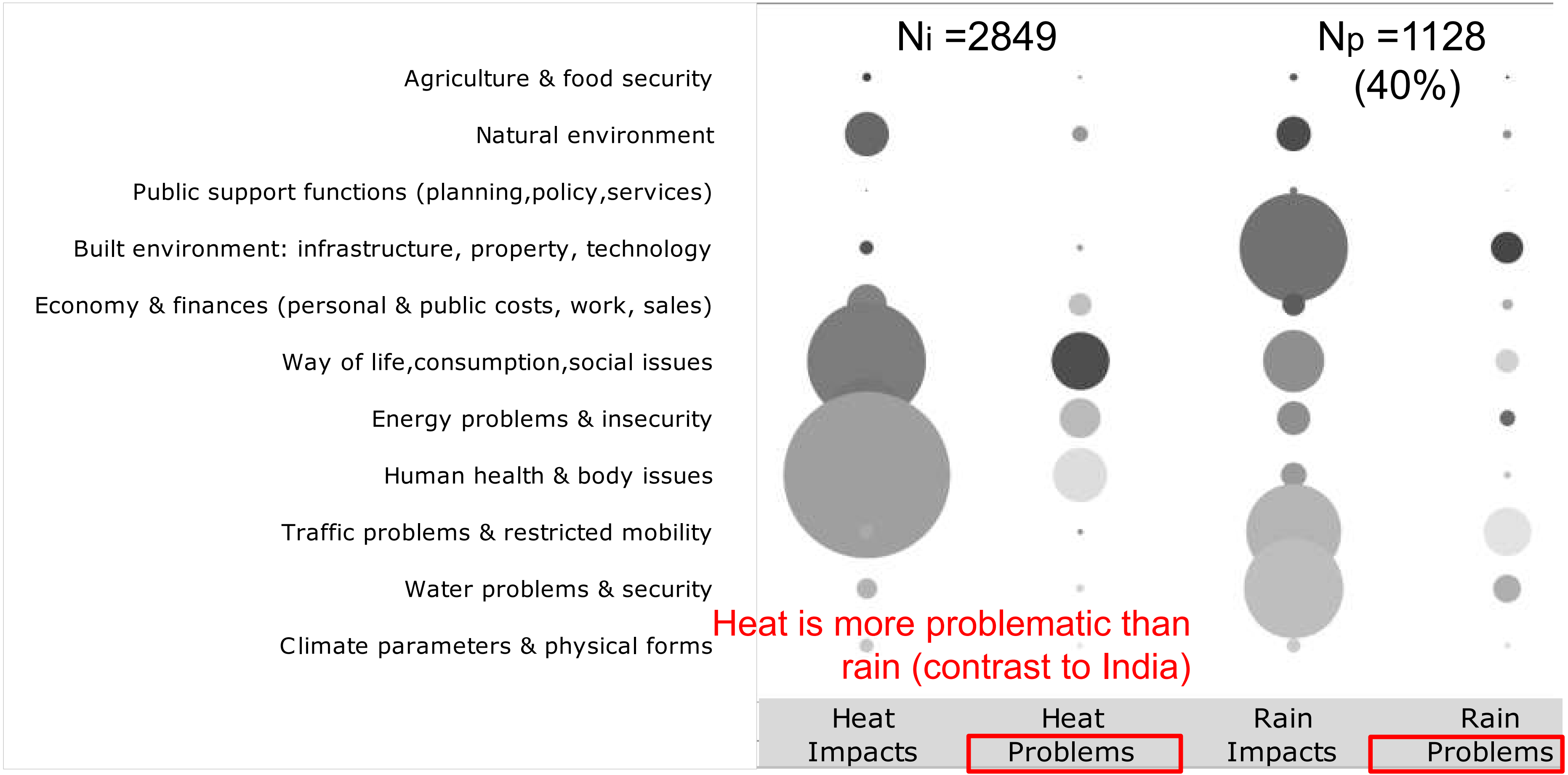
ADD ON: Do mentioned impacts pose a problem?

