

Public Disclosure Authorized

Secondary Towns Conference
World Bank
May 19, 2016

Big or small? Which type of urban growth matters to poverty reduction in rural India?

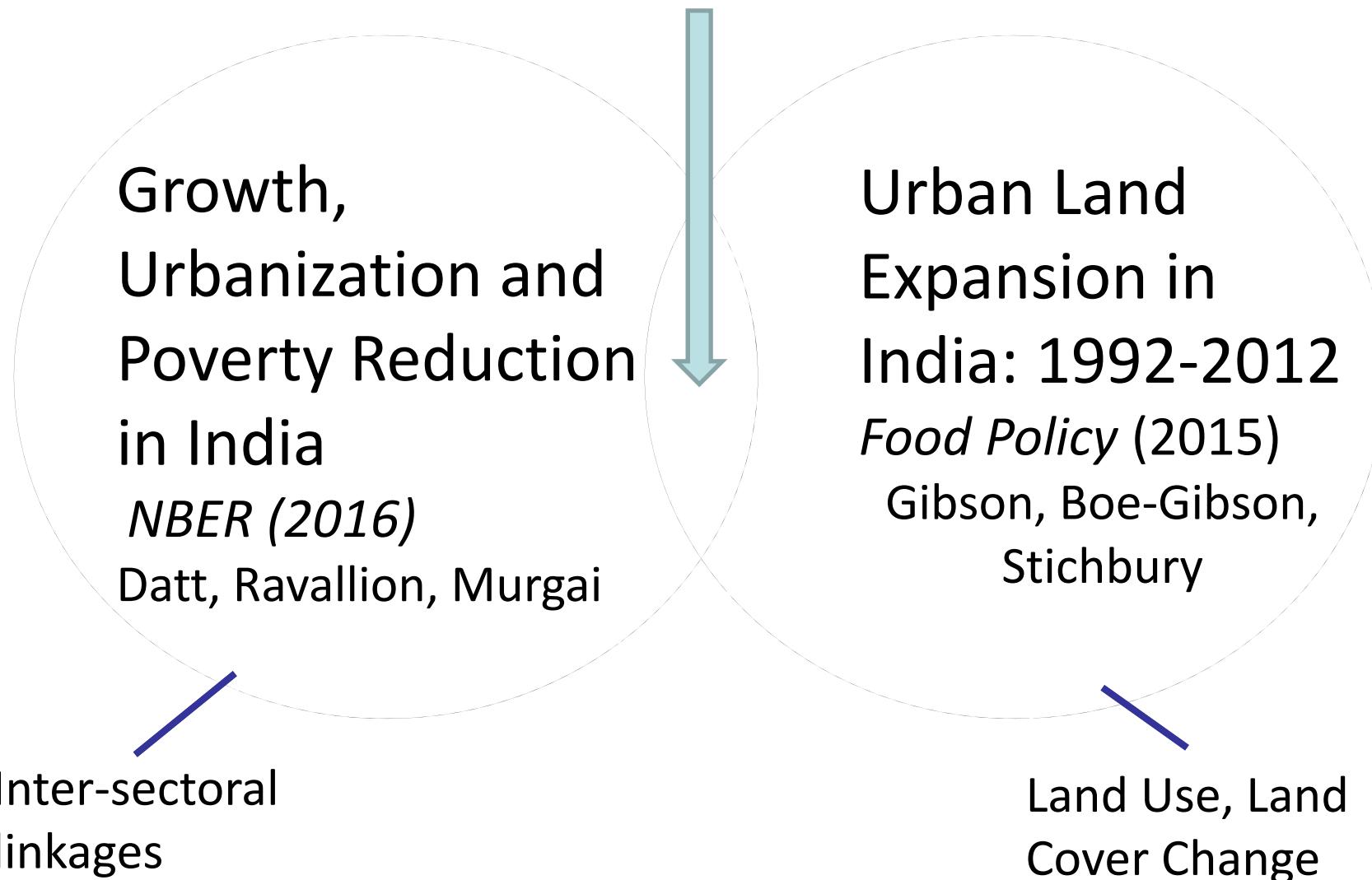
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(with Gaurav Datt, Rinku Murgai and Martin Ravallion)

Quick Preview

- Use night lights to measure urban growth in India between 1993/94 and 2011/12
 - Distinguish between growth in area (extensive margin) and growth in light intensity (intensive margin) and relate to changes in rural poverty over time and space
 - Accessing urban job opportunities from rural locations may be easier on the extensive than the intensive urban margin
 - Lower density → low skill services rather than high skill
 - Lower transport cost from hinterland to city edge than to CBD
 - Making the city ‘closer’ may alter rural prices, wages, behaviour
 - Distinguish effects of big city (million-plus) growth from growth of smaller (secondary) towns

A new collaboration at the intersection of two research programs



Datt, Ravallion, and Murgai

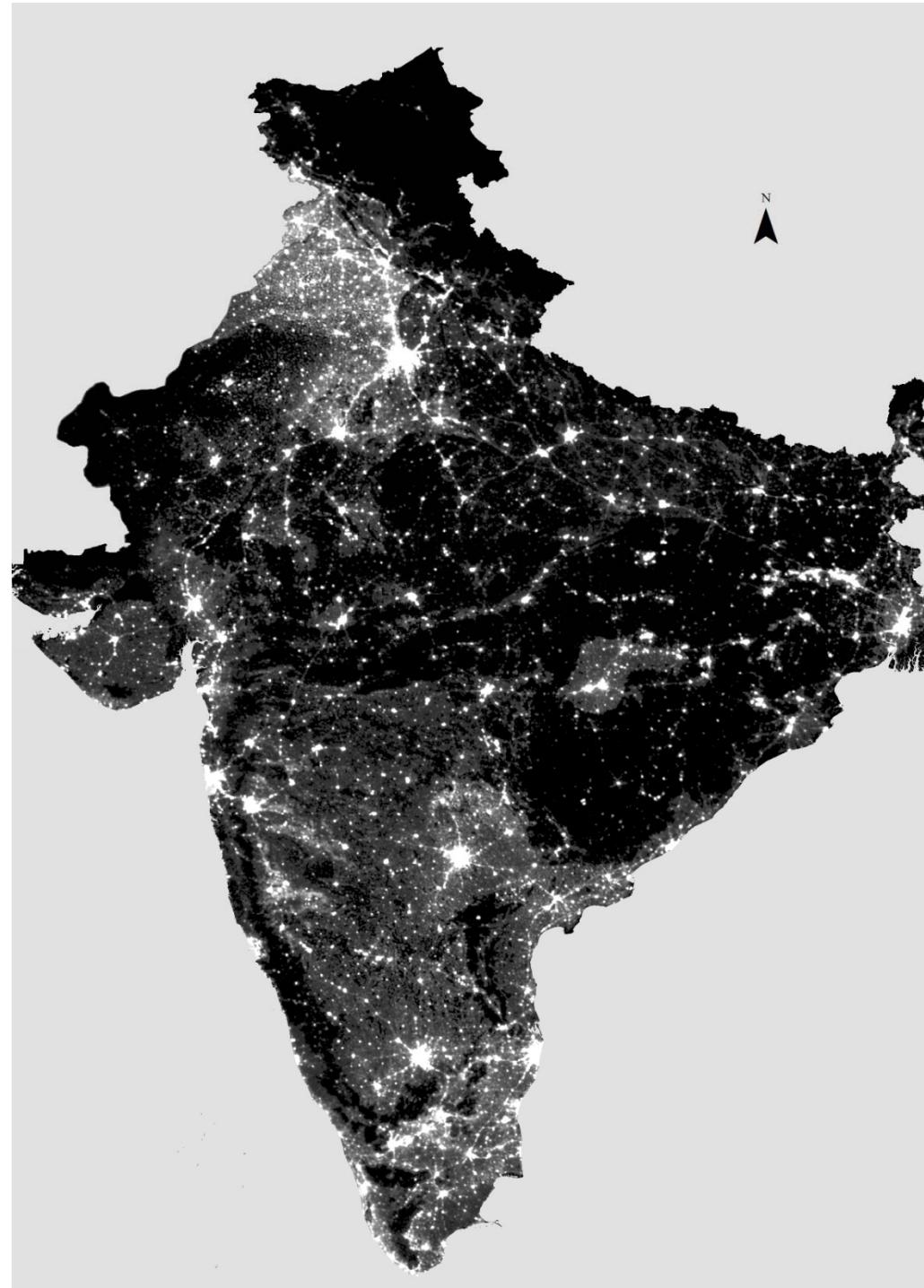
- Analysis of links between economic growth and poverty in India over 60 years
- Structural break around the time of liberalization
- Post-1991, urban growth emerged as a major driver of poverty reduction
 - Directly, as urban poverty has become significantly more responsive to urban growth,
 - Indirectly: urban growth has had significantly more effect on rural poverty since 1991
- Urban growth has helped to reduce rural poverty since 1991 but had no impact on rural poverty pre-1991

Gibson, Boe-Gibson, Stichbury

- Use night lights to estimate trend rate of area expansion for 47 of India's million-plus agglomerations
 - Expansion rate of 2.4% per annum over 1992-2012 using a luminosity threshold of 50% to demarcate edge of big cities
 - With different luminosity thresholds would get from 2 to 2.5%
 - Same data, method, and luminosity threshold applied to urban cores in China gives 8% per annum trend expansion rate
- Expansion rates vary widely over space; per annum rates range from 0 to 8% and are a bit faster in the south
- Almost three-quarters of expanded upon area had previously (between 1981-94) been woodland, shrub or grassland and only one-quarter was cropland

