Landmine Clearance & Economic Development

Evidence from Nighttime Lights, Multispectral Satellite Imagery, and Conflict Events in Afghanistan

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Motivation

- Wars end, but landmines remain
  - In 2021, over 100 million landmines remained in over 60 countries
- Landmines threaten lives and health (Frost et al. 2017)
- Landmines also limit:
  - The flow of people and goods
  - Productive use of contaminated and surrounding land
- Mines cost $3-$30 each, but removal costs $300-$1000
  - Even with no new mines planted, full worldwide clearance would take >1000 years
  - Recent rates of removal of 100,000-200,000, while >2M planted annually
- These constraints lead to targeting and prioritization debates

Prior literature

- Arcand, Rodella-Boitreaud, & Rieger (2015) in Angola
  - Cross-sectional evidence using IV
  - Suspected hazardous areas reduce child height and weight
- Merrouche (2008, 2011) in Mozambique and Cambodia
  - IV of distance to strategic borders, combined with age trends
  - Landmine intensity associated with greater poverty, lower consumption and education
- Chiovelli, Michalopoulos, and Papaioannou (2021) in Mozambique
  - By collecting comprehensive data on clearance location and timing, able to use panel design
  - Use nighttime lights to proxy for economic activity
  - Clearance of transport corridors and major hubs has large effects; effects in rural areas limited

Gaps in the literature

- Only one published study with panel design for identification, but this study only uses NTL, so does not identify effects in rural areas well
- Prior studies look at post-conflict settings, but many clearance efforts are in areas with continued conflict
- Although clearance allows new uses of land, no studies with land use as outcome

Our contributions

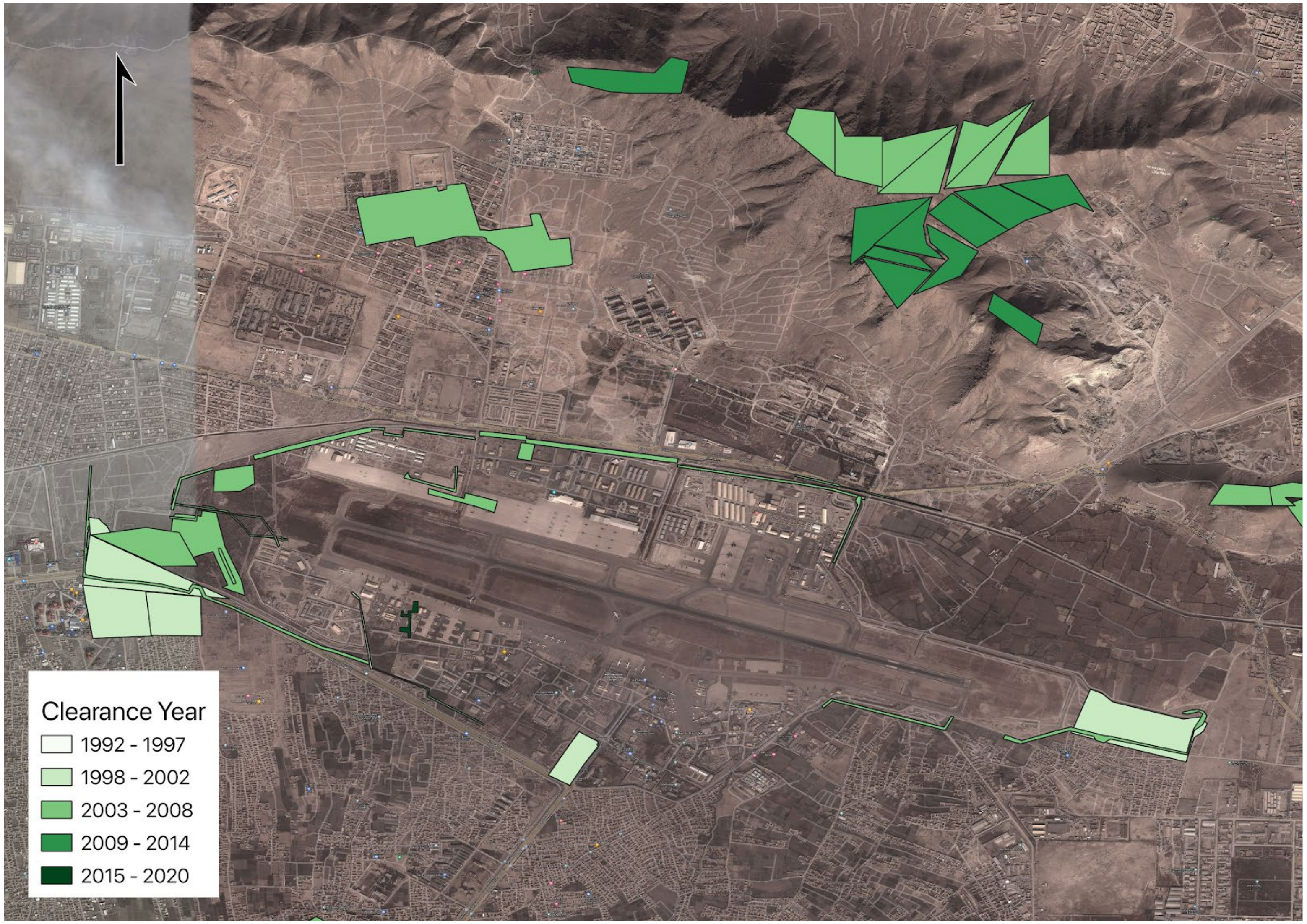
- We obtain a comprehensive, long-term, spatially precise dataset on hazardous area clearance in Afghanistan
- We combine this with not only NTL but also much finer resolution daytime satellite imagery reflecting changes in urban, peri-urban, and rural settings
  - Unlike Chiovelli et al, we find some of the largest effects in non-urban areas
  - We can examine very micro-scale
- We consider clearance in a setting with ongoing conflict
- We consider land use as an outcome
  - We find that clearance allows for more built-up uses even in remote areas