Across 5 boroughs: N_i = concepts = impacts = 2849

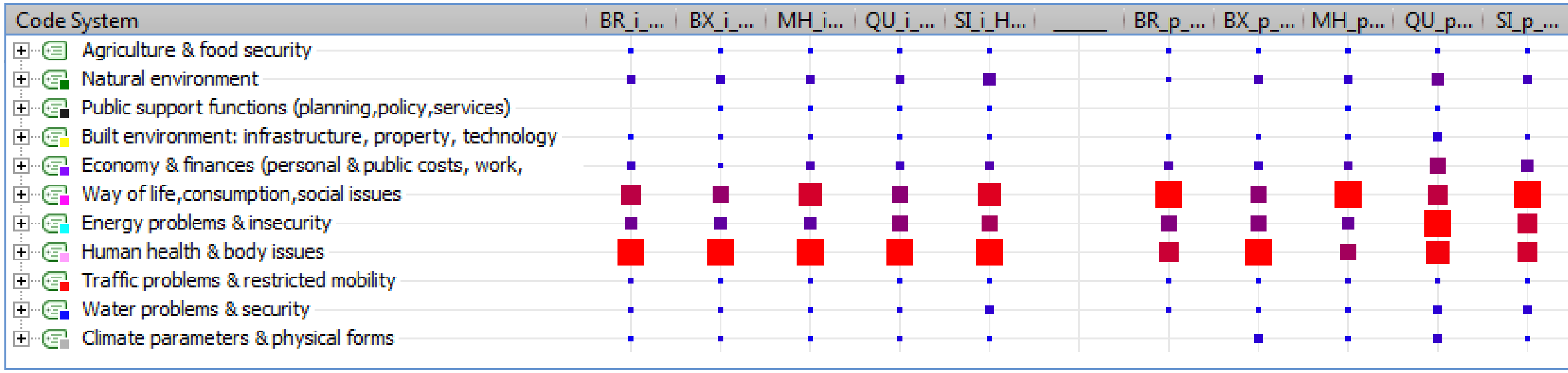
N_p = problematic impacts = 1128; i.e. 40%