(Most of) India at Night: Satellite F16, 2010

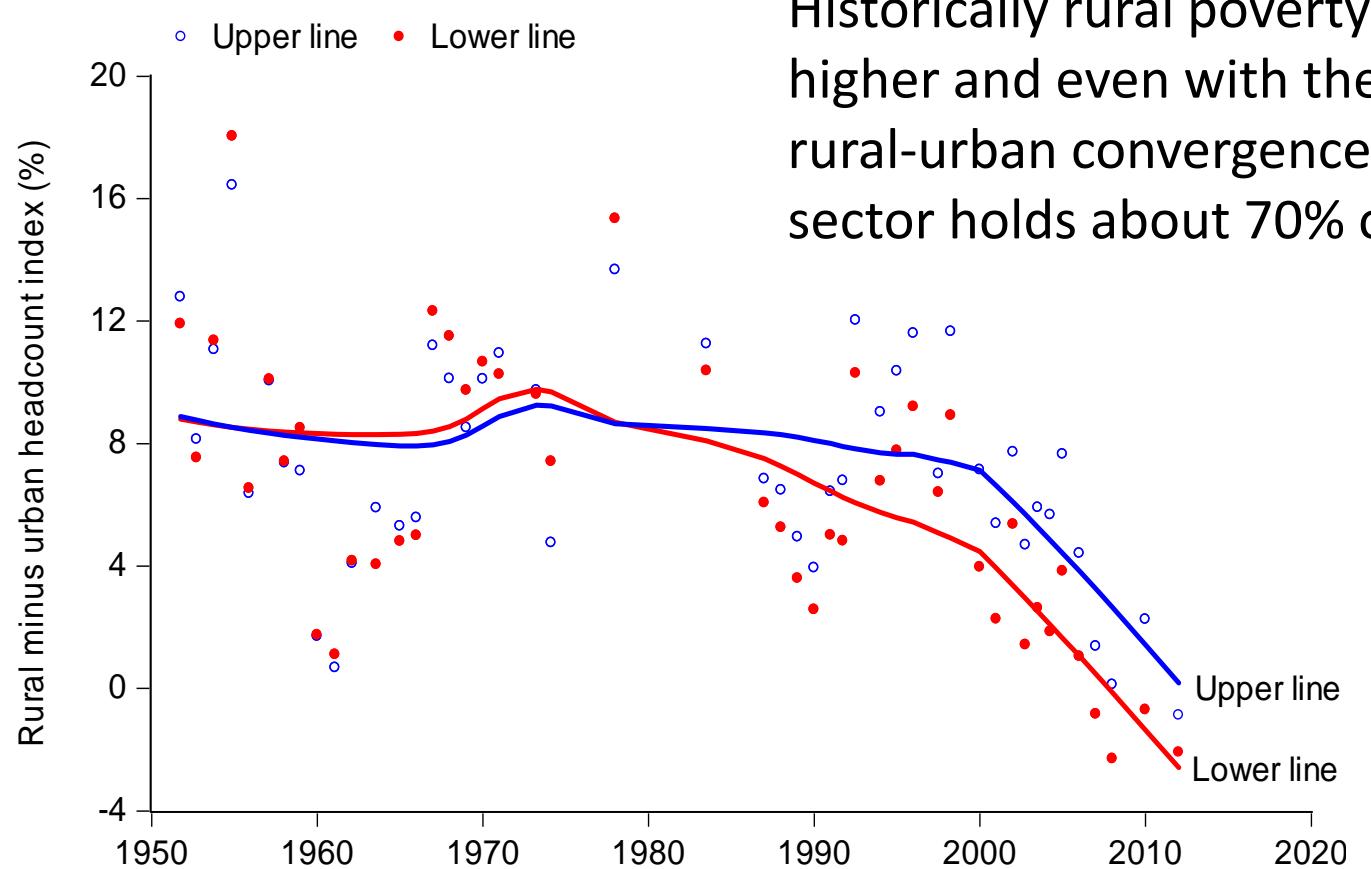
- major agglomerations clearly visible
- radial development along transport corridors, e.g. from Delhi north through Chandigarh to Amritsar, along Highway 1
- similarly for Hyderabad, Bangalore and Ahmadabad
- less brightly lit development in eastern areas of India
 - e.g. Kolkata has much slower expansion rate than the other major cities



Poverty Data

- NSS thick rounds in 1993/94, 2004/05, 2009/10, 2011/12
 - Reasonably comparable surveys over time
 - 30 day recall for food and other frequently consumed items and one year recall for other items
 - Dang and Lanjouw (2016) show slight design changes since mid-2000s don't threaten evidence of steep fall in poverty
- Tendulkar poverty lines:
 - India's official poverty lines, post-Planning Commission
 - Equivalent to \$1.17 a day at 2005 PPP
- Two poverty measures:
 - Headcount index, poverty gap index
- Focus on rural poverty, using NSS regions:
 - Group of districts from same state with similar geographic features and population densities
 - $N=59$ for the 19 major states we consider

Why focus on rural poverty?



Historically rural poverty rates were higher and even with the recent rural-urban convergence the rural sector holds about 70% of the poor

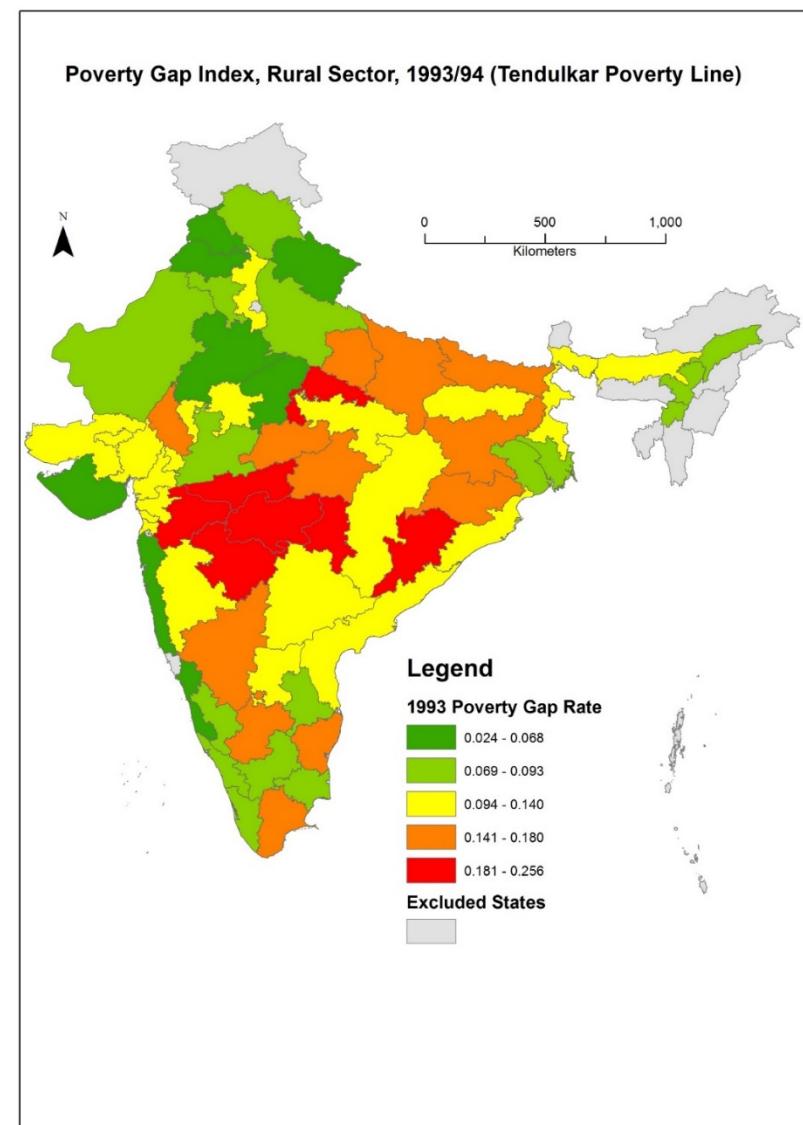
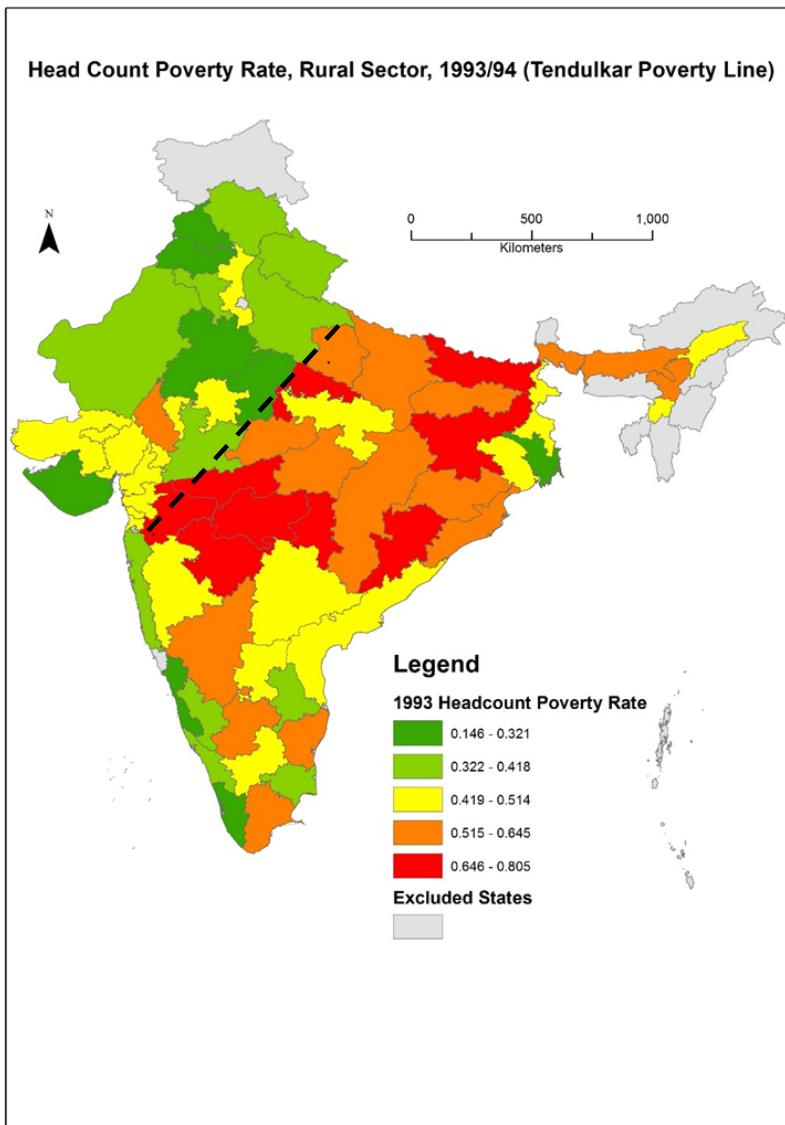
Source: Datt, Ravallion and Murgai (2016)

