Supplementary information. The implementation is provided in the GitHub repository accompanying this paper. Other urban scales for the existing cities can be run out of the box by following the instructions provided in the `readMe`. For new cities, data needs to be collected using the Here API. The OSM is readily collected on the fly. The code is optimised with end-to-end results for one city-scale being generated in approximately 5 hours on an 8-core 2.3 GHz machine. Different cities can be run in parallel using a shell script depending on the number of available cores.

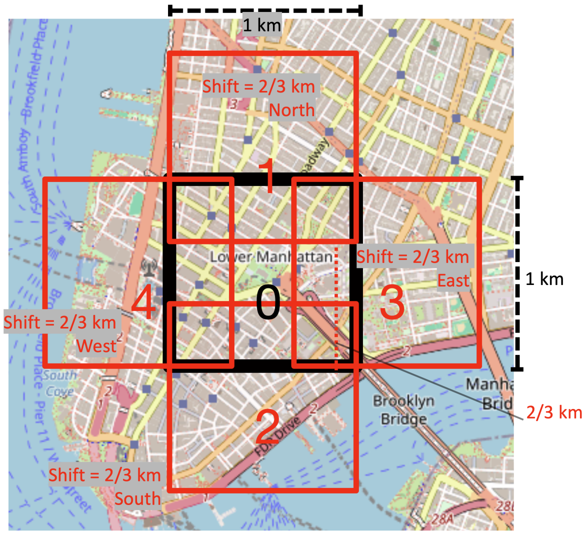


Fig. 6: Illustration of shift markers 1,2,3, and 4 for spatial perturbations by 2/3 km in North, South, East, and West directions respectively.

Table 4: Number of tiles in training data after filtering the tiles that were not associated with road networks..

City	total #tiles in X and Y direction	#tiles with traffic data
Auckland	50	895
Bogota	50	639
Cape Town	50	1126
Istanbul	75	1743
Mexico City	50	969
Mumbai	50	410
New York City	50	1641