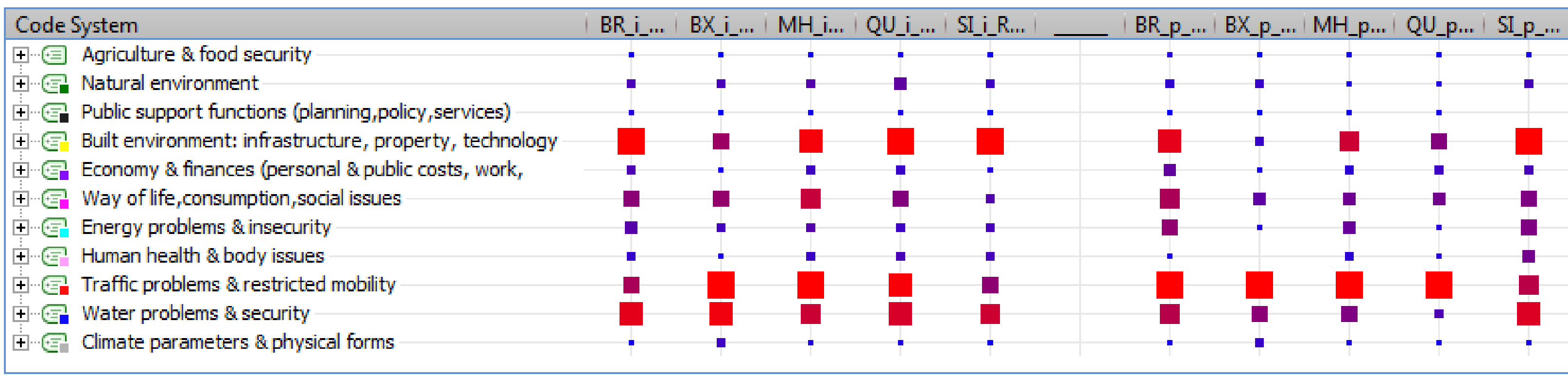
ADD ON: Sectoral impacts and problems

Column Sum: BOROUGH VIEW

Heat



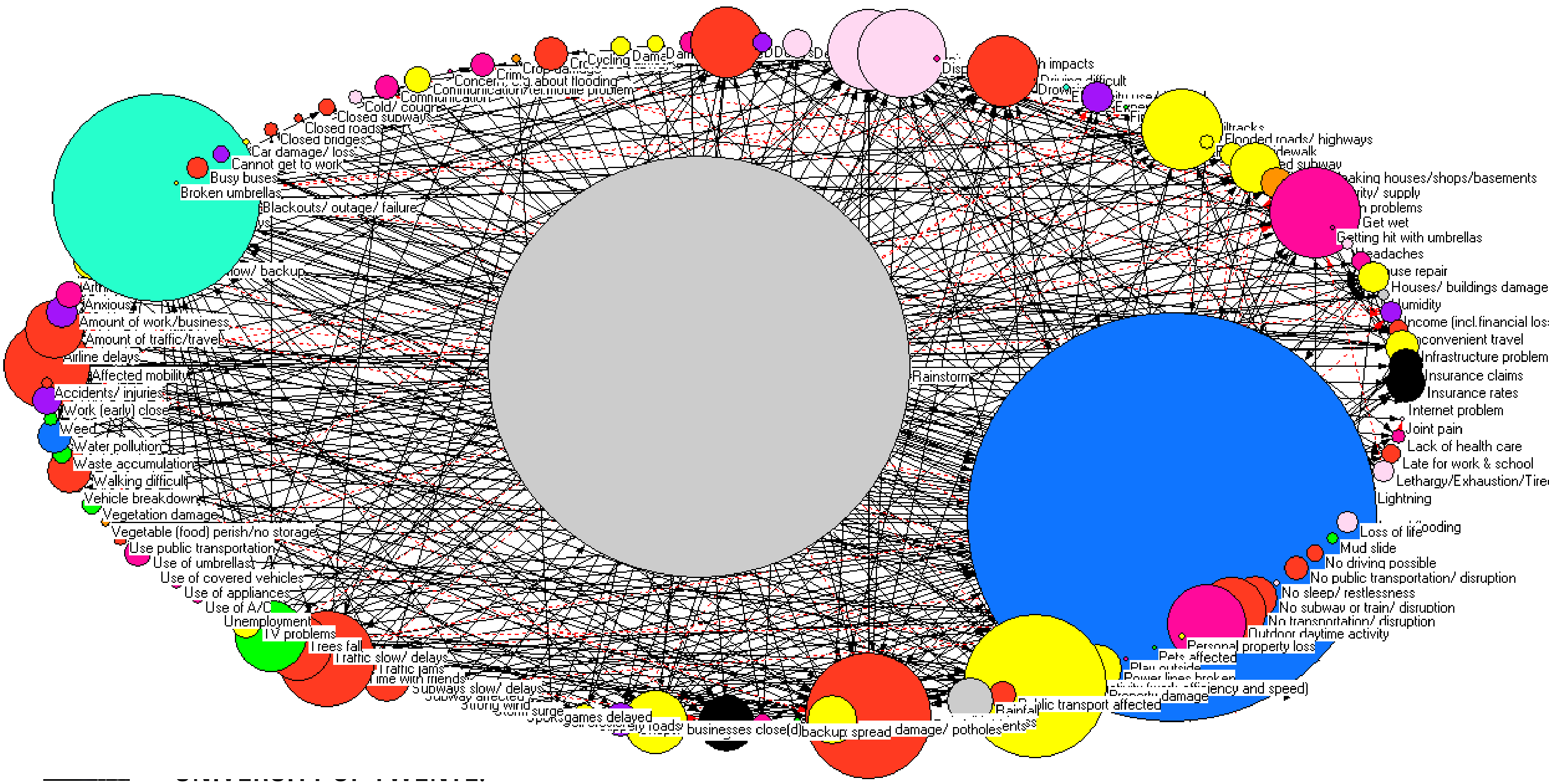
Rain



→ Problems differ across boroughs, not impacts (mostly)