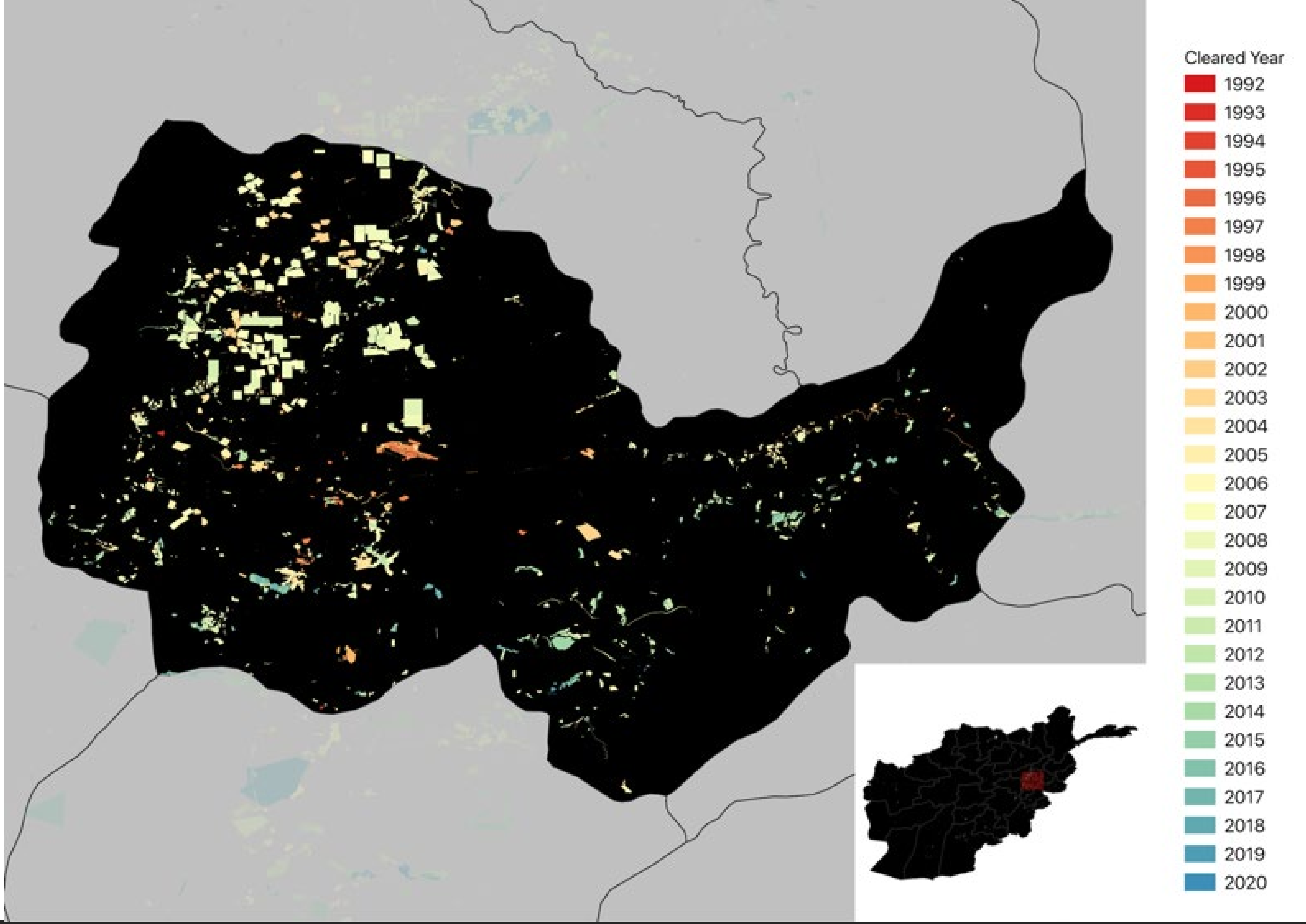
Context: Afghanistan Mine Action

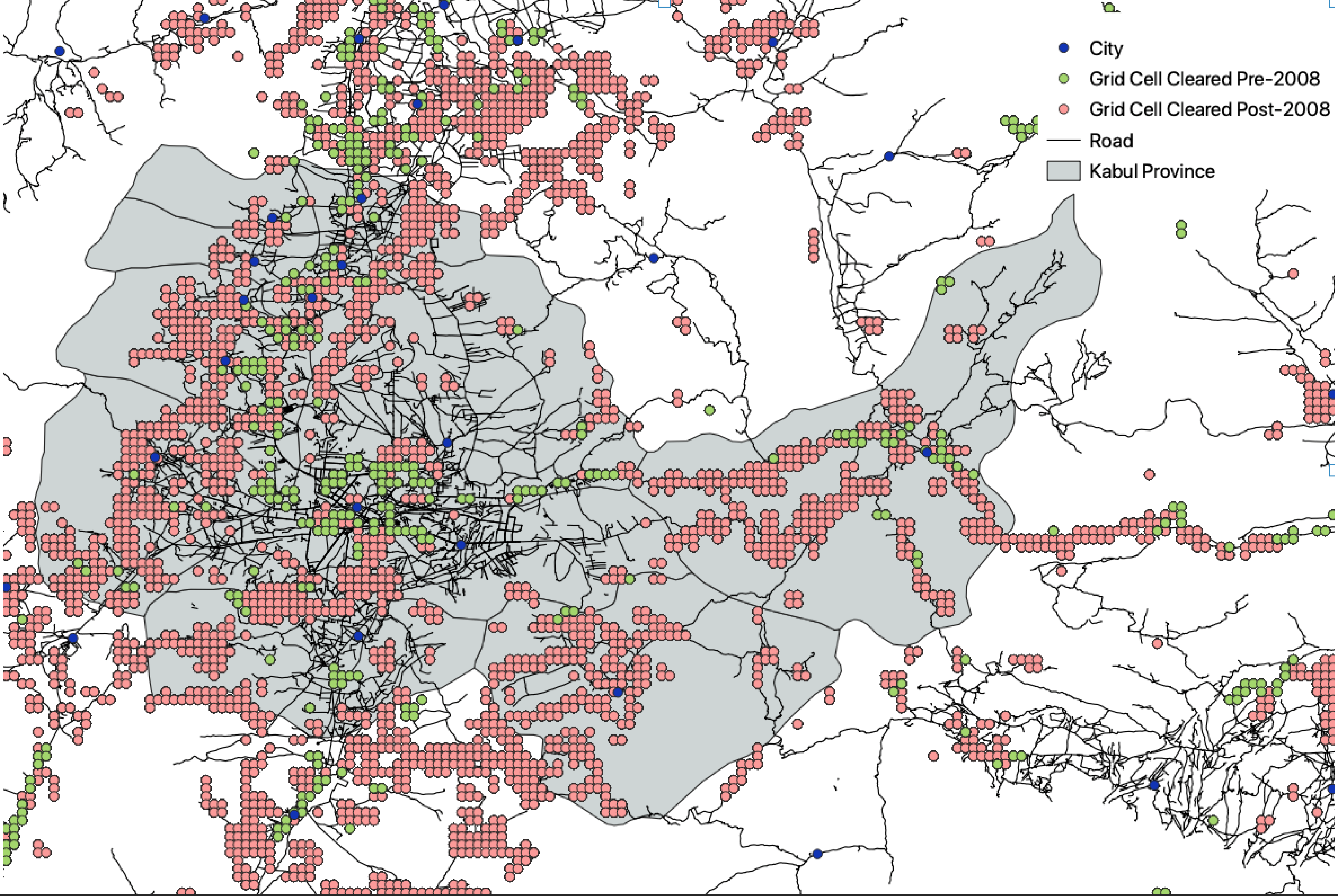
- 1979 Soviet invasion triggers decades of conflict
- After 1989 departure of Soviet forces, international community begins Mine Action Programme for Afghanistan (MAPA)
- 1989 – 2007: slow, sometimes faltering build-up of MAPA, largely with international actors
- In 2007, key reforms:
  - Prioritization of local staff and regionalization
  - Rapid scale-up of operations and funding
  - As a result, clearance reaches many more areas

Treatment data

- Provided by Directorate for Mine Action Coordination (DMAC)
- 17,913 georeferenced landmine-related hazard sites
- Each polygon represents an area with positive evidence of landmine contamination
- Precise hazard boundaries
- Exact dates for clearance status changes
- Blockage type