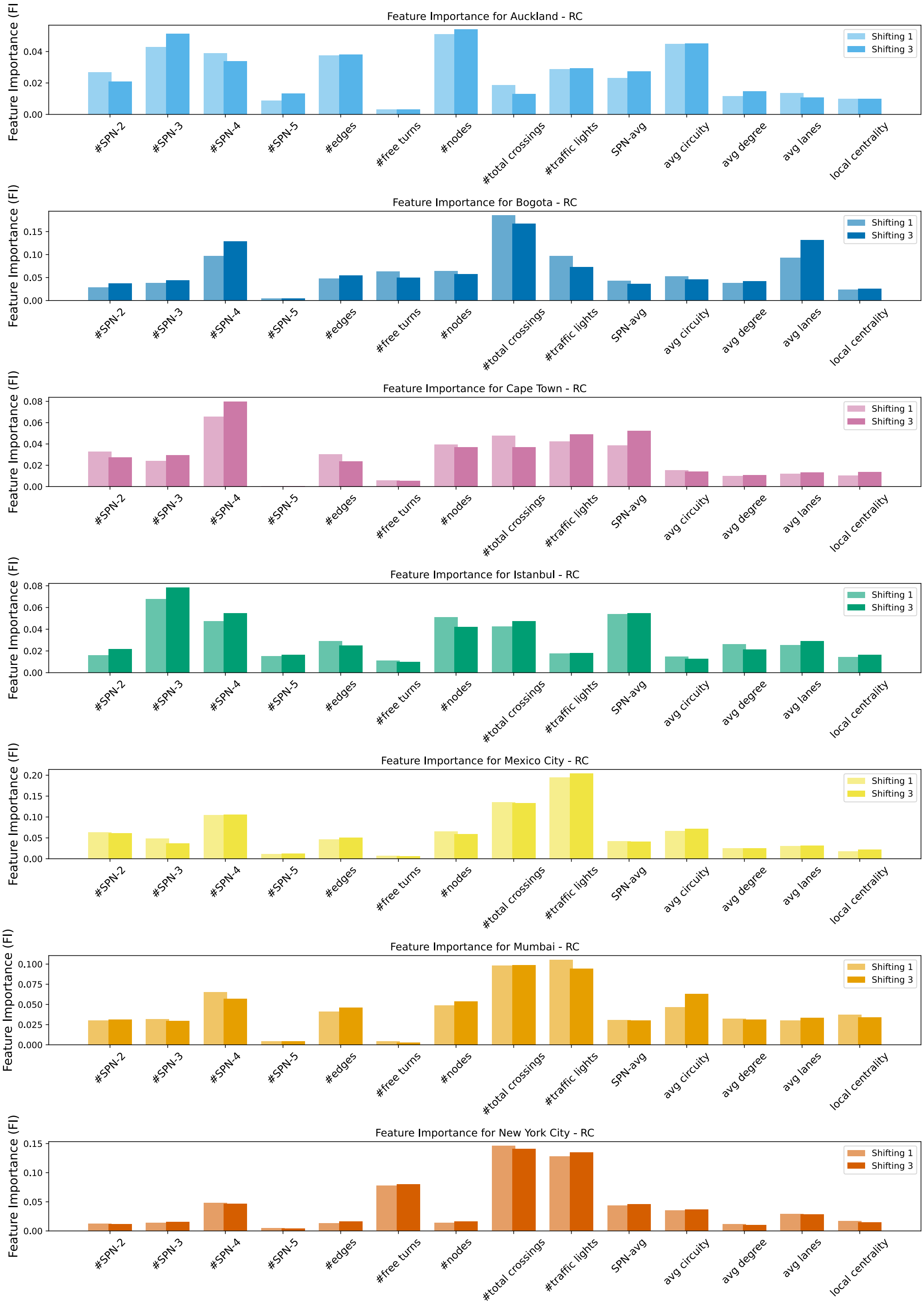


Fig. 7: SHAP-based feature importance values RC for two shifts at scale 1km^2. Shifts 1 and 3 as defined in the methods.