→ **People give relative reliable/ similar answers in the FCMs**

ADD ON: N=35 from one borough during heavy rainstorms



4. Generating FCM with different interview methods
- Implications and issues

Survey #	Location	Time(s)	Number of (qualified) interviewees	# of interview attempts	Number of (useful) Networks (heat + rain)	Objective: Testing structure and content of networks	Number of socio-economic groups interviewed	Number of interview locations	Remarks
1	Delhi, India: 1 sub-urban location	2 interview slots: April 2010	126	144	126	Across weather events and socio-economic groups	1) street vendors; 2) planners; 3) professionals; 4) researchers; 5) students	3 locations (street location; planning office; research institute)	1 interviewee = 1 map, but # of maps per group and weather event uneven → group networks not comparable
2	Hyderabad, India: 7 locations across urban area	1 interview slot: Feb-April 2011 (05.02.-30.04.2011)	193	Only documented for 1 location: 17 refusals for 30 qualified maps	386	Across urban locations, weather events and socio-economic groups	1) street sellers; 2) wholesale market sellers; 3) planners	5 street locations; 1 wholesale market; 1 planning office	1 interviewee = 2 maps, same 3 of people per group → single & group networks comparable
3	Chicago & New York City using MTURK sample 1	19.-26.12.2012	5	125	10	Across network elicitation and weighting method, cities, and weather events	A number of socio-economic markers: age, gender, income, residence time,	Across all of NY and Chicago	1) Line-by-line vs matrix AND EACH 1) 0-1 Strength 2) 0-100 Strength 3) 0-100 Percent
4	Chicago & New York City using qualified MTURK sample 2	02.02.-13.03.2013	172	485	344	Across weighting method, cities, and weather events	A number of socio-economic markers: age, gender, income, residence time,	Across all of NY and Chicago	See further down
5	New York City using Qualtrics Survey sample	05.11.-08.12.2013	762	1178	938	Across boroughs and socio-economic groups	A number of socio-economic markers: age, gender, income, residence time,	Across all of NY	See further down

Face to face: Delhi

C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15
	Maps	**# of Nodes/ map**			**# of Edges/ map**			**Weights/ map**			**Density**			**Confusion (weights, or other)**
HEAT	***N***	$\bar{x}$	**Range**	**SD**	$\bar{x}$	**Range**	**SD**	$\bar{x}$	**Range**	**SD**	$\bar{x}$	**Range**	**SD**	
Planners	4	12.25	6-17	4.57	14.50	6-24	7.37	.54	.25-.80	.23	.12	.09-.20	.06	80% (8/10)
Wallahs	23	6.61	3-10	2.19	9.39	2-10	5.33	.60	.15-.86	.23	.26	.13-.50	.10	Interviewer draw map
Profess	13	13	6-24	6.33	14.46	6-31	7.91	.58	.28-.75	.14	.12	.05-.37	.09	29% (4/14)
Research	8	9.75	7-14	2.67	12.50	5-25	6.39	.54	.38-.70	.11	.15	.09-.24	.05	25% (2/8)
Students	11	11	6-19	4.11	15.25	12-22	6.92	.62	.44-.78	.11	.13	.05-.21	.07	42% (5/12)
RAIN	***N***	$\bar{x}$	**Range**	**SD**	$\bar{x}$	**Range**	**SD**	$\bar{x}$	**Range**	**SD**	$\bar{x}$	**Range**	**SD**	
Planners	7	10.29	7-14	2.56	11.14	6-20	4.45	.54	.36-.71	.13	.12	.09-.21	.04	66% (8/12)
Wallahs	26	7.29	2-15	3.70	10.12	1-20	5.76	.61	.20-.95	.16	.22	.09-.50	.12	Interviewer draw map
Profess	13	13.69	5-27	7.16	16.15	4-44	10.95	.62	.40-.98	.16	.12	.05-.27	.07	31% (5/16)
Research	7	8.71	7-11	1.72	9.57	6-14	3.19	.57	.30-.82	.16	.14	.11-.21	.04	30% (3/9)
Students	14	11.07	6-22	3.97	12.86	6-22	4.55	.63	.53-.79	.08	.13	.05-.21	.05	21% (3/14)