Cleared Year
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020

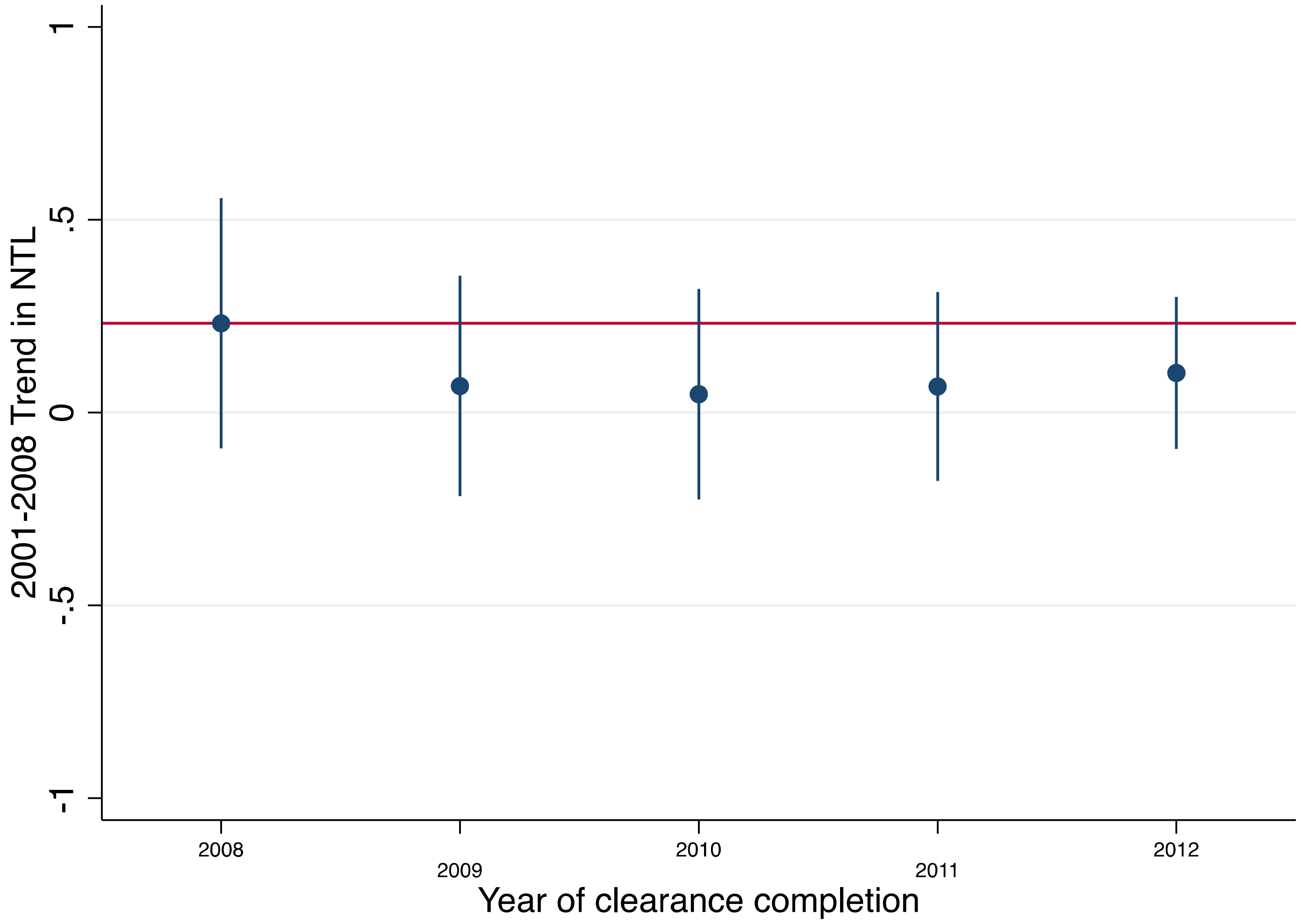

City
Grid Cell Cleared Pre-2008
Grid Cell Cleared Post-2008
Road
Kabul Province

Causal identification

- Quasi-random roll-out of clearance activities
- Difference-in-difference with two-way fixed effects
  - Cell or hazard FEs
  - Province*year FEs
  - Relies on parallel counterfactual trends in cleared vs. not-yet-cleared cells

$$Y_{jpt} = \alpha + \beta Cleared_{jpt} + D_j + D_{pt} + \epsilon_{jpt}$$

- Recent literature shows this can be biased if dynamic/heterogeneous treatment effects exist (de Chaistemartin & D'Haultefoeuille 2020, Callaway & Sant'Anna 2021)
  - We also adopt their alternative estimators



2001-2008 Trend in NTL
1
.5
0
-.5
-1
2008
2009
2010
2011
2012
Year of clearance completion

