### Using deep learning to identify (urban) form and function in satellite imagery - the case of Great Britain

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The Alan Turing Institute



Geographic Data Science Lab

### How we arrange "stuff" in cities matters...





Source: A map of every building in America (New York Times)

### ... it matters a lot









OECD



ARTICLE

### Effects of Income and Urban Form on Urban $NO_2$ : Global Evidence from Satellites

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## Spatial Signatures









## The issue

### Data



- OS OpenMap
- OS OpenRoads

- Sentinel 2
- (Business) Census • OpenStreetMap • Geolytix • Listed buildings • CDRC • CORINE /

- VIIRS

### Function

## Possible solution?





## Sentinel 2





## What do we want to do?

train a neural network understand the role of geography



## Image classification

## Neural network architecture



## Chip size effect



![](_page_23_Figure_0.jpeg)

![](_page_24_Figure_0.jpeg)

320x320m: 423 chips within, which is 35 % of maximum

![](_page_25_Picture_0.jpeg)

640x640m: 38 chips within, which is 13 % of maximum

### validation accuracy

![](_page_26_Figure_1.jpeg)

Urbanity -	0.45	0.18	0.11	0.04	0.03	0.08	0.02	0.01	0.08	0.01	0.00	0.00
Dense urban neighbourhoods	0.05	0.22	0.08	0.08	0.02	0.18	0.02	0.07	0.17	0.04	0.04	0.02
Dense residential neighbourhoods	0.02	0.06	0.24	0.03	0.03	0.35	0.01	0.08	0.15	0.02	0.02	0.00
Connected residential neighbourhoods	0.01	0.04	0.04	0.51	0.01	0.22	0.01	0.04	0.07	0.02	0.01	0.00
Gridded residential quarters	0.06	0.10	0.06	0.11	0.23	0.27	0.04	0.02	0.10	0.01	0.00	0.00
Accessible suburbia	0.01	0.02	0.04	0.07	0.01	0.66	0.01	0.05	0.04	0.03	0.04	0.01
Disconnected suburbia	0.02	0.03	0.02	0.12	0.03	0.34	0.25	0.07	0.07	0.04	0.01	0.00
Open sprawl	0.00	0.02	0.03	0.02	0.01	0.13	0.01	0.30	0.13	0.13	0.14	0.07
Warehouse_Park land	0.01	0.01	0.02	0.03	0.00	0.09	0.01	0.16	0.33	0.12	0.13	0.08
Urban buffer	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.10	0.07	0.22	0.43	0.15
Countryside agriculture	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.04	0.03	0.15	0.58	0.18
Wild countryside	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.01	0.05	0.18	0.74
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### Overall accuracy 42.8%

![](_page_27_Figure_2.jpeg)

![](_page_27_Figure_3.jpeg)

![](_page_28_Picture_0.jpeg)

### Wild countryside

![](_page_28_Figure_2.jpeg)

![](_page_29_Picture_0.jpeg)

![](_page_29_Picture_1.jpeg)

![](_page_29_Figure_2.jpeg)

### Co-location

## Multi-output regression

![](_page_32_Figure_0.jpeg)

320x320m, chips capturing the proportion

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Urbanity	0.68	0.11	0.02	0.07	0.02	0.01	0.02	0.02	0.02	0.01	0.00	0.00
Dense urban neighbourhoods	0.11	0.41	0.05	0.20	0.04	0.03	0.04	0.03	0.04	0.04	0.01	0.00
Dense residential neighbourhoods	0.05	0.11	0.25	0.21	0.05	0.11	0.06	0.07	0.05	0.04	0.00	0.00
Connected residential neighbourhoods	0.02	0.05	0.03	0.61	0.04	0.09	0.05	0.04	0.04	0.03	0.01	0.00
Gridded residential quarters	0.02	0.04	0.03	0.22	0.48	0.08	0.05	0.04	0.02	0.01	0.00	0.00
Accessible suburbia	0.01	0.03	0.04	0.25	0.03	0.34	0.11	0.08	0.04	0.05	0.01	0.01
Disconnected suburbia	0.02	0.02	0.01	0.24	0.02	0.08	0.47	0.07	0.04	0.03	0.01	0.00
Open sprawl	0.02	0.03	0.03	0.15	0.02	0.10	0.13	0.21	0.10	0.15	0.05	0.02
Warehouse_Park land	0.03	0.05	0.03	0.15	0.01	0.07	0.07	0.08	0.27	0.15	0.05	0.03
Urban buffer	0.00	0.01	0.00	0.03	0.00	0.03	0.03	0.04	0.05	0.41	0.27	0.12
Countryside agriculture	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.24	0.56	0.17
Wild countryside	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.09	0.16	0.75
Overall accuracy 43.5%												

![](_page_33_Figure_2.jpeg)

![](_page_33_Figure_3.jpeg)

![](_page_34_Picture_0.jpeg)

### Wild countryside

![](_page_34_Figure_2.jpeg)

![](_page_35_Picture_0.jpeg)

![](_page_35_Picture_1.jpeg)

![](_page_35_Figure_2.jpeg)

## Probability modelling

![](_page_36_Picture_1.jpeg)

![](_page_37_Figure_0.jpeg)

# A way forward

- 1. Deploy probability modelling on GB
- 2. Image segmentation
- 3. Alternative NN architecture including additional context in a single model

## Conclusions

- 1. Relationship between signatures and satellite data is fuzzy
- 2. Chip size needs to balance information and relation to input geometry
- 3. Co-location information needs to be embedded in the model

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![](_page_40_Picture_4.jpeg)

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![](_page_40_Picture_8.jpeg)