Face to face: Hyderabad

C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
	Maps	**# of Nodes/ map**			**# of Edges/ map**			**Weights/ map**			**Density**		
HEAT	***N***	$\bar{x}$	**Range**	**SD**	$\bar{x}$	**Range**	**SD**	$\bar{x}$	**Range**	**SD**	$\bar{x}$	**Range**	**SD**
Barkatpura	30	3.48	2-6	1.35	2.48	1-5	1.35	.50	.25-.80	.16	.21	.14-.25	.04
Jambagh	30	3.87	2-7	1.28	2.87	1-6	1.28	.56	.25-1	.19	.20	.12-.25	.04
Old City	30	4.70	2-8	1.64	3.80	1-8	1.77	.52	.13-.84	.20	.18	.11-.25	.04
Srinagar	30	3.32	2-7	1.42	2.39	1-6	1.47	.57	.1-1	.24	.22	.12-.33	.05
Tarnaka	30	4.72	2-10	1.94	3.76	1-9	2.01	.55	.07-1	.20	.18	.09-.25	.04
Madannapet	30	3.76	2-7	1.68	2.79	1-6	1.72	.45	.02-.80	.21	.20	.12-.25	.05
HMDA	8	8.88	5-16	3.87	8.75	4-20	5.63	.39	.25-.58	.10	.12	.08-.16	.03
RAIN	***N***	$\bar{x}$	**Range**	**SD**	$\bar{x}$	**Range**	**SD**	$\bar{x}$	**Range**	**SD**	$\bar{x}$	**Range**	**SD**
Barkatpura	30	3.37	2-8	1.45	2.47	1-7	1.55	.64	.19-1	.22	.22	.11-.33	.04
Jambagh	30	4.40	2-8	2.52	3.43	1-8	1.72	.57	.23-1	.21	.18	.08-.31	.05
Old City	30	5.87	2-17	2.70	5.40	1-20	3.49	.58	.10-.98	.19	.16	.07-.25	.04
Srinagar	30	4.20	2-7	1.47	3.27	1-6	1.57	.58	.1-1	.21	.19	.12-.25	.04
Tarnaka	30	4.87	2-8	1.76	4.13	1-9	2.05	.57	.22-.91	.18	.18	.11-.31	.05
Madannapet	30	4.50	2-8	1.61	3.87	1-8	2.08	.45	.05-.78	.19	.19	.13-.25	.03
HMDA	8	8.88	4-17	3.87	8.50	4-17	4.17	.48	.21-.80	.19	.12	.06-.25	.06

Conclusion: Face to face interviews

- 2-17 concepts; # concepts increases with time/ education
- 0.1- 1: large range of weights:
  - lower income people put sign. larger weights
- Obstacles:
  - Many low-income respondents cannot write: interviewer draws (OK)
  - Unified language might ‘filter’ responses to Western/ English words

- **Fuzzy linguistics** (weak, medium, strong) was tried:
  - interviewees did not understand it; did not work. Used numbers instead.
- **Different numbering scales** were also tried, such a 0-10, 0-1, -10 to 10.
  - -10 to 10 did not work at all; the other options worked out alright.
  - 0-1 worked best (0-100 was not tested), although still difficult for a good share of the interviewees.
  - Experts feel more uneasy than lay people to give crisp numbers.

Online: Testing more generation methods

Approach:

- 1) Line by line for each possible connection, the direction, and weight
- 2) all this information into matrix.

- → Quality issues: large number of uncompleted tasks: 12% of people who started the task completed (line); 14% (matrix)

- → More people completed successfully with line approach; matrix approach was often interpreted incorrectly
- → Line-by-line cognitively easier

	Attempts	Completes		Usefully completed	
LINE APPROACH	**N**	**N**	**%**	**N**	**% of attempts**
Chicago_line_0100%	10	2	20.0	1	10
Chicago_line_01strength	11	3	27.3	0	
Chicago_line_ 0100strength	8	1	12.5	1	12.5
NY_line_0100%t	11	0	0.0	0	
NY_line_01strength	6	1	16.7	1	16.7
NY_line_0100strength	13	0	0.0	0	
Sum	59	7	11.9	3	5.1
MATRIX APPROACH					
Chicago_matrix_0100%	8	1	12.5		
Chicago_matrix_ 01strength	10	2	20.0	0	
Chicago_matrix_ 0100strength	9	2	22.2	1	11.1
NY_matrix_0100%	12	0	0.0	0	
NY_matrix_01strength	11	1	9.1	0	
NY_matrix_ 0100strength	16	3	18.8	1	6.3
Sum	66	9	13.6	2	3.0

