

Longevity-19 Conference

Mortality Forecasting with Satellite Imaging and Machine Learning

Presented by:

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Longevity 19: The Nineteenth International Longevity Risk and Capital Markets Solutions Conference

Amsterdam, Netherlands

Parallel Session III

17th Sept 2024, 0900-11:00

Joint work with Prof Zhu Wenjun

Data is an important resource to insurance companies but it can be difficult to come by

Introduction – Overall Research Objective

Objectives

Data used for forecasting can be limited especially when it comes to climate data



01

To incorporate the **use of images** in more risk management techniques

02

To incorporate the **use of machine learning** to achieve these risk management techniques

Examples in General Insurance



Modelling for **catastrophe insurance** may make use of Geographic Information Systems to run tests



Using driving habits as factors for pricing **vehicle insurance** such as speeding, mileage, etc.

Use of images is commonly found in general insurance but it could be useful on the life and medical side

Satellite images can be useful for incorporating information about the living environment

Introduction – Research Inspiration

Existing Literature 1

Using satellite images for poverty prediction
(Jean et al., 2016)

Consumption and
assets **survey**
data from 5
African countries

+

Satellite images
of survey clusters
with up to 10km
of noise

Existing Literature 2

Using satellite images for crude mortality rates
(Levy et al., 2021)

County level
mortality
&
Mortality death
certificates from
CDC Wonder

+

Satellite images
of
neighbourhoods
surrounding
schools

Such granular level of data (e.g. mortality rates, surveys, addresses) may not always be available

Living environments have been shown to have effects on mortality

Introduction – Research Relevance

Effects of Living Environments



Higher amount of greenness was associated with **lower mortality** for adult women for all causes, non-accidental (US-based study) (James et al., 2016)



Urban island heat effect along with high temperatures and low wind speeds can lead to **higher mortality** (Hong Kong-based study) (Goggins et al., 2012)

Areas to Explore in this Research

01

Satellite images may be **useful proxies** for living environments effects

02

Satellite images are widely available which can be used for **estimating information on locations we do not have information on**

03

Starting point for incorporating living environment effects on mortality

We narrow our research objective as seen below...

Introduction – Narrowed Research Objective

Situation

- Effects of living conditions on mortality can be **difficult to quantify**, in addition to **climate change concerns**
- Data collection requires **great efforts**

Complication

Actuaries require ways to manage mortality risks while **accounting for potential effects** of living environments which can affect mortality

Opportunity

- Satellite images are readily available on Google Earth Engine
- Satellite images or remote sensing can potentially provide large amounts of data

Objective

Assessing the feasibility of using satellite images with machine learning to construct mortality tables for actuaries

Satellite images can provide lots of information via different bands

Data – Satellite Images

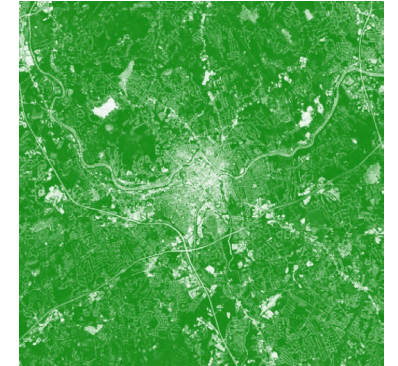
Satellite Bands

- Each satellite comes with different bands
- Each band provides different information
 - SR_B1 (Blue surface reflectance)
 - SR_B2 (Green surface reflectance)
 - SR_B3 (Red surface reflectance)
 - *(U.S. Geological Survey, 2024)*
- Auxiliary bands can be calculated from the default bands
 - Normalized Difference Vegetation Index (NDVI)
 - Normalized Difference Water Index (NDWI)
- We choose to use the .png instead of .tiff formats due to computation limitations

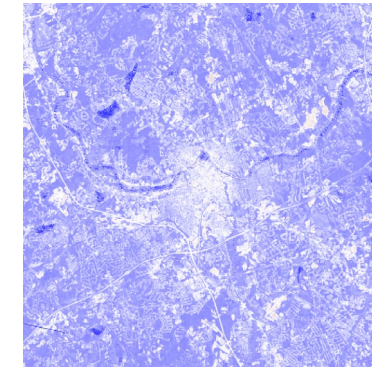
Example: Lowell City, 2011 (Landsat 5)