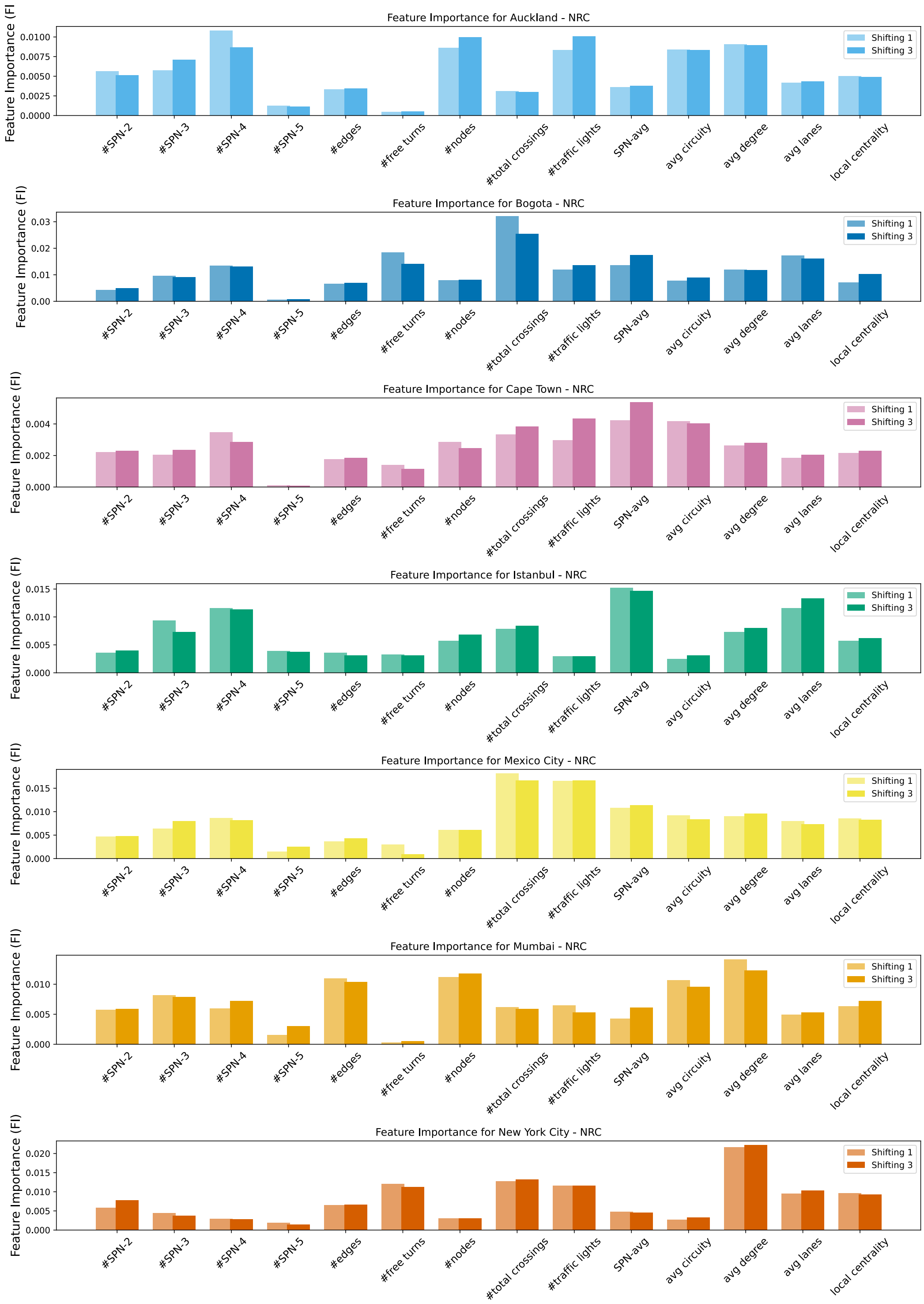
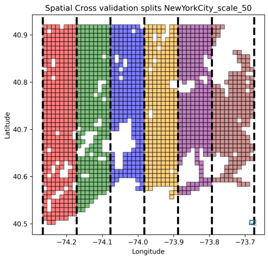
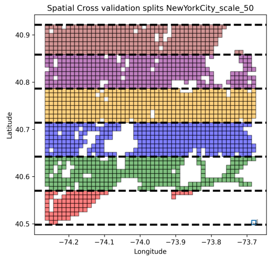


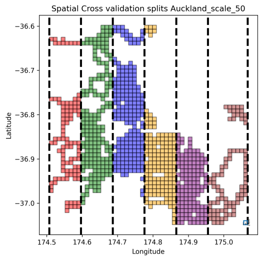
Fig. 8: SHAP-based feature importance values NRC for two shifts at scale 1km^2. Shifts 1 and 3 as defined in the methods.



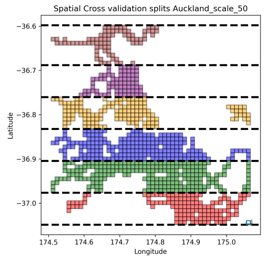
(a) NYC passes vertical @ km^2 RC



(b) NYC passes horizontal @ km^2 RC



(c) Auckland fails vertical @ km^2 RC



(d) Auckland passes horizontal @ 1 km^2 RC

Fig. 9: Spatial splits used for spatial cross-validation tests. **(a)** and **(b)** show that cities whose overall boundaries were closer to a square as per our dataset (*e.g.* New York City) pass both the vertical and horizontal cross-validation test. **(c)** and **(d)** show that cities with asymmetrical shapes pass only one of the tests.

Table 5: GoF using R^2 for two spatial perturbations represented by shifts 3 and 1. LR stands for Linear Regression, LLR stands for Lasso Linear Regression, RF stands for Random forests, RLR stands for Ridge Linear Regression.