Patterns of Rural Poverty Over Time and Space

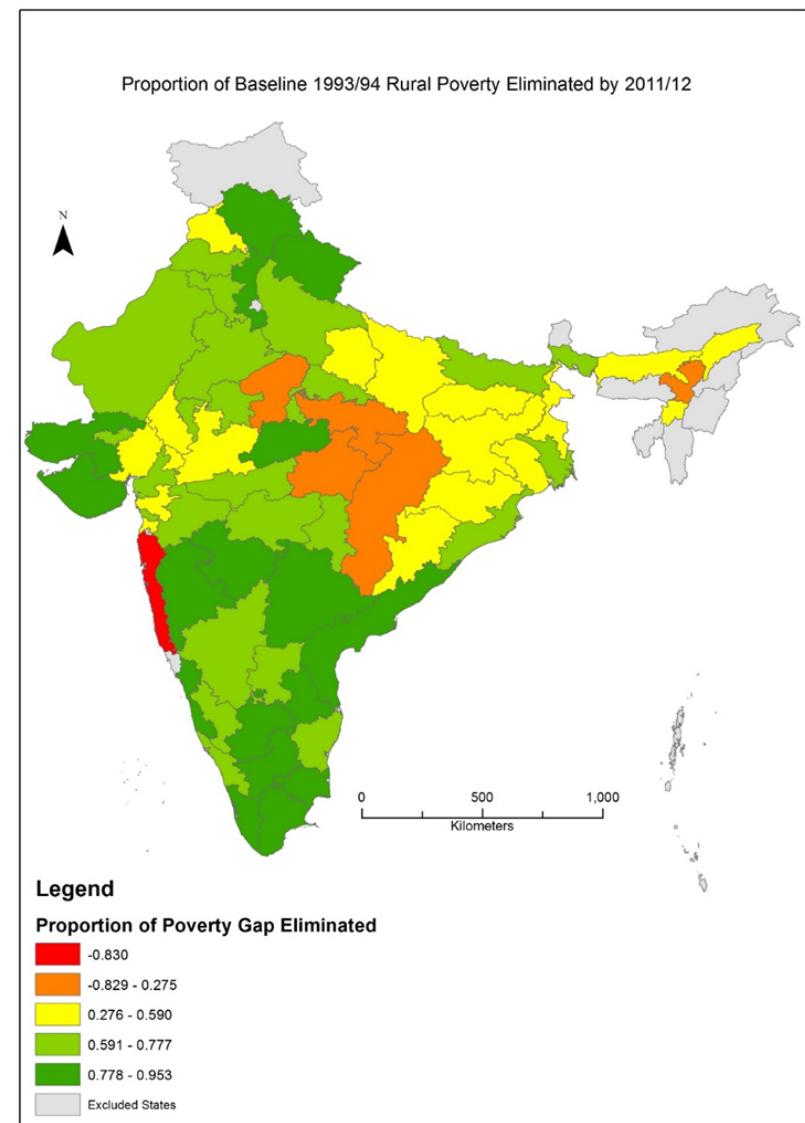
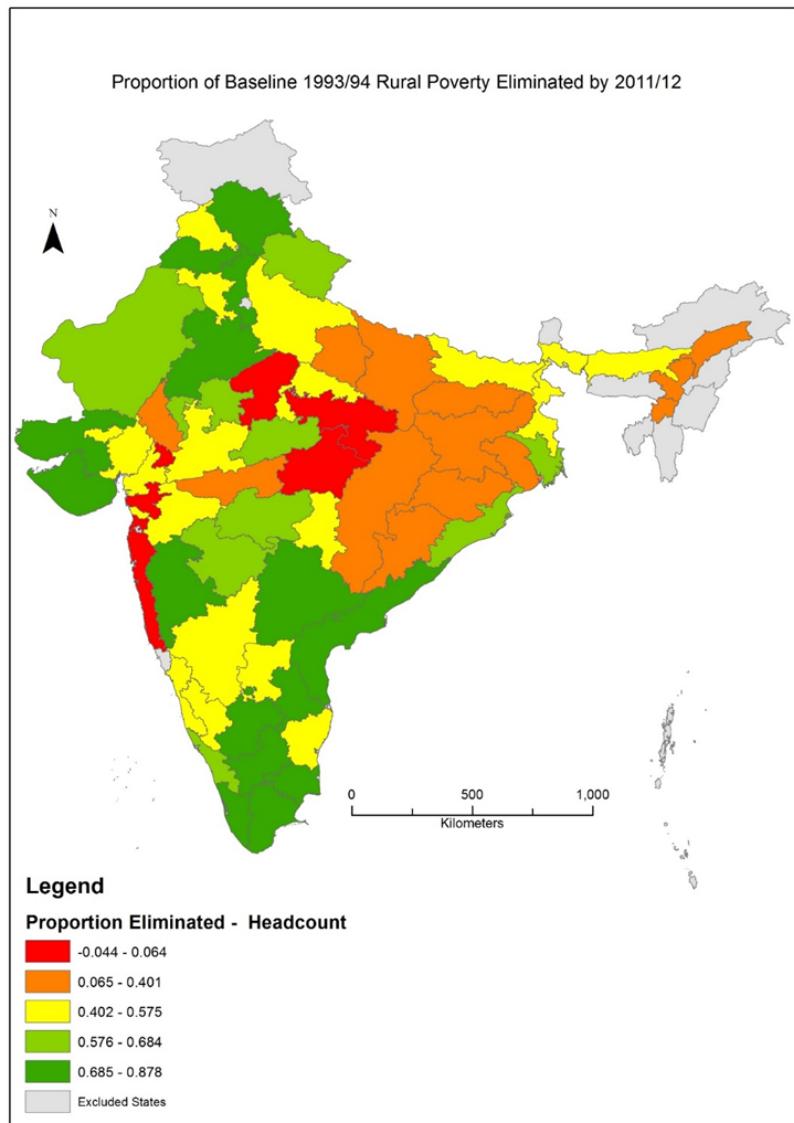
For 19 major states, using NSS region/sector averages

- Head count poverty rate for rural sector halved from 1993/94 to 2011/12
 - From 50% to 25%
- Poverty gap index fell from 0.13 to 0.05
 - Weighted and unweighted show same fall, subsequent econometric results use unweighted results
- Spatial autocorrelation increased
 - Moran's I went from 0.3 to 0.43 for headcount and 0.28 to 0.38 for poverty gap index
 - Rural poverty spatially concentrated and became more so

Baseline Poverty Rates Show Significant Spatial Autocorrelation



Spatial Autocorrelation in Poverty Reduction



Estimation Issues

- Allow for the spatial autocorrelation apparent in the poverty data using two spatial panel estimators:
- SAR with spatial errors

$$y_t = \rho W y_t + X_t \beta + \mu + \nu_t \quad \text{with} \quad \nu_t = \lambda M \nu_t + \varepsilon_t$$

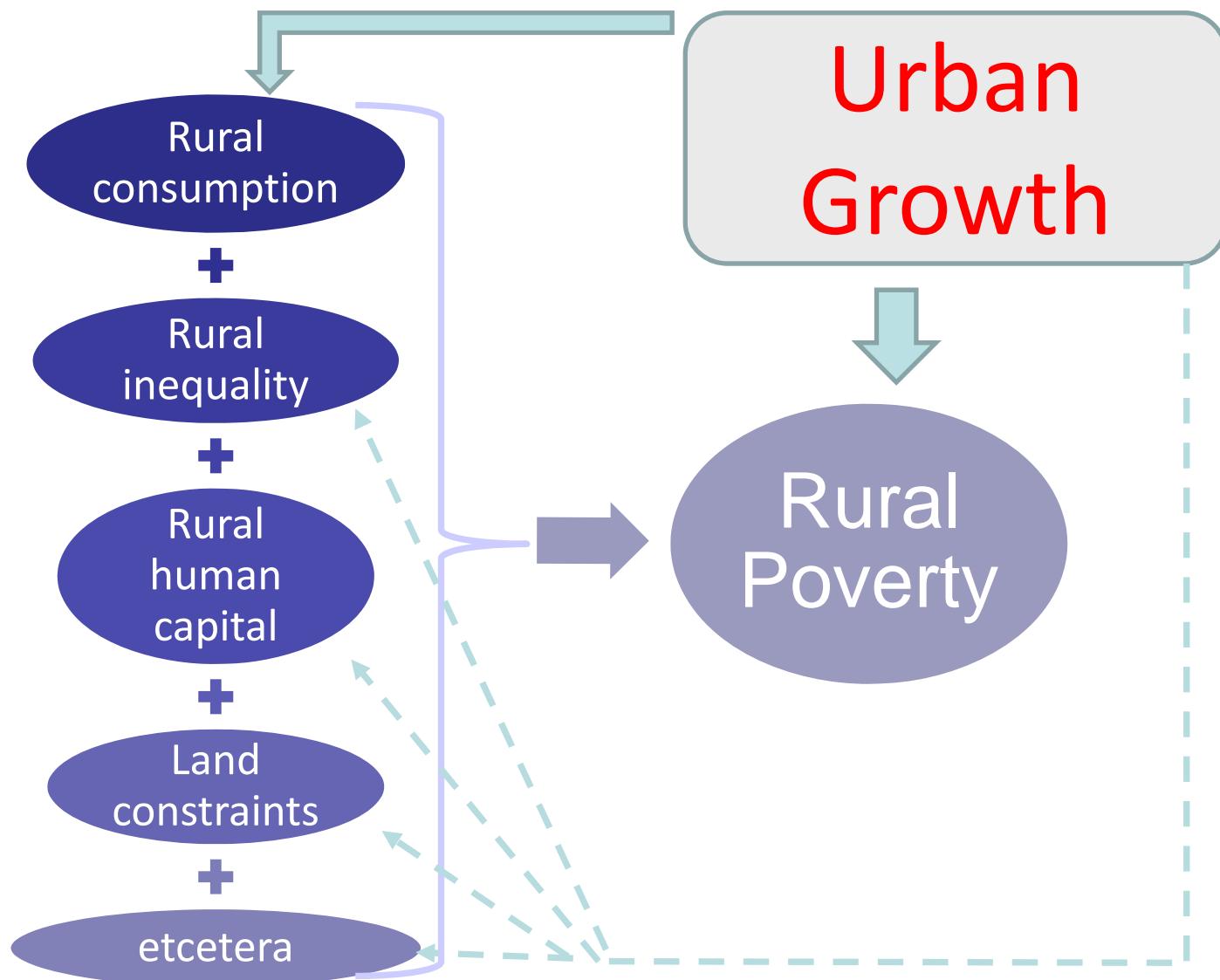
- Spatial error model

$$y_t = X_t \beta + \mu + \nu_t \quad \text{with} \quad \nu_t = \lambda M \nu_t + \varepsilon_t$$