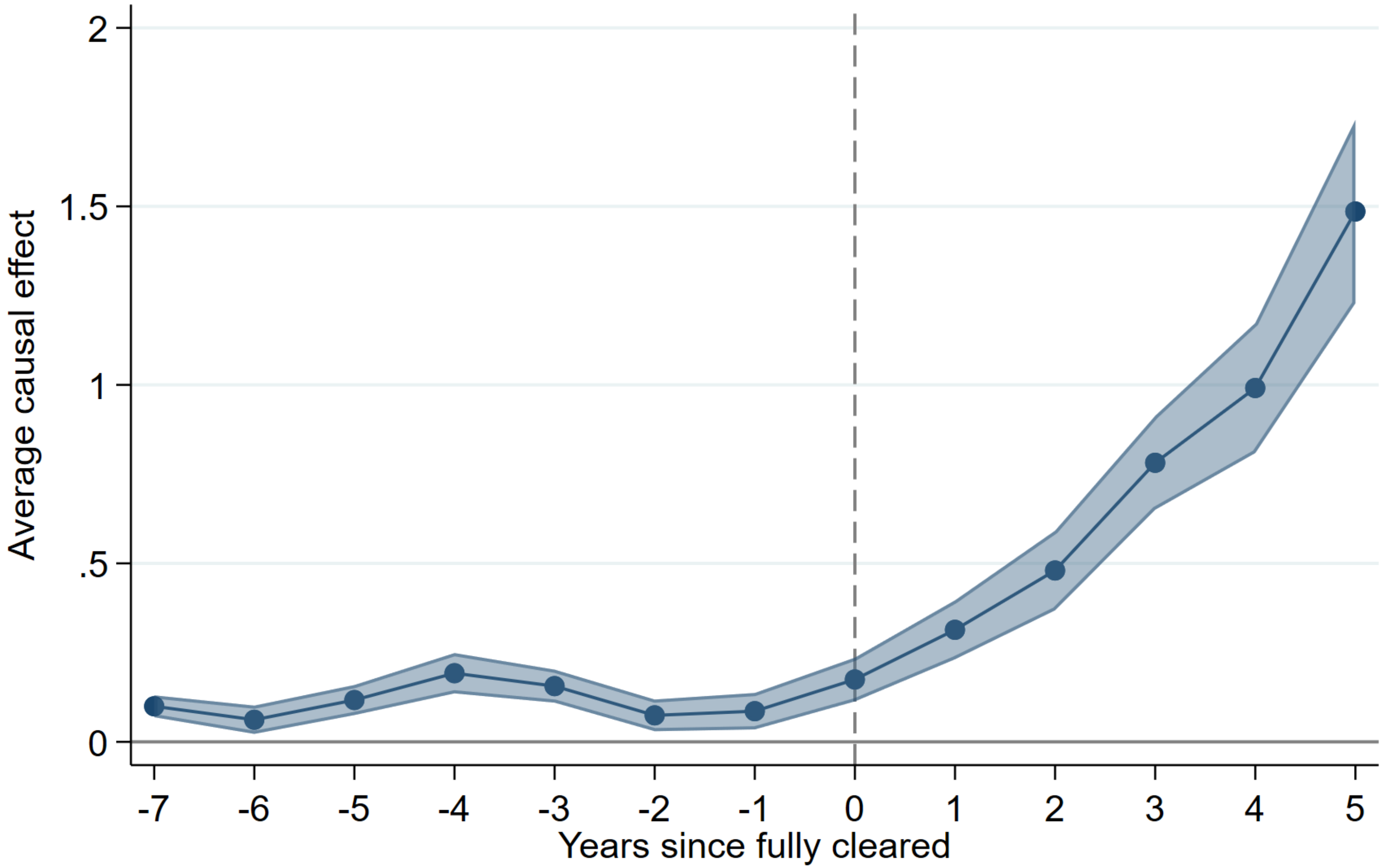
Impacts on nighttime lights

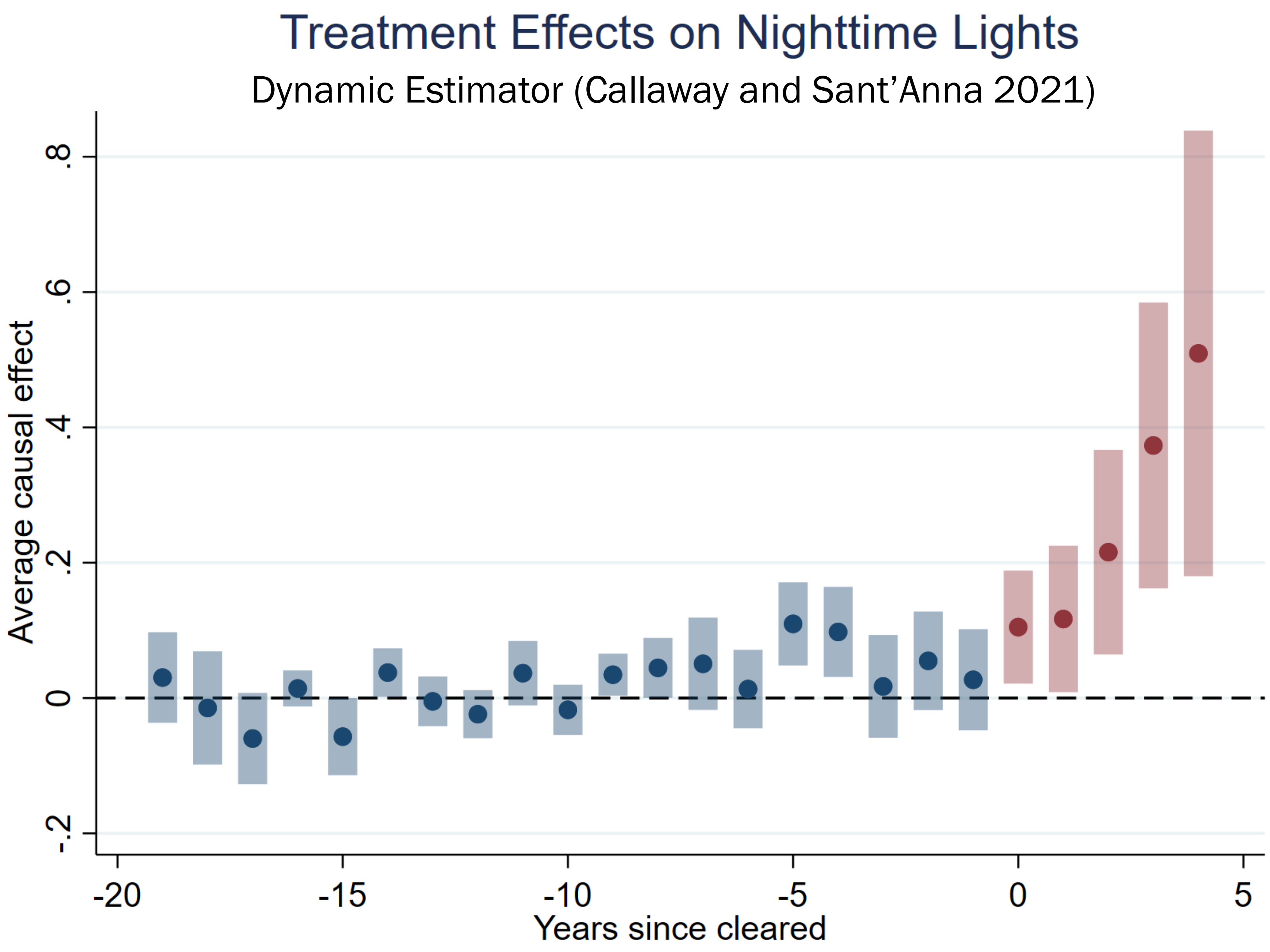
DV=Nighttime Lights	(1)	(2)	(3)
Cleared of Landmines	.699***	1.047***	0.0801
	(0.209)	(0.296)	(0.162)
Cleared * Dist. to Road		-0.230**	
		(0.0825)	
Cleared * Baseline Pop.			0.00220***
			(0.000538)
Observations	121,968	121,968	121,968
R-squared	0.627	0.629	0.646
Control Mean	0.459	0.459	0.459

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. All models include grid cell and province-year fixed effects, and are weighted by percent cell covered by hazardous area. Standard errors clustered by district and year in parentheses.

Treatment Effects on Nighttime Lights

Dynamic Estimator (de Chaisemartin and D'Haultfoeuille 2020)