Natural Colour



NDVI



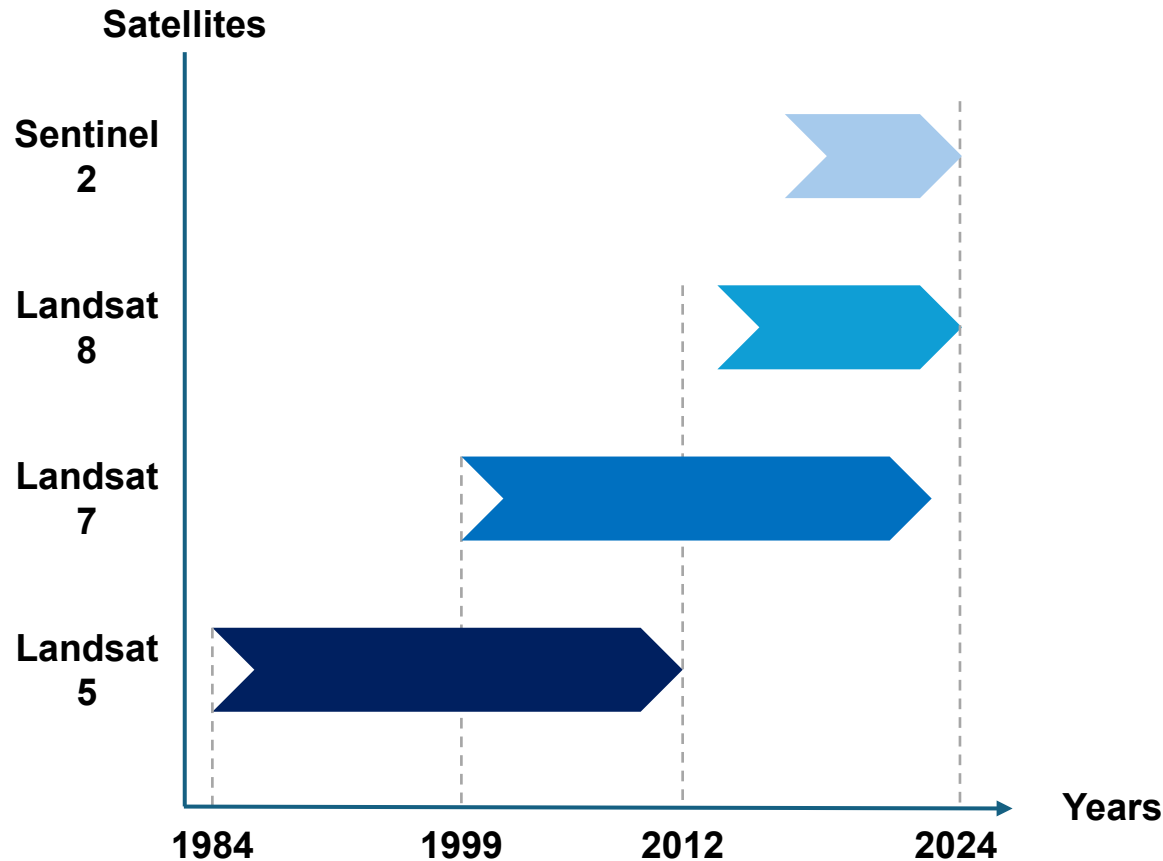
NDWI

Satellite images can provide different information about the living environment

Satellite images can come from different satellites and time period

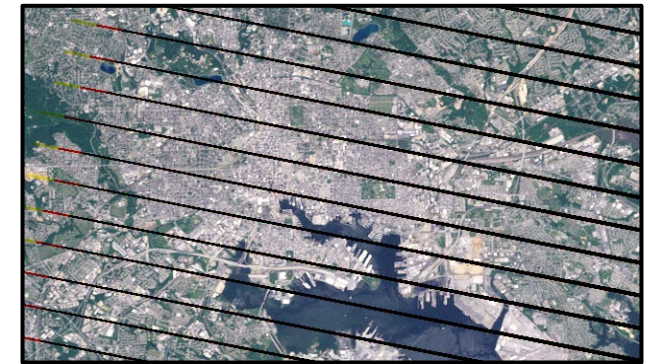
Data – Satellite Images

Satellite Coverage



Challenges

- Different satellites have **different image resolutions and available bands**
- Images retrieved from different satellites **may not always line up properly** (important if attempting time-series models)
- Landsat 7 encountered sensor problems (NASA Earth Observatory, n.d.)