with first-order contiguity weights

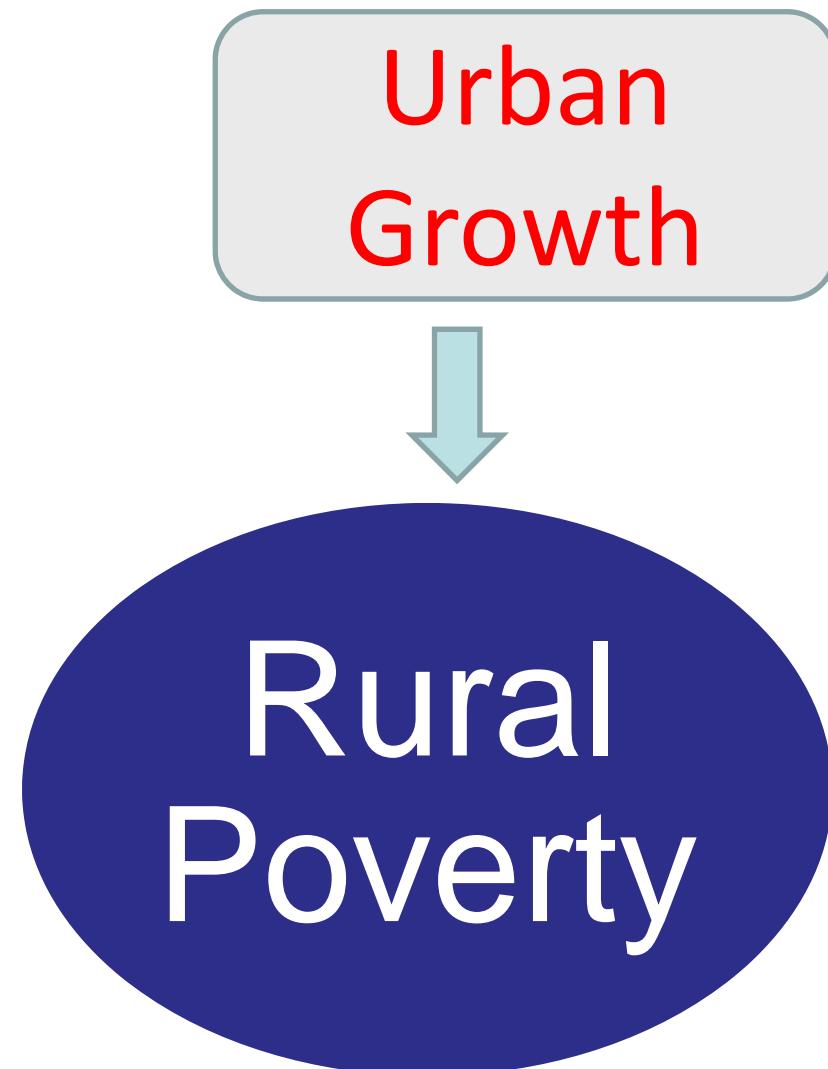
- what paths of influence from cities to regions allowed
 - Reduced form (these slides)
 - Control for lots of X's (draft paper)
- Linking cities to regions

(At least) Two Ways to Estimate Paths of Influence from Urban to Rural



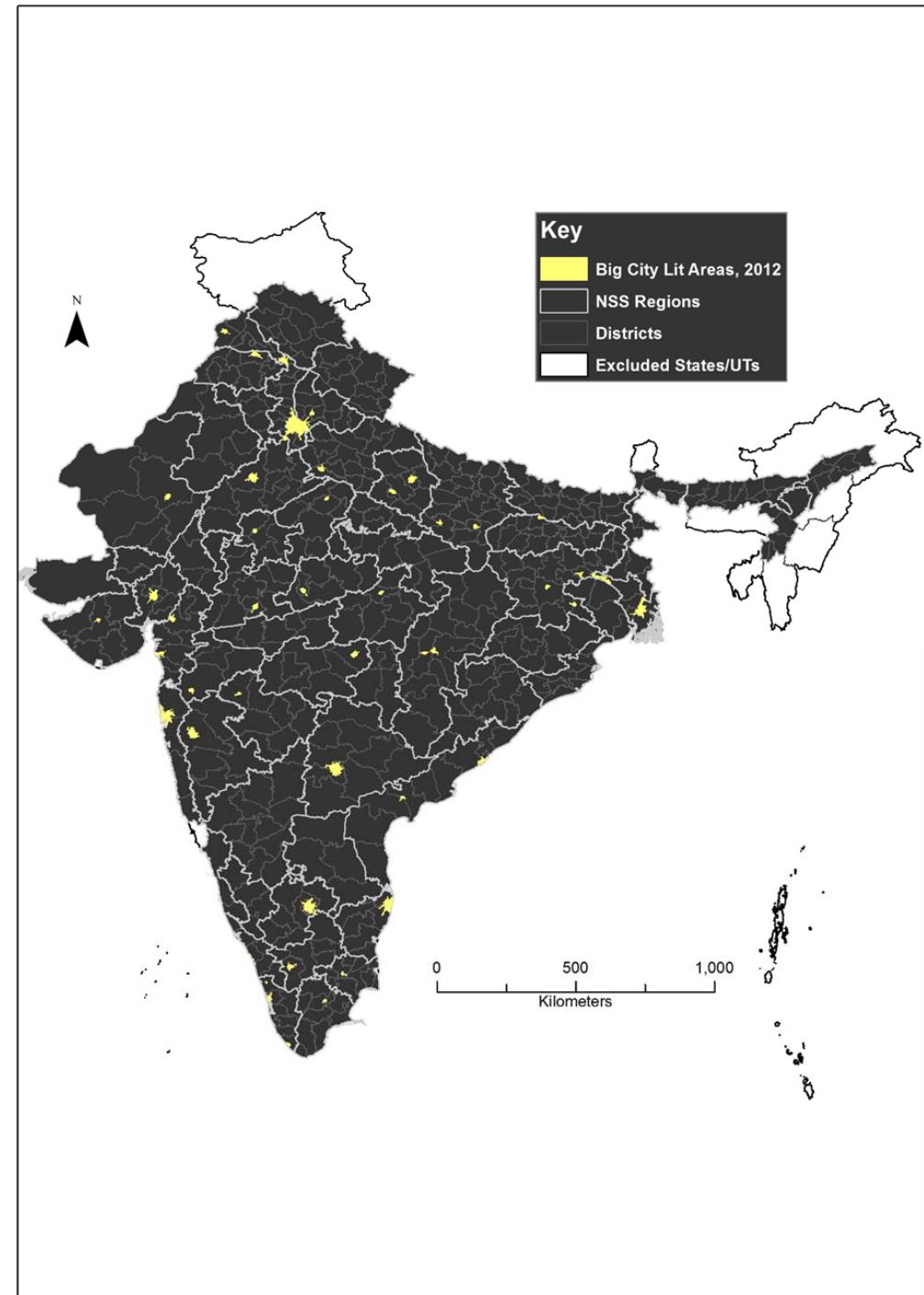
Nothing held constant

- Qualitative patterns of effect of urban growth on rural poverty are largely the same with or without the covariates
- The spatial autocorrelation expresses itself differently



Linking Big Cities to Regions

- only 39 of 59 NSS regions have a big city (partially) within their boundaries
- all NSS regions except those in Assam at least neighbour a region with a big city
 - a path of influence could operate with the SAR model
- also use an *ad hoc* linkage by allowing for big cities within either a 50km or 100km buffer of the NSS region



Measuring Growth of Different Types of Urban Areas

- Census data only line up (roughly) with two of the NSS thick rounds
 - Lack economic details and are for administratively rather than economically defined cities
 - India lacks “metropolitan statistical area” boundaries and lacks sub-national statistics collated for such units
 - e.g. Gross District Product data not available for all states and time series typically ends in 2007/08
- Use evidence on expansion of big cities, derived from DMSP night lights and already published, and develop similar measures for the growth of smaller, secondary, urban areas

Pros and Cons of DMSP Night Lights

DMSP designed for visual interpretation of clouds for Air Force weather forecasts NOT to help economists form a time-space consistent record of on-the-ground changes

- Over-glow
 - Large pixel size (1000 times that of Landsat)
 - Reflectance from water etc
 - Allocation errors at extremities of the scan arc
- No record of signal amplification
 - To get similar illumination of clouds the signal is amplified as move out of the full moon phase and these changes not recorded in the data → DN may not map to same lighting but hopefully for stable (non-ephemeral) lights averages out
- Despite these weaknesses, a comparison with Landsat estimates of city core area for China gives $r=0.86$

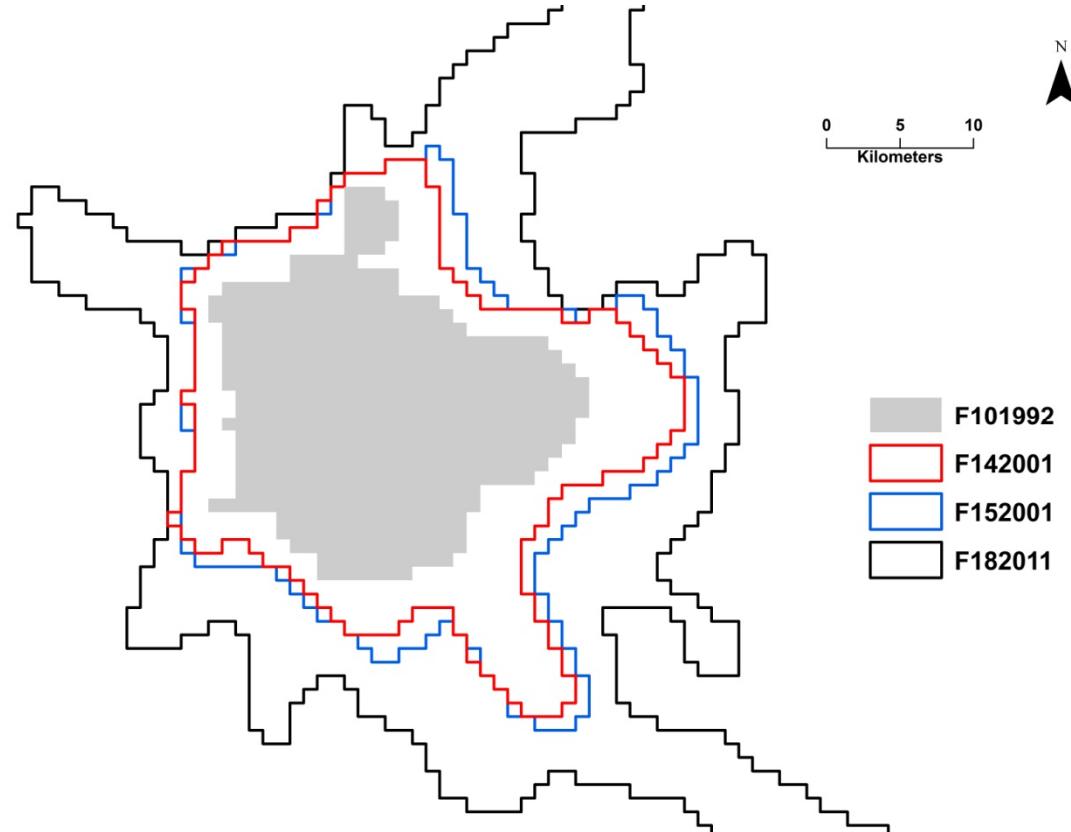
(Idiosyncratic) Features of DMSP Use Here