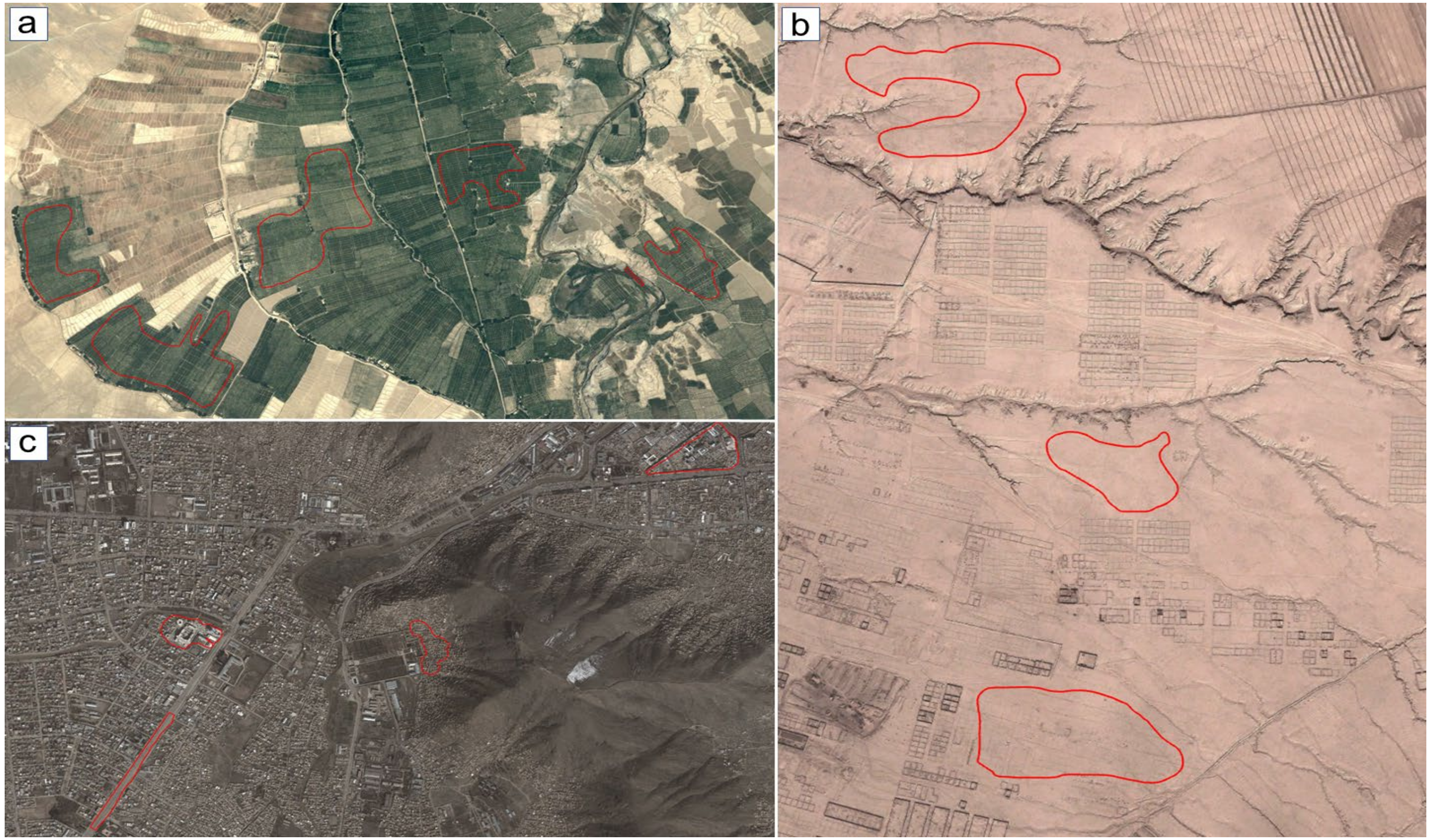


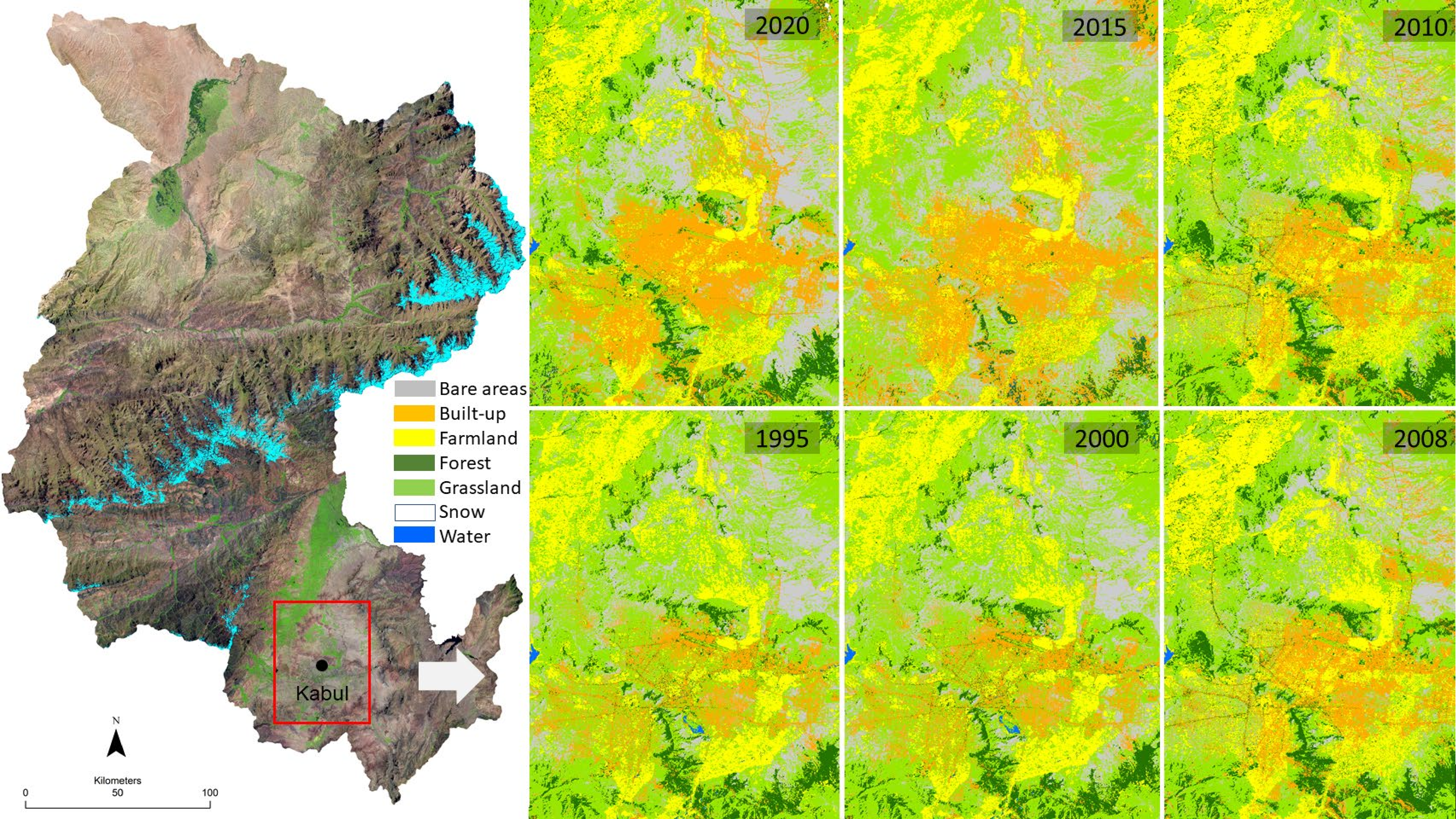

Treatment Effects on Nighttime Lights
Dynamic Estimator (Callaway and Sant'Anna 2021)
Average causal effect
.8
.6
.4
.2
0
-.2
-20
-15
-10
-5
0
5
Years since cleared

Beyond NTL: Land use data

- Land-use and land-cover (LULC) classification using visible + near-infrared from Landsat (30-m) imagery at five-year intervals from 1995-2020
- We visually inspect and classify training and testing sets
- We then implement Random Forest (RF) algorithms in Google Earth Engine (GEE)
  - Resulting overall accuracies are >83% for every period (and >90% for most recent)
- We focus on three provinces: Baghlan, Parwan, and Kabul

Training dataset examples




2020
2015
2010
1995
2000
2008
Bare areas
Built-up
Farmland
Forest
Grassland
Snow
Water
Kabul
N
Kilometers
0
50
100