CityName	n #tiles=(n×n)	Tile Area	Model	R^2 (NRC) Shift 3	R^2 (RC) Shift 3	R^2 (NRC) Shift 1	R^2 (RC) Shift 1
Auckland	100	0.25	LLR	-0.004	-0.003	-0.003	-0.002
Auckland	100	0.25	LR	0.247	0.299	0.27	0.322
Auckland	100	0.25	RF	0.358	0.355	0.374	0.347
Auckland	100	0.25	RLR	0.247	0.299	0.27	0.322
Bogota	100	0.25	LLR	-0.004	-0.002	-0.003	-0.002
Bogota	100	0.25	LR	0.288	0.292	0.29	0.275
Bogota	100	0.25	RF	0.368	0.31	0.395	0.335
Bogota	100	0.25	RLR	0.288	0.292	0.29	0.275

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CityName	n #tiles=(n×n)	Tile Area	Model	R^2 (NRC) Shift 3	R^2 (RC) Shift 3	R^2 (NRC) Shift 1	R^2 (RC) Shift 1
Cape Town	100	0.25	LLR	-0.003	-0.002	-0.001	-0.002
Cape Town	100	0.25	LR	0.031	0.277	0.071	0.292
Cape Town	100	0.25	RF	-0.216	0.299	0.071	0.312
Cape Town	100	0.25	RLR	0.031	0.277	0.071	0.292
Istanbul	150	0.25	LLR	-0.002	-0.002	-0.002	-0.001
Istanbul	150	0.25	LR	0.168	0.26	0.172	0.29
Istanbul	150	0.25	RF	0.182	0.25	0.183	0.281
Istanbul	150	0.25	RLR	0.168	0.26	0.172	0.29
Mexico City	100	0.25	LLR	-0.002	-0.001	-0.004	-0.006
Mexico City	100	0.25	LR	0.143	0.371	0.139	0.361
Mexico City	100	0.25	RF	0.201	0.414	0.182	0.407
Mexico City	100	0.25	RLR	0.143	0.371	0.139	0.361
Mumbai	100	0.25	LLR	-0.015	-0.007	-0.015	-0.002
Mumbai	100	0.25	LR	0.035	0.113	0.074	0.109
Mumbai	100	0.25	RF	0.07	0.116	0.063	0.099
Mumbai	100	0.25	RLR	0.035	0.114	0.074	0.109
New York City	100	0.25	LLR	-0.001	-0	-0.001	-0.002
New York City	100	0.25	LR	0.208	0.378	0.203	0.376
New York City	100	0.25	RF	0.239	0.445	0.228	0.44
New York City	100	0.25	RLR	0.208	0.378	0.203	0.376

Table 6: Hyperparameters for the best RF model for each city-scale combination.

City	n #tiles=$(n \times n)$	RC `n_estimators`	 `max_depth`	NRC `n_estimators`	 `max_depth`
Auckland	20	300	10	500	10
Auckland	30	400	10	600	50
Auckland	40	400	10	200	10
Auckland	60	600	10	400	50
Auckland	70	300	10	300	10
Auckland	80	400	50	600	10
Auckland	90	300	10	500	10
Auckland	25	50	50	100	50
Auckland	50	300	20	400	10
Auckland	100	400	10	600	10
Mexico City	30	600	10	600	10
Mexico City	40	300	10	300	10
Mexico City	60	400	10	600	10
Mexico City	70	600	10	600	10
Mexico City	80	200	10	200	10