- Consider lit area separate from average Digital Number (DN) values within lit area
 - Also combine the two using “sum of lights” approach
 - split reflects DMSP measurement features as well as possible relevance of intensive margin versus extensive margin growth
- Average over all satellite-years in data window matched to timing of NSS thick rounds
- Use multiple thresholds of DN values (in % of max DN for semantic reasons) to look for robust patterns
 - 50% threshold (DN=32) to distinguish big cities from others (40% and 60% gave similar trends in *Food Policy* paper)
 - 20% and 30% (DN 13 and 19) to distinguish smaller towns from non-urbanized areas – lots of different DN thresholds used in the literature but 20% similar to Small & Elvidge for Asia-wide

Inter-satellite comparability

- some satellites distribute measured light less intensely over wider area, others focus it into smaller area

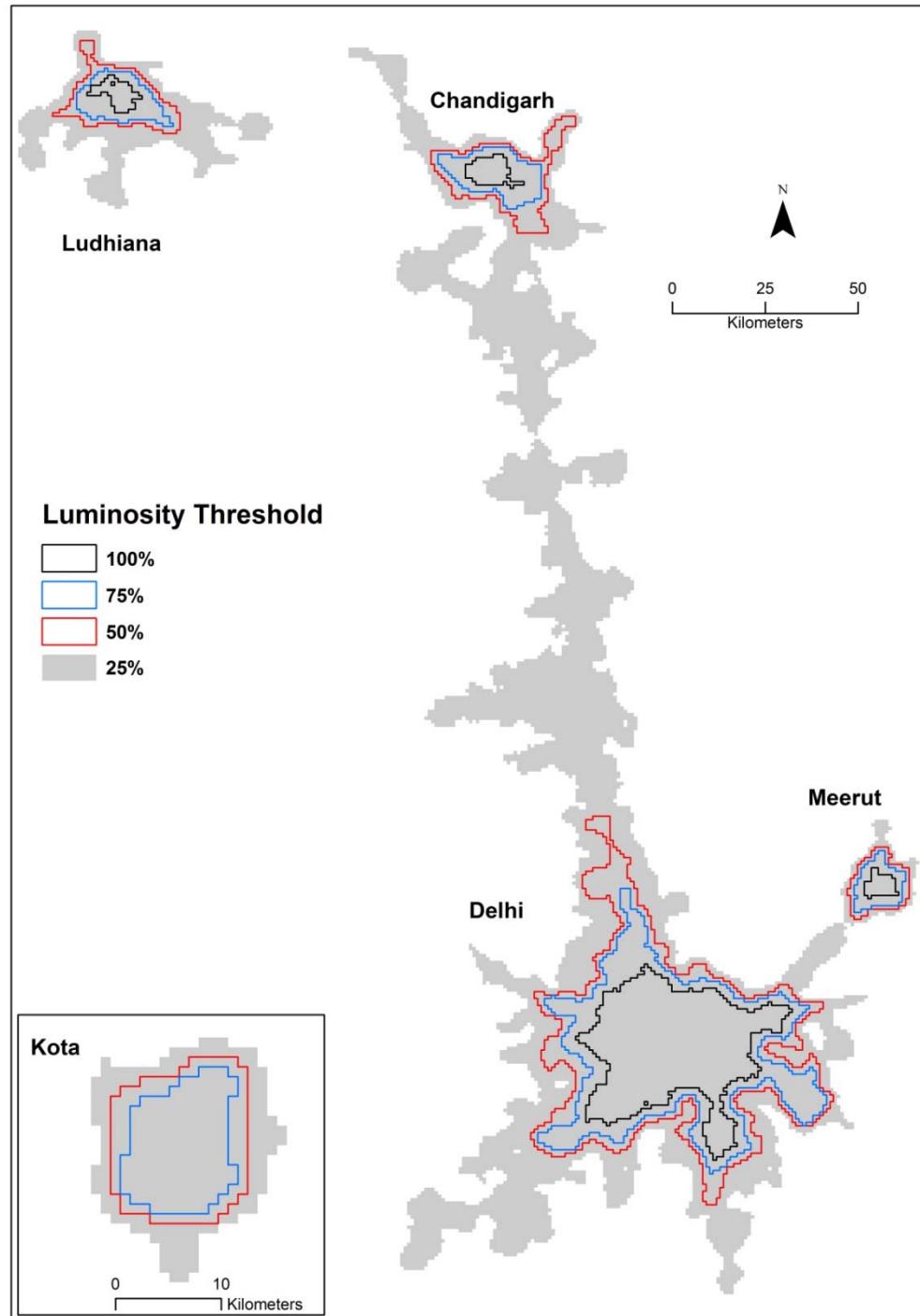
e.g. F15 in 2008 gave a China-wide DN value of 16.6 spread over 0.9m lit pixels, F16 in same year had DN of 10.7 but spread over 1.7m lit pixels



- Apparent area of Bangalore using a 50% luminosity threshold
- compare F14 and F15, both orbiting in 2001
- 85 km² difference in estimated area that year
- Discrepancy equivalent to 11% of mean
- ‘noise’ less than signal, of 300-400 km² growth from 1992 to 2001 and 900-1000 km² after 2001.

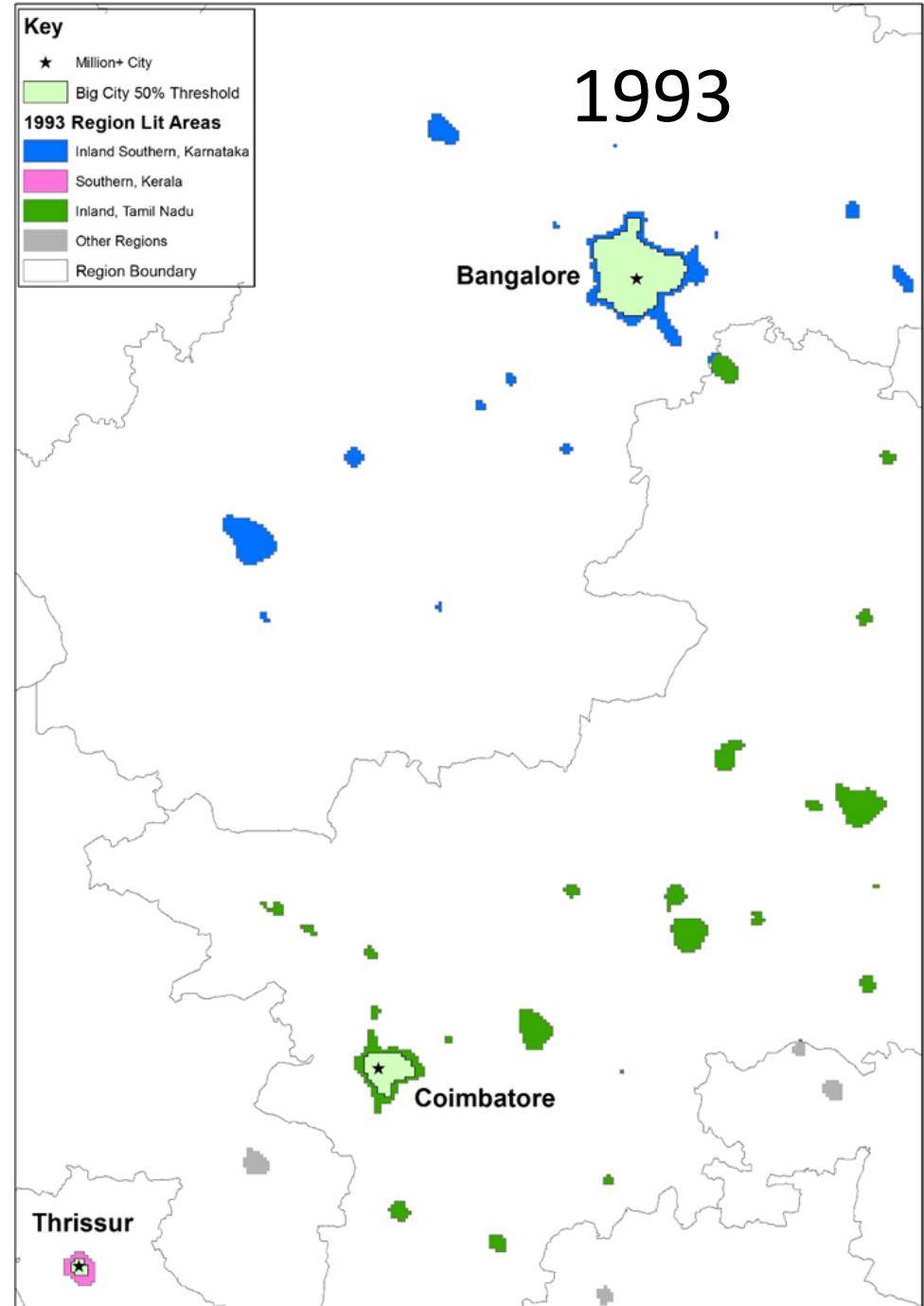
Threshold Choice

- Semantic but use % of max DN value for urban edge
 - Emphasize relative luminosity
- At low luminosity threshold, cities clump together along built-up corridors
 - E.g. for National Highway 1, from Delhi to Chandigarh (250km apart)
- At higher thresholds, less brightly-lit cities disappear
 - Kota (1 million) has no core at 100% brightness level



Splitting Urban Growth into Big City and Small Town Components (1)