Impact on built-up

DV = Pct. Built-Up	(1) All	(2) Grazing	(3) Agriculture	(4) Road	(5) Housing	(6) Infrastructure	(7) Water
Cleared	0.0227**	0.0212**	0.0326	0.0114	0.00983	-0.00398	0.0794**
	(0.00728)	(0.00756)	(0.0171)	(0.0122)	(0.0202)	(0)	(0.0293)
Observations	33,972	26,874	6,366	2,604	2,130	720	582
R-squared	0.656	0.664	0.641	0.649	0.684	0.702	0.740
Hazard FEs	Y	Y	Y	Y	Y	Y	Y
Year*Prov. FEs	Y	Y	Y	Y	Y	Y	Y
Pre-clearance builtup	.11	.104	.113	.101	.16	.308	.149

Column headings reflect blockage type subsamples
Standard errors in parentheses clustered by district and year
*** p<0.01, ** p<0.05, * p<0.1

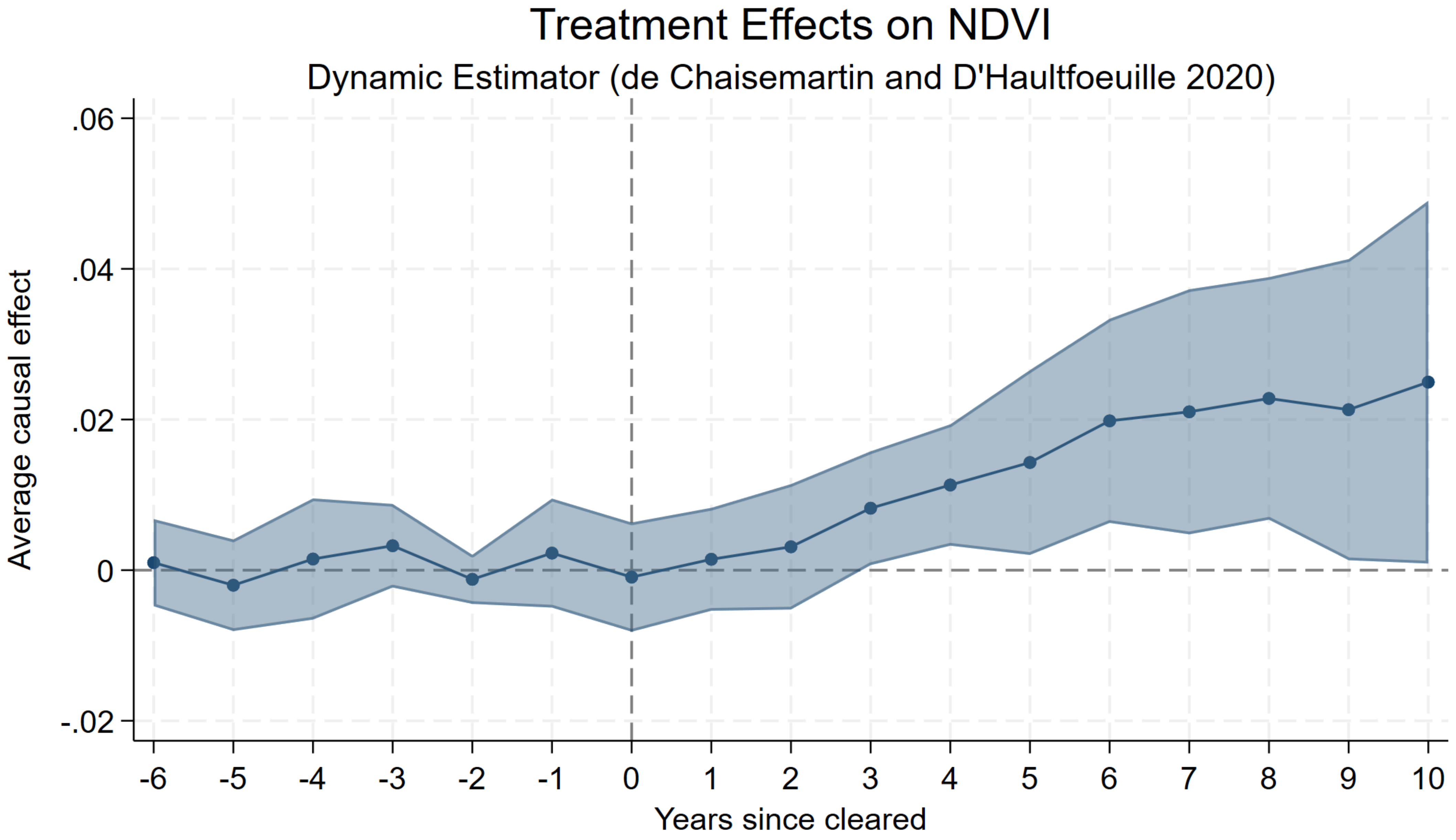
Impact on farmland

DV=Pct. Farmland	(1) All	(2) Grazing	(3) Agriculture
Cleared	-0.00488	-0.00236	0.00306
	(0.00553)	(0.00347)	(0.0119)
Observations	33,972	22,332	3,534
R-squared	0.657	0.605	0.702
Hazard FEs	Y	Y	Y
Year*Prov. FEs	Y	Y	Y

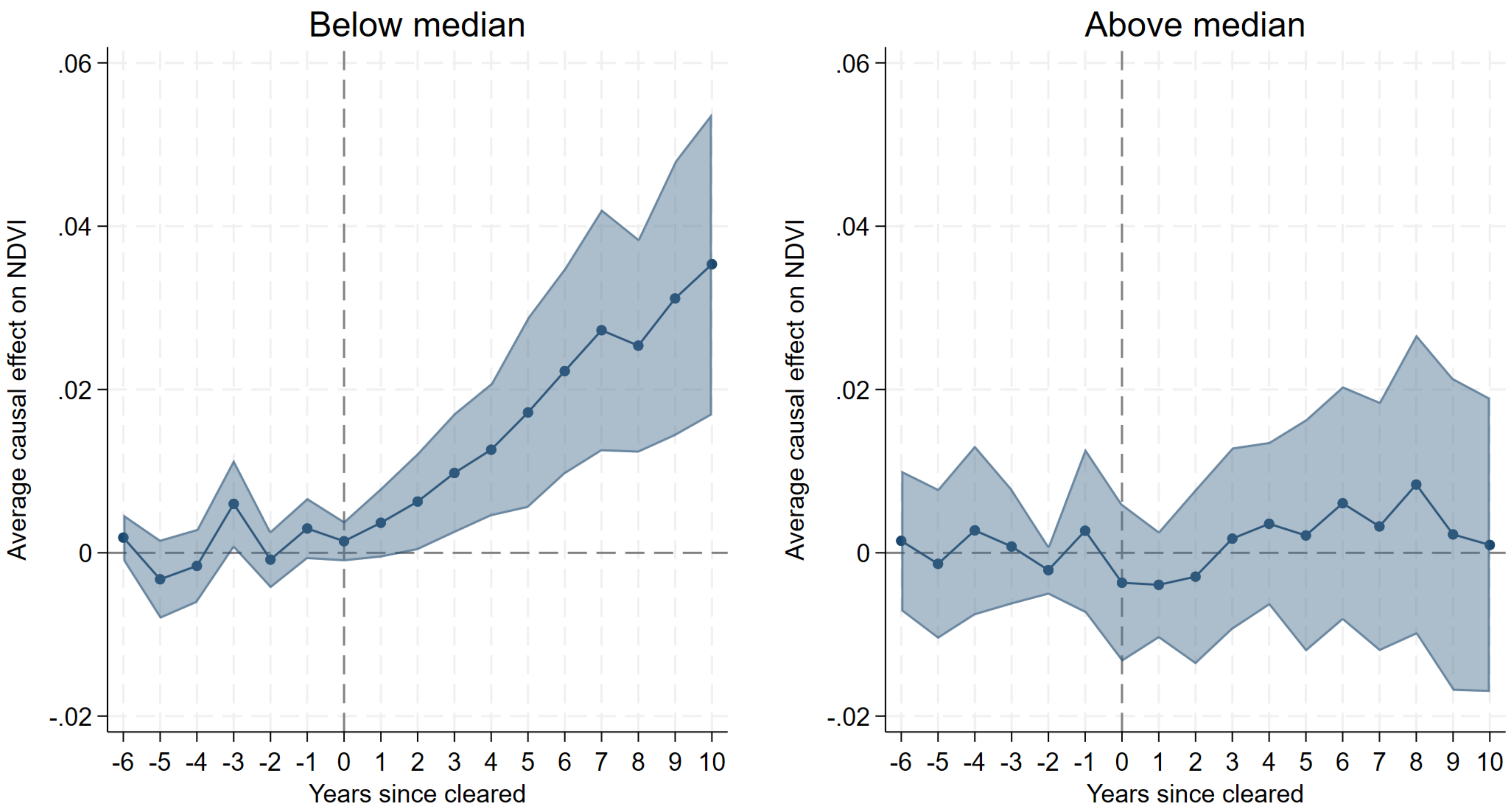
Column headings reflect blockage type subsamples
Standard errors in parentheses clustered by district and year
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Detecting farming intensity