Landsat 7 Image for Baltimore, Maryland (Simmon, 2009)

Careful selection of satellite images and cleaning is required before using them

Satellite images with lots of clouds, errors or other problems were filtered

Data – Satellite Images

Data Retrieved

Retrieved satellite images from [Landsat 5](#)

- Between 1985 to 2011
- Between April and October
- 50 US states, top 5 cities from each state by population
- 10km radius of city centre (approximated)
- Natural colour

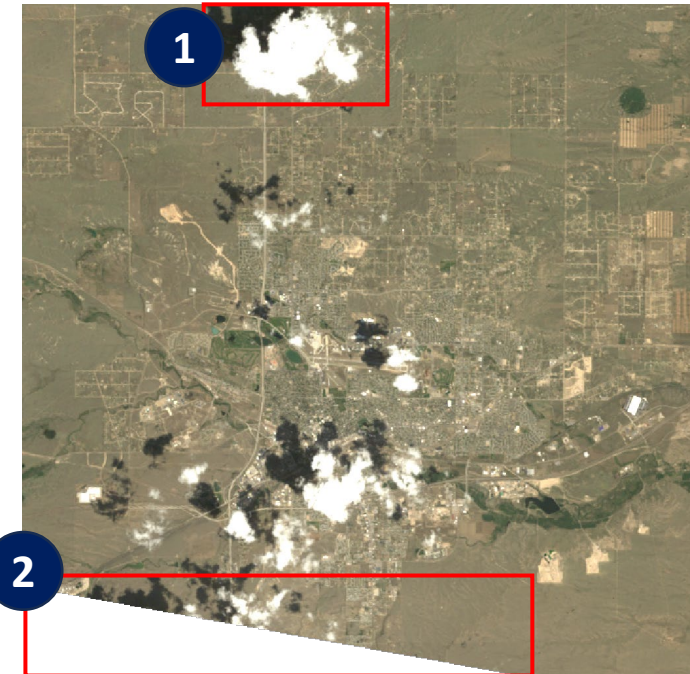
Data Used

- 3,442 images were used

Largest no. of images in 1 state	110
Smallest no. of images in 1 state	23
Largest no. of images in 1 year	144
Smallest no. of images in 1 year	89

Examples of Images Filtered Out

Cheyenne City, WY, 2008, Landsat 5



01

Presence of clouds

02

Gaps

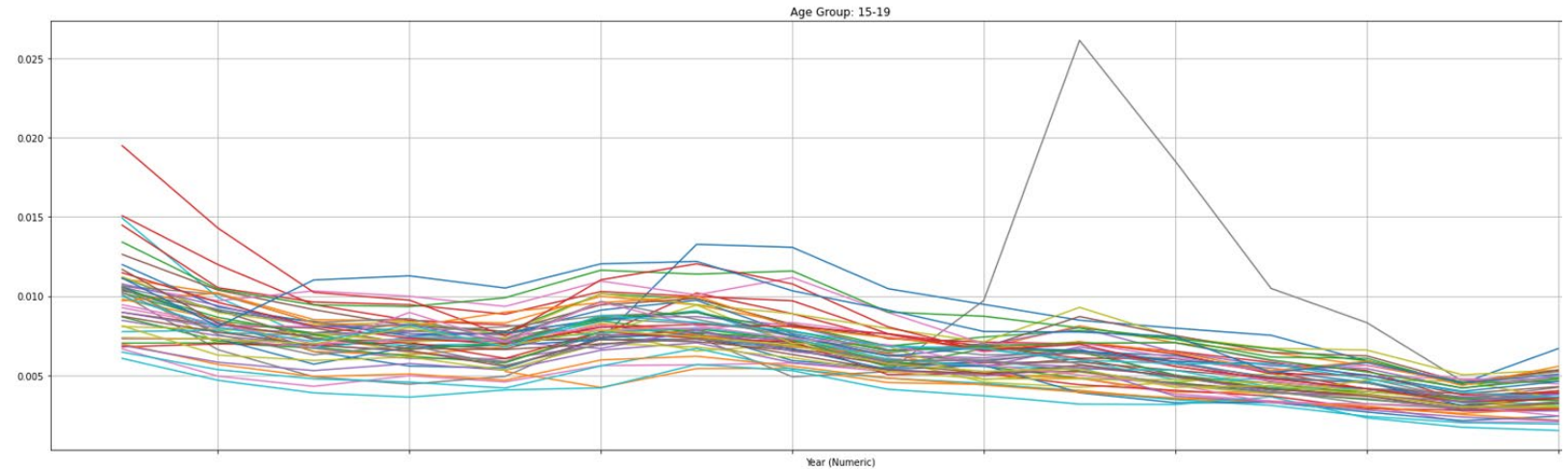
Mortality rates from United States Mortality Database (USMD) was used