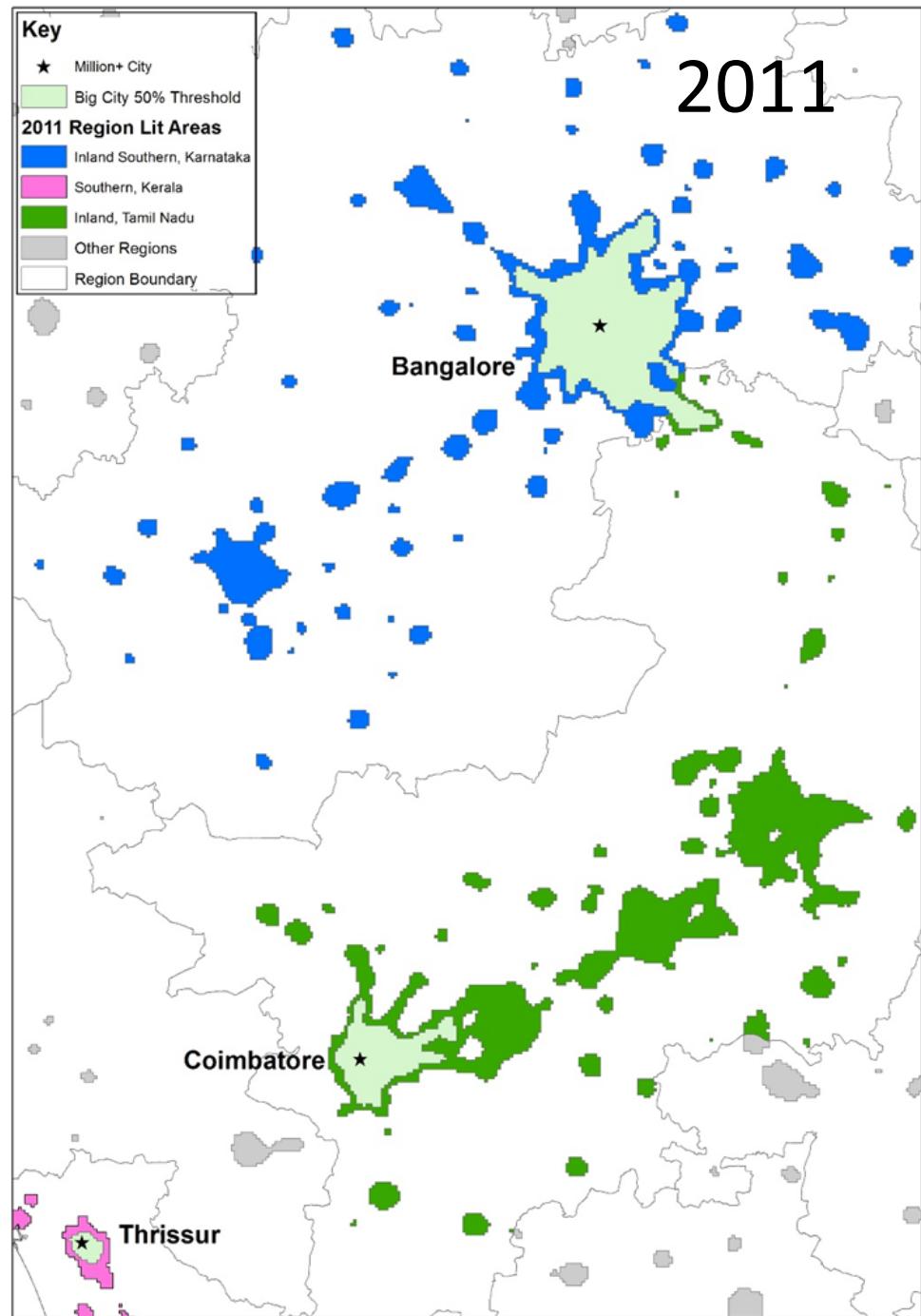
- big city area (and average DN) at 50% threshold calculated for every satellite-year
- area (and DN) within each NSS region lit at above 20% (or 30%) threshold, except for area already taken by the big city
- less brightly lit fringe of big city (or could be outlying small towns) allocated to the small town component



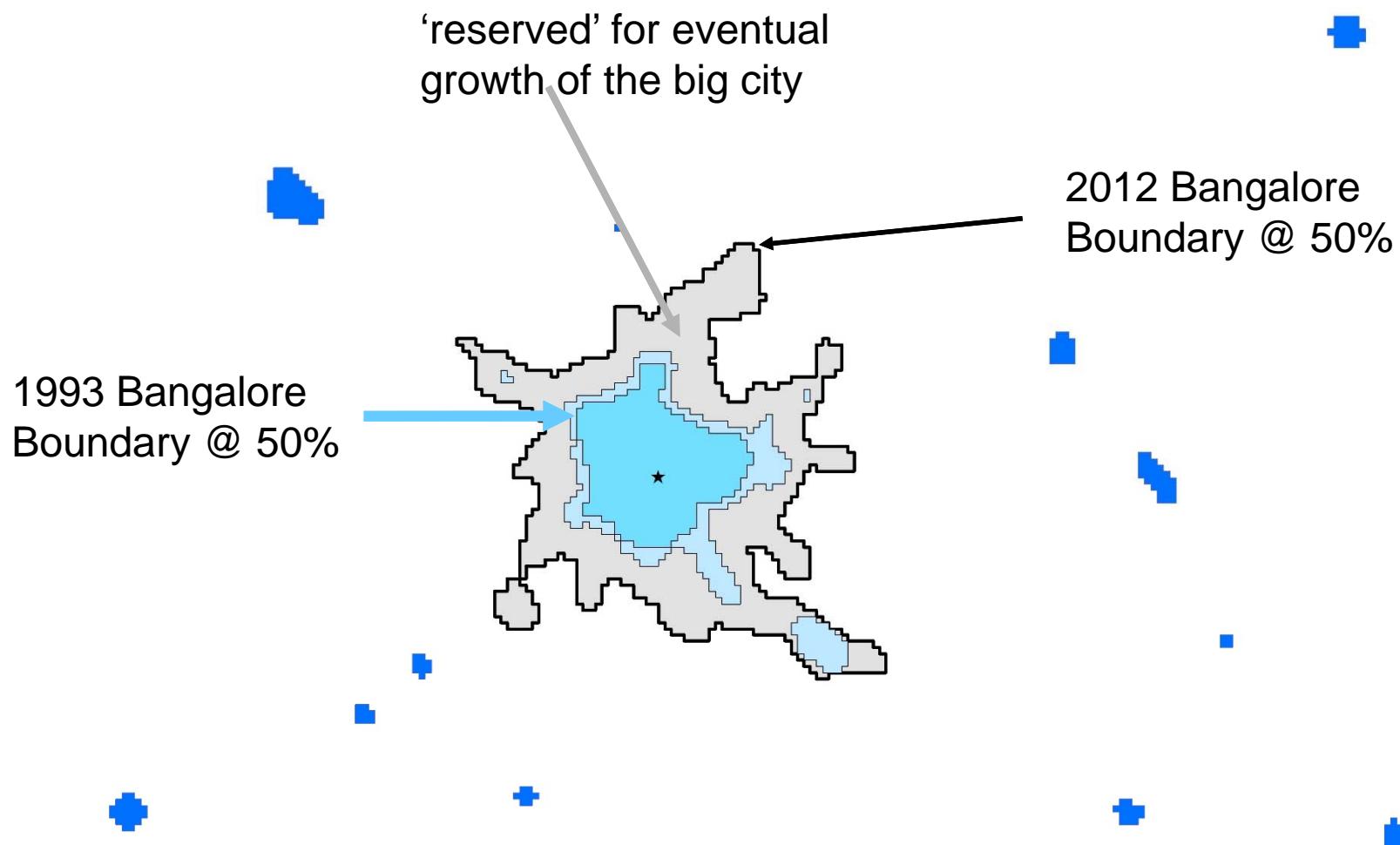
Splitting... (2)

Example

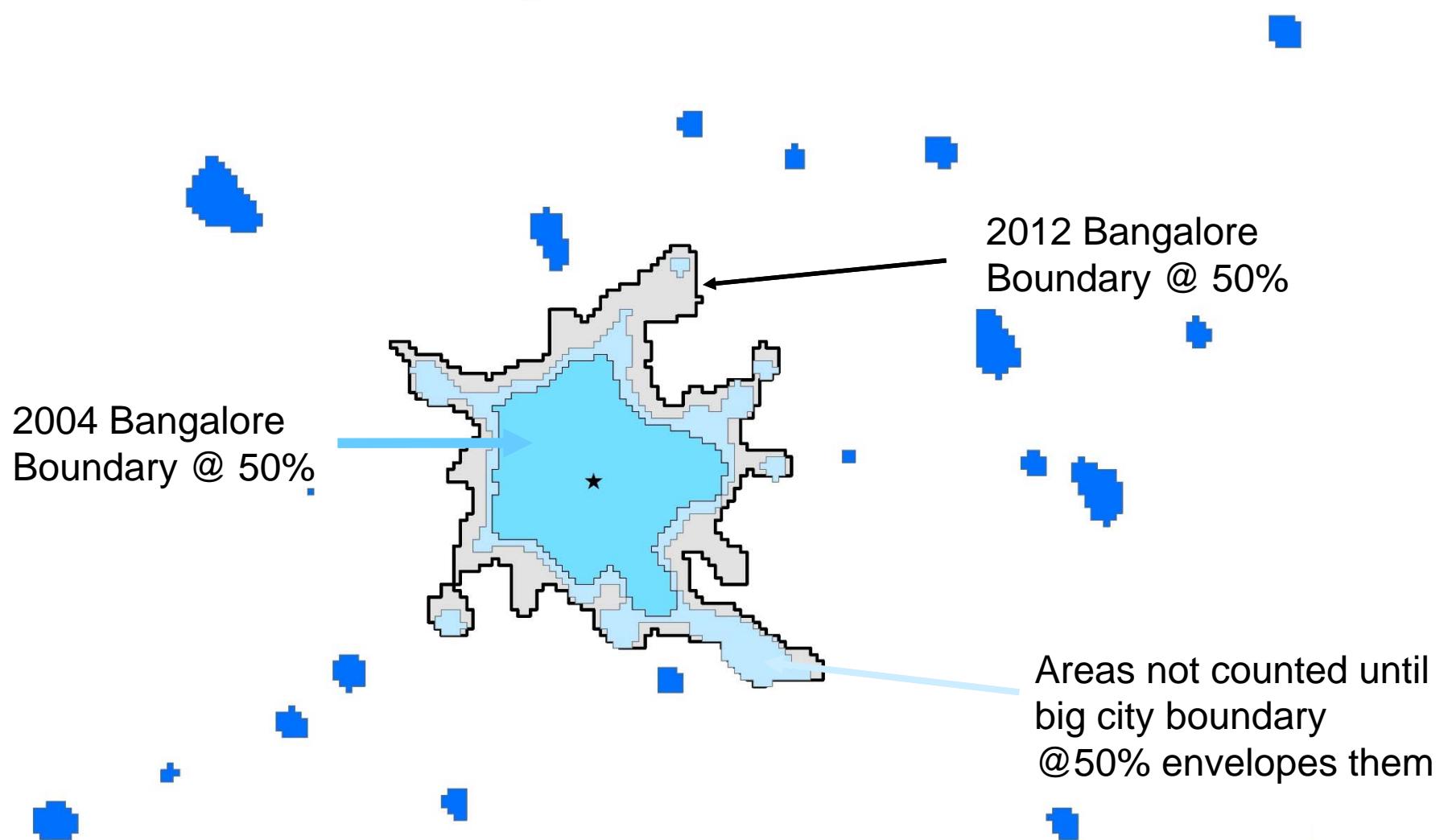
- Bangalore and Coimbatore both rapidly expanding big cities
 - 4.9% and 4.6% per annum
- more of overall urban area expansion in Inland Southern Karnataka concentrated on Bangalore (35% of the total) compared to expansion of Inland Tamil Nadu (where Coimbatore contributed 12% of the total)
- further variation from differences between NSS regions in rates/types of urban growth (e.g. Thrissur slow growing but in a three-pole region)