- Land-use and land-cover (LULC) classification may not detect finer changes in farming
- Focus on hazardous areas identified as blocking agriculture uses by field teams
- Use 30-m Landsat normalized difference vegetation index (NDVI)
  - Widely used for staple crop productivity estimates, including in Afghanistan (BenYishay et al *EDCC forthcoming*)
- Identify the seasonal peak NDVI for each 30-m pixel, then aggregate to mean over each hazardous area X year
- Countrywide coverage of 4,122 hazardous areas X annual measures for 2005-2020


Treatment Effects on NDVI
Dynamic Estimator (de Chaisemartin and D'Haultfoeuille 2020)
Average causal effect
.06
.04
.02
0
-.02
-6
-5
-4
-3
-2
-1
0
1
2
3
4
5
6
7
8
9
10
Years since cleared

Treatment Effects by Baseline NDVI



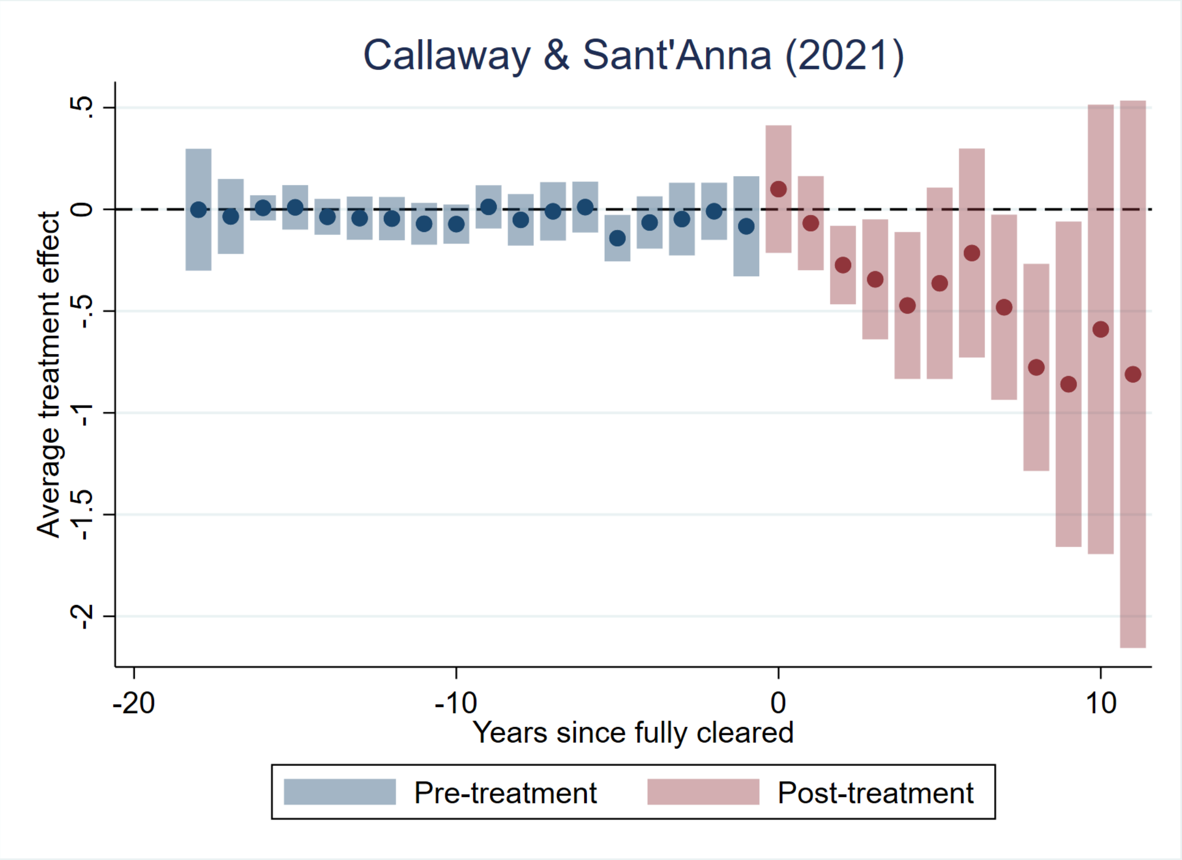
The role of conflict

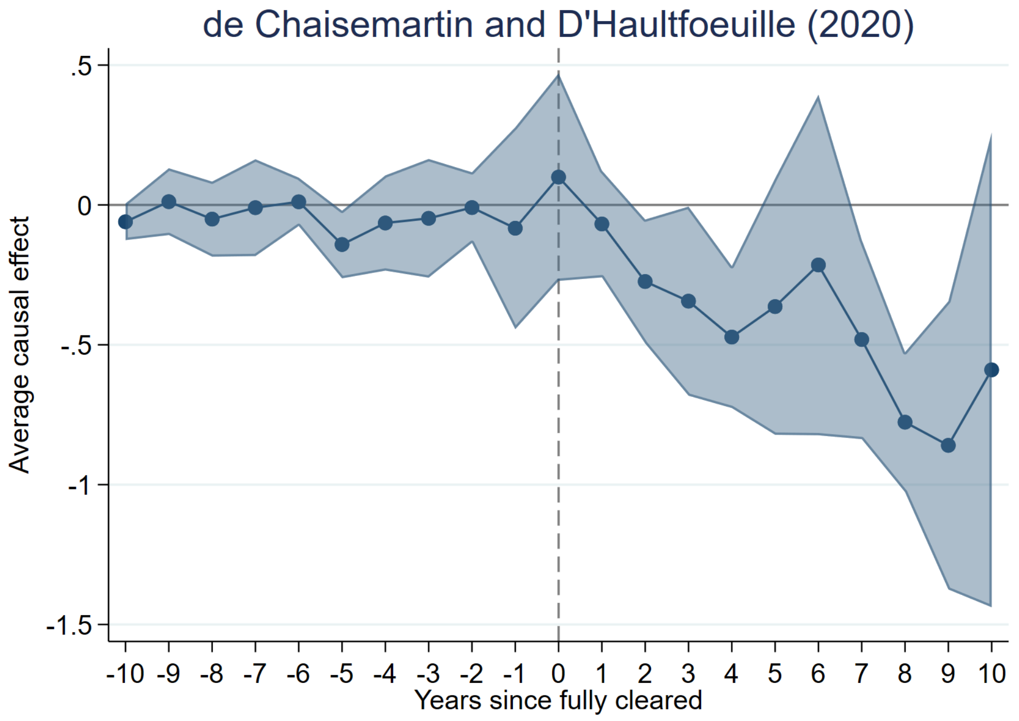
- Is clearance targeted on the basis of declining or worsening conflict?
- Does clearance reduce or increase conflict?
- Are effects on economic development heightened or dampened by conflict?