Data – Mortality Rates

Data Used

- USMD has US state level mortality rates up to 2020
- Use 1985 to 2011 mortality rates
- Use a **5x1 mortality table** (5-year age group intervals)
- **Rationale:** To reduce the number of models to be trained

General Trends Using 5x5 Mortality Rates (Males)



01

As well-known, mortality rates are **generally declining** with advancements in cities

02

Mortality rates between different states are generally close to each other but **start to differ in older age groups**

With the acquired data, we trained individual machine learning models for each age group

Methodology

Steps

01

Set the mortality rates as labels for each satellite image. Year data is not used.

02

Split the dataset into 70% train, 10% validation, 20% test sets for each state

03

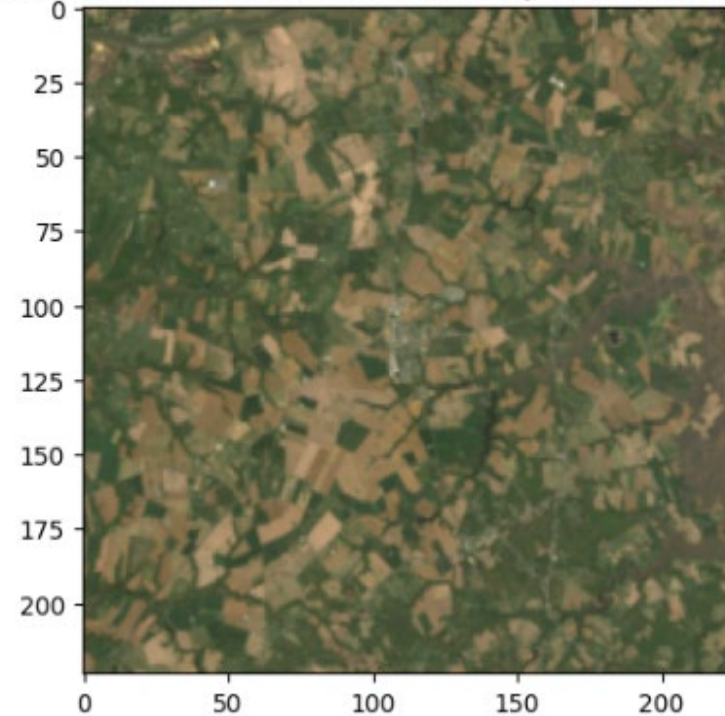
Define the machine learning model in PyTorch and start training on GPU