Illustrating Fixed Mask Approach (1)



Illustrating Fixed Mask Approach (2)



Overview of the Results

- expansion of lit urban area is closely associated with declines in rural poverty
 - Especially for the poverty gap index
 - No similar relationship for average DN values
 - Doesn't depend on threshold for small town versus rural, or how treat spatial autocorrelation
- Expansion of lit area for secondary towns has larger effect than big city expansion, when focus within NSS regions and on boundaries
 - Using buffers increases big city effect

Rural headcount poverty responds to the extensive margin of urban growth

Table 3: Total Effects from Spatial Autoregressive Models for the Effects of Unmasked Regional Lights (at 20% threshold) on Rural Poverty Rates for NSS Regions From 1993/94 to 2011/12

	Headcount Poverty Rate – Rural Sector			
	(1)	(2)	(3)	(4)
Lit area in the NSS region	-0.621 (9.61)***		-0.623 (9.91)***	
Average DN within lit areas		5.242 (1.61)	-0.074 (0.07)	
Sum of lights (lit area × average DN)				-0.631 (9.63)***
Rho	0.700 (9.68)***	0.925 (45.44)***	0.699 (9.59)***	0.699 (9.64)***
Lambda	-0.624 (3.92)***	-0.857 (7.21)***	-0.622 (3.90)***	-0.622 (3.92)***
R^2 (overall)	0.418	0.122	0.410	0.380

Total effects from SAR model are ca. one-third direct and two-thirds indirect

Rural poverty gap index also responds to the extensive margin of urban growth

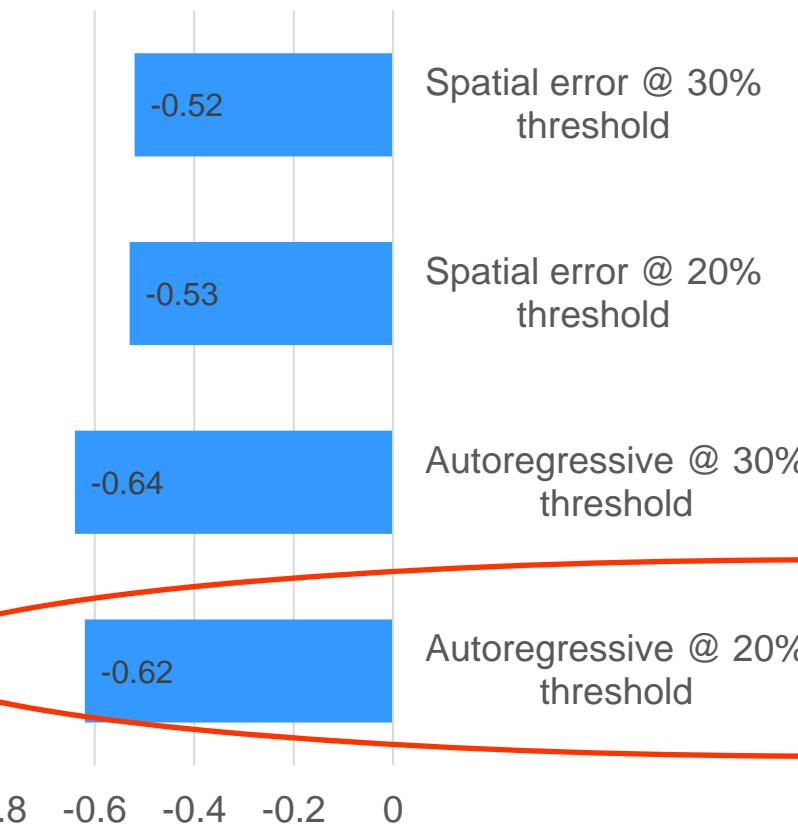
Table 3: Total Effects from Spatial Autoregressive Models for the Effects of Unmasked Regional Lights (at 20% threshold) on Rural Poverty Rates for NSS Regions From 1993/94 to 2011/12

	Poverty Gap Index – Rural Sector			
	(1)	(2)	(3)	(4)
Lit area in the NSS region	-0.882 (9.65)***		-0.906 (10.30)***	
Average DN within lit areas		4.346 (1.00)	-1.255 (0.88)	
Sum of lights (lit area × average DN)				-0.899 (9.91)***
Rho	0.703 (9.92)***	0.928 (46.23)***	0.693 (9.56)***	0.693 (9.54)***
Lambda	-0.612 (3.84)***	-0.839 (6.89)***	-0.602 (3.78)***	-0.602 (3.76)***
R^2 (overall)	0.362	0.136	0.306	0.324

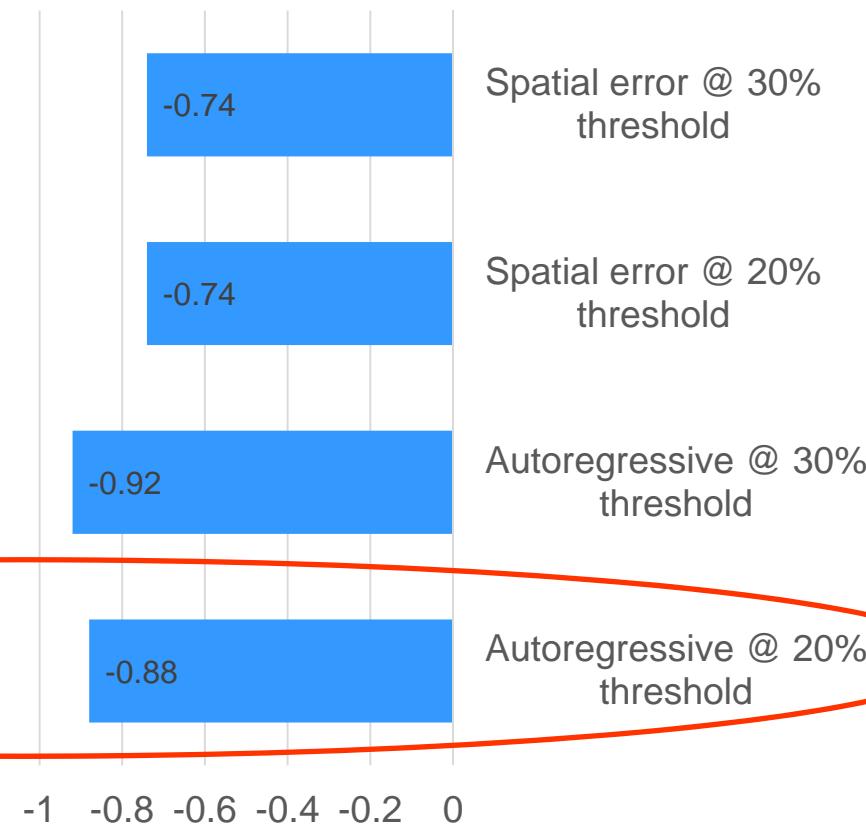
Same patterns are apparent if using 30% luminosity threshold, or using spatial error model

Robust to other thresholds for urban-rural edge and to different spatial models

Effect of Urban Area on Headcount Poverty Rate

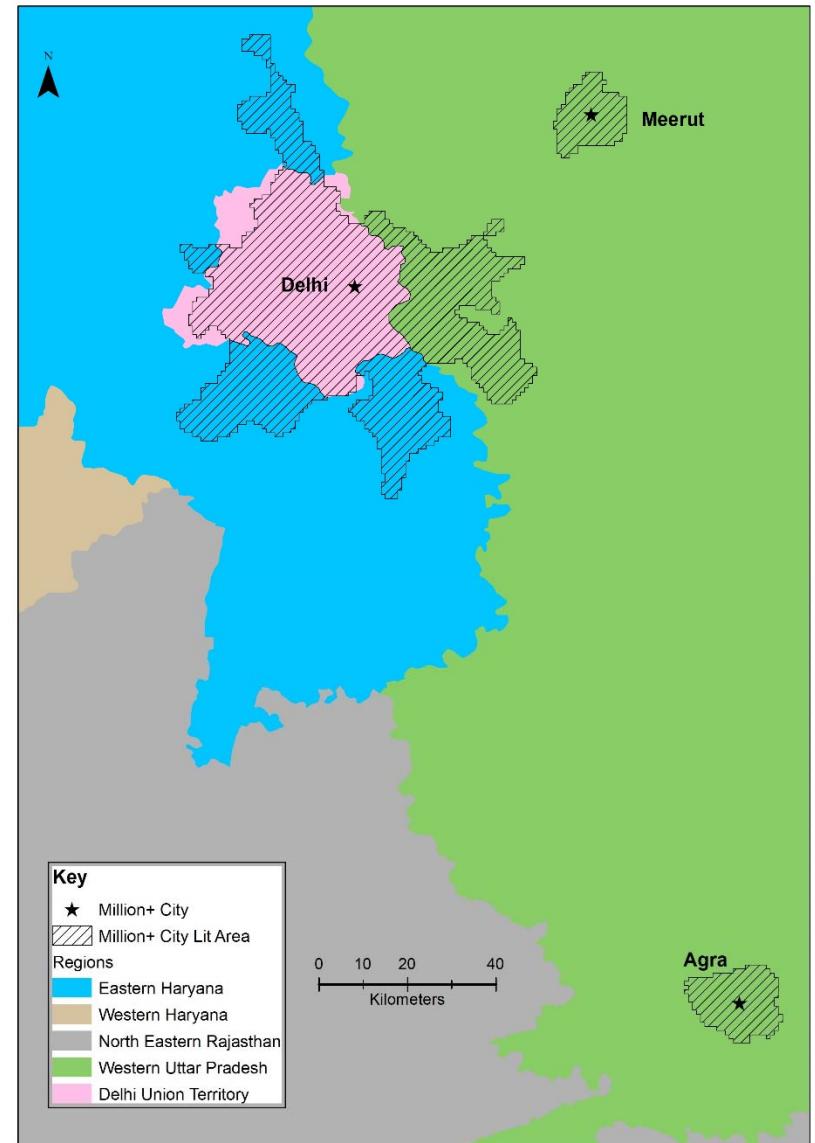


Effect of Urban Area on Poverty Gap Index



Comparing effects of big city and secondary town growth

- (part) of the big city within each NSS region
- Union of the NSS region and any big city within or intersecting the NSS boundary
 - Some parts of the big city get counted twice
- Including big cities in the 50km (100km) buffer