We use Uppsala Conflict Data Program (UCDP)

- Geocoded data on individual events of organized violence (state-based armed conflict, non-state conflict, or one-sided violence)
- 10km grid cells

Impact on conflict





Heterogeneous effects: NTL

High Baseline Conflict

	(1) NTL	(2) NTL	(3) NTL
Cleared of Landmines	1.210***	1.195***	0.508
	(0.416)	(0.400)	(0.450)
Conflict (5km)		-0.143**	-0.168***
		(0.0607)	(0.0469)
Cleared * Conflict(5km)			0.330**
			(0.104)
Observations	34,738	34,738	34,738
R-squared	0.734	0.741	0.745
Year FEs	N	N	N
Grid Cell FEs	Y	Y	Y
Year*Prov. FEs	Y	Y	Y

Standard errors in parentheses clustered by district and year
Weighted by percent cell covered by hazardous area.
*** p<0.01, ** p<0.05, * p<0.1

Low Baseline Conflict

	(1) NTL	(2) NTL	(3) NTL
Cleared of Landmines	.458***	.465***	.446***
	(0.158)	(0.159)	(0.157)
Conflict (5km)		-0.0763**	-0.138**
		(0.0351)	(0.0664)
Cleared * Conflict (5km)			0.0960
			(0.0783)
Observations	87,230	87,230	87,230
R-squared	0.572	0.572	0.573
Year FEs	N	N	N
Grid Cell FEs	Y	Y	Y
Year*Prov. FEs	Y	Y	Y

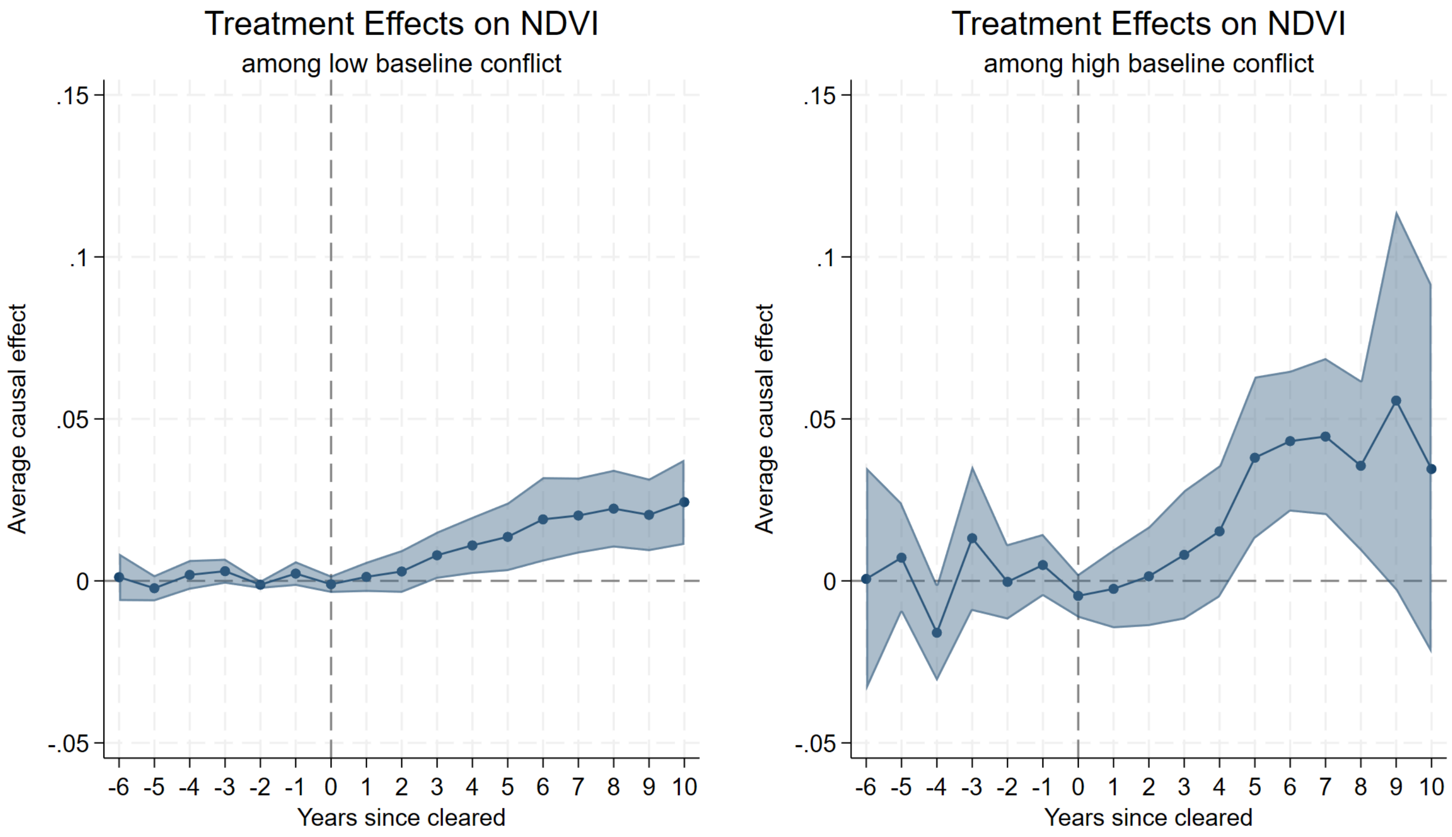
Standard errors in parentheses clustered by district and year
Weighted by percent cell covered by hazardous area.
*** p<0.01, ** p<0.05, * p<0.1

Heterogeneous effects: Built-up

	(1) Built-Up (High Conflict)	(2) Built-Up (Low Conflict)
Cleared	0.0289*	0.0158**
	(0.0117)	(0.00465)
Conflict (2km)	0.00712***	-0.0113*
	(0.00118)	(0.00426)
Cleared x Conflict (2km)	0.00372	0.000737
	(0.00806)	(0.0189)
Observations	4,950	23,350
R-squared	0.621	0.643

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Heterogeneous effects: NDVI



Conclusions

- Landmine clearance has large impact on nighttime lights, built-up land use, and NDVI in a setting with ongoing conflict
- We find large impacts even in rural areas, suggests more equitable targeting warranted
- Clearance impacts are detectable in both high and low conflict conditions, but strongest in high conflict areas