04

Repeat step 1 to 3 for each age group and gender

Example of Image Inputs

Label: 0.0005699999746866524, State: DE, City: Middletown town, Year: 1996



This results in 23 models for each gender

The Resnet18 architecture was used for the model

Methodology

Configurations for Training

Details

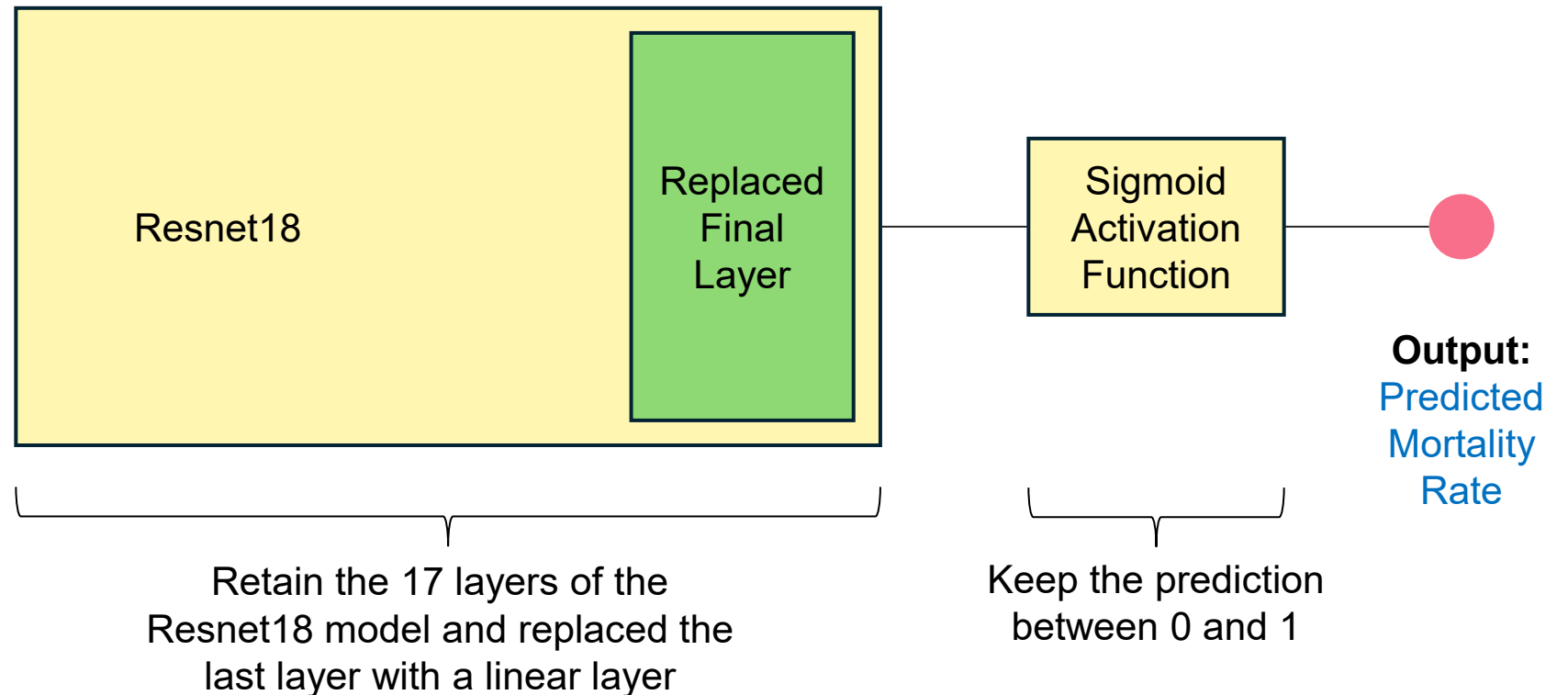
Choice of Resnet18:

- Performs well on image classification
- Use it with transfer learning

Training Details:

- Epochs: 100
- Learning rate: 0.001
- Batch size: 64
- Loss function: MSE
- Trained on GPU

General Architecture for Model



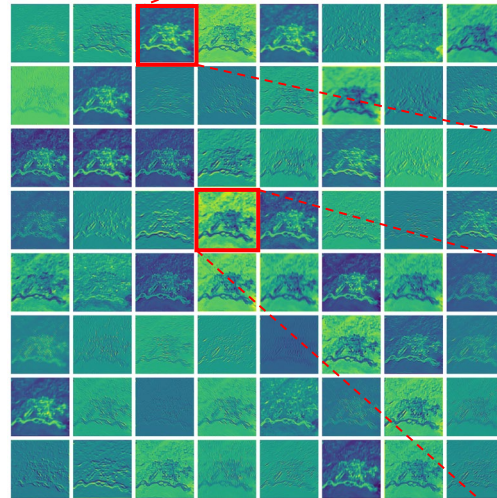
Initial layers of Resnet18 indicate certain areas which are important in predictions (1 of 2)