Online: New York City - Chicago

C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16
	Maps	**# of Nodes/ map**				**# Edges**	**# of Edges/ map**			**Weights/ map**	**# of Nodes/ map**		**Density**		
HEAT	N	N	$\bar{x}$	**Range**	**SD**	N	$\bar{x}$	**Range**	**SD**	$\bar{x}$	**Range**	**SD**	$\bar{x}$	**Range**	**SD**
NY - Bronx	11	68	6.18	4-9	1.66	138	12.55	4-28	7.61	.60	.25-.81	.17	.37	.23-.57	.09
NY - Brooklyn	25	158	6.32	3-9	1.75	310	12.40	2-26	6.46	.65	.43-1	.17	.37	.17-1	.18
NY - Manhattan	29	184	6.34	3-9	1.95	360	12.41	3-38	8.27	.59	.23-.9	.18	.36	.10-.70	.14
NY - Queens	19	108	5.68	2-9	2.24	227	11.95	1-37	9.33	.63	.25-1	.21	.41	.23-.70	.14
Chicago	88	541	6.15	3-9	5.15	1249	14.19	0-61	10.80	.68	.29-1	.18	.43	.14-.85	.17
RAIN	N	N	$\bar{x}$	**Range**		N	$\bar{x}$	**Range**	**SD**	$\bar{x}$	**Range**	**SD**	$\bar{x}$	**Range**	**SD**
NY - Bronx	11	42	3.82	2-6	1.08	50	4.55	2-9	2.38	.72	.37-1	.21	.45	.25-1	.21
NY - Brooklyn	25	97	3.88	2-6	1.20	131	5.46	1-13	3.66	.72	.32-1	.18	.42	.25-.58	.10
NY - Manhattan	29	104	3.59	2-5	1.05	124	4.28	1-12	2.78	.55	.55-1	.25	.45	.15-1	.16
NY - Queens	19	69	3.63	2-6	1.30	87	4.58	1-11	3.10	.71	.34-1	.17	.46	.30-.83	.12
Chicago	88	325	3.69	2-9	1.31	440	5.00	1-26	4.22	.72	.15-1	.22	.47	.16-1	.17

Online: New York City

C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15
NY	**Maps**	**# Nodes**	**# Nodes/ map**			**# Edges**	**# of Edges/ map**			**Weights/ map**			**Density**	
HEAT	***N***	***N***	$\bar{x}$	**Range**	**SD**	***N***	$\bar{x}$	**Range**	**SD**	$\bar{x}$	**Range**	**SD**		
Bronx	111	456	4.11	2-9	1.49	1112	10.11	1-51	8.12	.69	.17-1	.21	.74	.16-1
Brooklyn	194	843	4.35	2-9	1.78	2129	11.26	1-69	10.59	.65	.01-1	.20	.71	.15-1
Manhattan	200	960	4.80	2-9	1.90	2700	13.57	1-72	13.68	.59	.05-1	.20	.65	.13-1
Queens	177	816	6.61	2-9	1.83	2313	13.14	1-72	13.48	.64	.1-1	.21	.69	.10-1
Staten Island	80	4066	5.07	2-9	2.08	1283	16.24	1-64	15.43	.66	.18-1	.19	.68	.14-1
RAIN	**N**	**N**	$\bar{x}$	**Range**	**SD**	**N**	$\bar{x}$	**Range**	**SD**	$\bar{x}$	**Range**	**SD**	$\bar{x}$	**Range**
Bronx	111	461	4.15	2-9	1.70	1252	11.38	1-64	10.9	.63	.14-1	.21	.78	.25-1
Brooklyn	194	853	4.40	2-9	1.83	2219	11.62	1-67	11.43	.63	.03-1	.22	.70	.19-1
Manhattan	200	923	4.61	2-9	1.75	2425	12.37	1-72	10.80	.60	.06-1	.21	.68	.17-1
Queens	177	829	4.68	2-9	1.89	2409	13.61	1-72	12.653	.63	.1-1	.21	.72	.24-1
Staten Island	80	395	4.94	2-9	1.93	1130	14.13	1-63	12.25	.62	.07-1	.21	.67	.23-1

Summary: Online interviews

- Quality issues:
  - 1178 respondents attempting to take the survey; 938 completed it.
  - After thorough data screening, the number of responses reduced to 762 completed tasks (81.2%).
- Sincere note of caution in mind: Use of online questionnaires produces more connections between the nodes as compared with FCMs drawn on paper
    - Drawings on paper might miss (important) influential relations

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THANKS.

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