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City	n #tiles=$(n \times n)$	RC n_estimators	 max_depth	NRC n_estimators	 max_depth
Mexico City	90	600	10	300	10
Mexico City	25	50	10	500	10
Mexico City	50	600	10	400	10
Mexico City	100	600	10	500	10
Istanbul	75	500	10	500	10
Istanbul	37	100	10	400	50
Istanbul	135	600	10	600	10
Istanbul	120	600	10	400	10
Istanbul	105	500	10	600	10
Istanbul	90	600	10	600	10
Istanbul	60	400	10	500	10
Istanbul	45	600	10	600	10
Istanbul	30	600	50	100	10
Istanbul	150	600	10	600	10
Mumbai	20	400	10	500	20
Mumbai	30	400	20	600	20
Mumbai	40	600	50	500	10
Mumbai	60	500	10	500	50
Mumbai	70	300	10	200	10
Mumbai	80	300	10	300	10
Mumbai	90	600	10	400	50
Mumbai	25	400	50	400	20
Mumbai	50	400	10	600	10
Mumbai	100	400	10	600	10
Bogota	20	600	10	200	20
Bogota	30	50	20	600	10
Bogota	40	200	10	50	50
Bogota	60	200	10	600	10
Bogota	70	200	10	300	10
Bogota	80	100	10	300	10
Bogota	90	500	10	600	10
Bogota	25	300	10	200	20
Bogota	50	300	10	50	10
Bogota	100	500	10	400	10
New York City	20	500	10	600	20
New York City	30	400	20	100	20
New York City	40	500	10	50	50
New York City	60	500	10	400	10
New York City	70	600	10	400	10
New York City	80	600	10	300	10
New York City	90	300	10	600	10

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Table 6 Continued from previous page

City	n #tiles=$(n \times n)$	RC n_estimators	 max_depth	NRC n_estimators	 max_depth
New York City	25	100	10	500	10
New York City	50	300	10	200	10
New York City	100	400	10	600	10
Mexico City	20	600	50	600	10
Cape Town	30	100	10	100	20
Cape Town	40	500	10	400	20
Cape Town	60	500	10	600	10
Cape Town	70	300	10	300	10
Cape Town	80	500	10	300	10
Cape Town	90	600	10	400	10
Cape Town	25	200	10	500	10
Cape Town	50	600	10	600	10
Cape Town	100	200	10	50	50
Cape Town	20	100	50	500	20

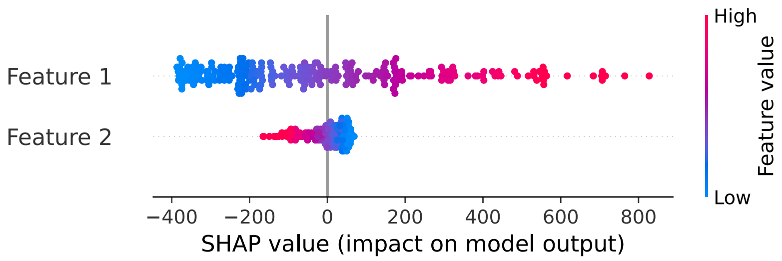

Fig. 10: Here we demonstrate how the Sensitivity Ratio (SR) as formalised in Equation 6 can be used to summarise the direction and magnitude of the direction of influence of $X \rightarrow Y$ for regression tasks. Assuming a linearly dependent variable (Y) such that $Y = 500 \times X_{\text{Feature 1}} - (X_{\text{Feature 2}})^2 + \mathcal{N}(0, 0.5)$, if we fit an RF model to X, Y and then explain the RF model using SHAP values, the beeswarm plots would look like the figure shown. The SR computed using these values are 496.80 and -81.3 for Feature 1 and Feature 2, respectively.

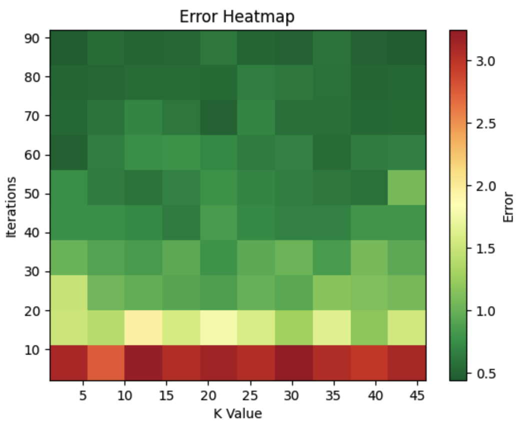

Fig. 11: Errors in computing betweenness centrality measures using approximation. k nodes are used to compute the betweenness every time, and the process is repeated # *iterations* times and averaged to estimate the betweenness centrality in an efficient manner. 20 Iterations were used in this paper.