Effects of big city and secondary town area expansion on rural headcount poverty rate

Table 4: Total Effects from Spatial Autoregressive Models for the Effects of Big City Lights versus Smaller City Lights on Rural Poverty Rates for NSS Regions From 1993/94 to 2011/12 (at 20% threshold)

	Headcount Poverty Rate – Rural Sector			
	(1)	(2)	(3)	(4)
Big city area within NSS region	-0.068 (0.65)			
Big city area union with NSS region		-0.419 (1.99)**		
Big city area within 50km of region			-0.469 (2.35)**	
Big city area within 100km of region				-0.388 (1.88)*
Lit area in remainder of NSS region	-0.567 (6.29)***	-0.419 (3.93)***	-0.364 (3.22)***	-0.364 (2.63)***
Rho	0.701 (9.75)***	0.655 (7.79)***	0.624 (6.40)***	0.648 (7.39)***
Lambda	-0.626 (3.92)***	-0.566 (3.29)***	-0.523 (2.78)***	-0.578 (3.40)***
R^2 (overall)	0.412	0.247	0.160	0.188

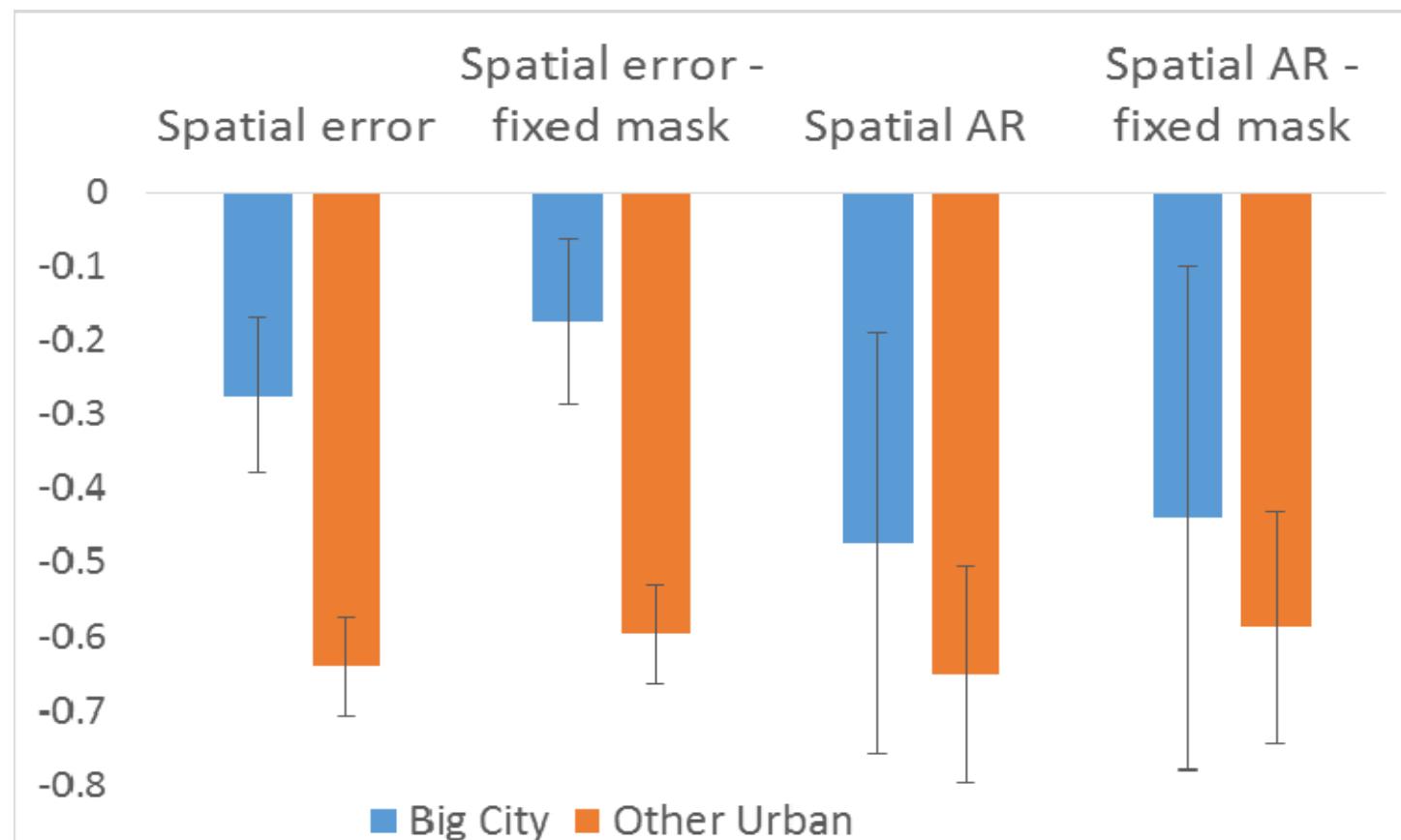
Effects of big city and secondary town area expansion on rural poverty gap index

Table 4: Total Effects from Spatial Autoregressive Models for the Effects of Big City Lights versus Smaller City Lights on Rural Poverty Rates for NSS Regions From 1993/94 to 2011/12 (at 20% threshold)

	Poverty Gap Index – Rural Sector			
	(1)	(2)	(3)	(4)
Big city area within NSS region	-0.003 (0.02)			
Big city area union with NSS region		-0.474 (1.63)		
Big city area within 50km of region			-0.604 (2.17)**	
Big city area within 100km of region				-0.647 (2.31)**
Lit area in remainder of NSS region	-0.865 (6.90)***	-0.651 (4.35)***	-0.550 (3.46)***	-0.456 (2.43)**
Rho	0.705 (9.98)***	0.671 (8.53)***	0.640 (7.16)***	0.636 (7.26)***
Lambda	-0.609 (3.80)***	-0.578 (3.48)***	-0.540 (3.04)***	-0.567 (3.38)***
R^2 (overall)	0.386	0.219	0.115	0.112

Robust to different masking approach and to different spatial models

Elasticity of Rural Poverty Gap Index w.r.t. City Area

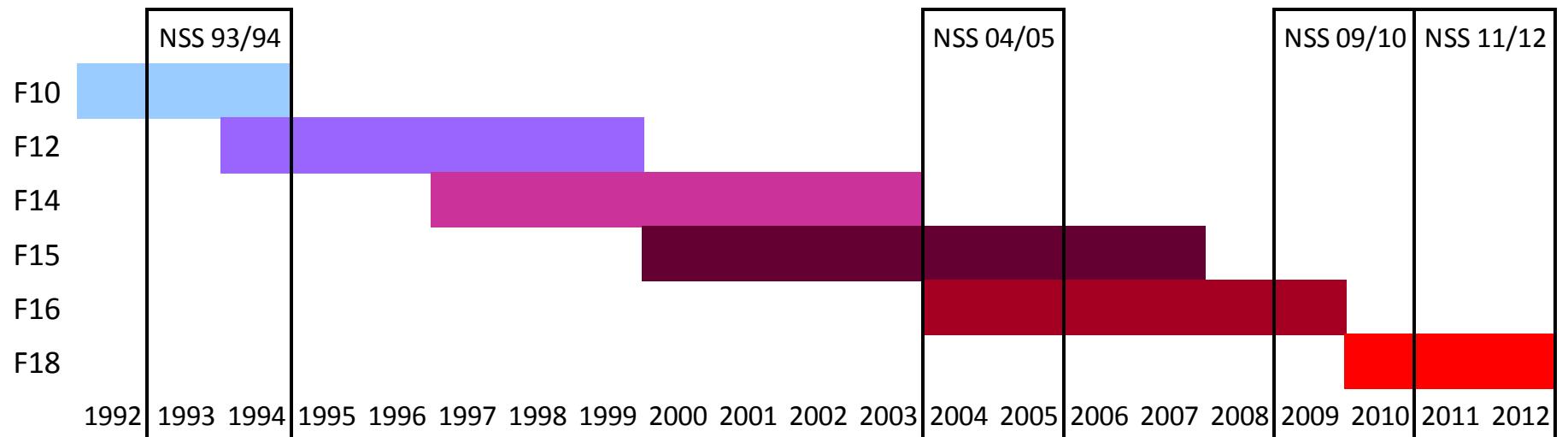


Next Steps (1)

- IV approach to reduce threat that it is reductions in rural poverty that are causing the estimated effects of urban growth on poverty
 - Or omitted factors causing both
- Height restrictions that vary by city or floor area ratio as a possible IV for city expansion
 - Brueckner and Sridhar (2012) results suggest there will be a strong first stage

Next Steps (2)

- Use satellite fixed effects to adjust lights before averaging
 - Elsewhere I find that satellite effects matter more than year effects: satellite effects stat sig for 156/179 countries c.f. year effects in only 133/179, and 75% of countries have smaller *p*-value on satellites than on years (ditto at sub-national level for Indonesia)
- With our limited windows of overlap with NSS thick round timing it may not matter as much



Thank you for listening

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