Results – Feature Maps

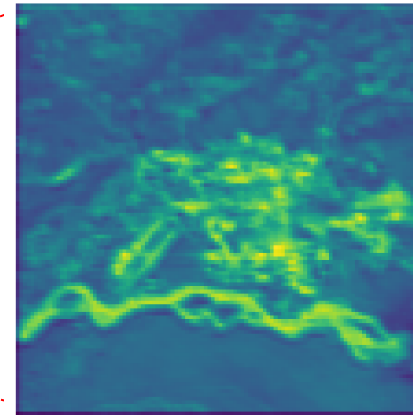
Selected Feature Maps of Conv1 Layer



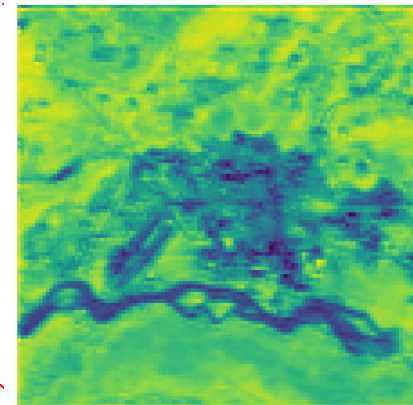
Fairbanks, AK, 2003
(Natural Colour)



Feature Map
Visualization



Urban built-up areas are causing stronger activations



Generally green areas are causing stronger activations

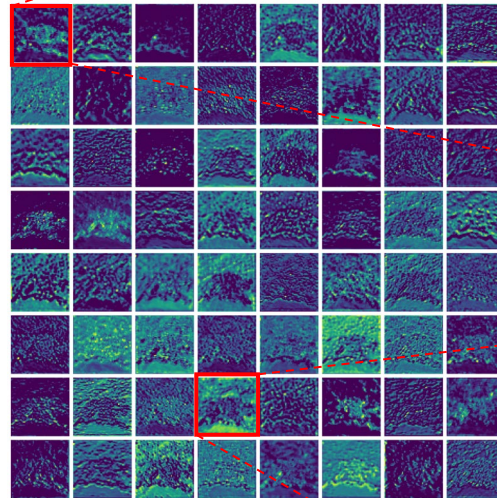
Initial layers of Resnet18 indicate certain areas which are important in predictions (2 of 2)

Results – Feature Maps

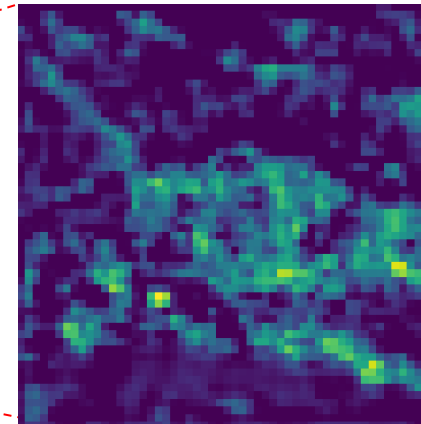
Selected Feature Maps of Layer2



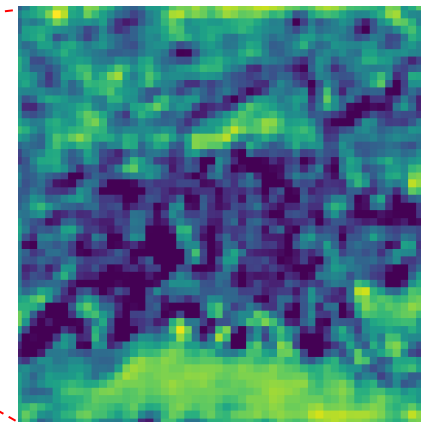
Fairbanks, AK, 2003
(Natural Colour)



Feature Map
Visualization



Certain parts of urban built-up areas are causing stronger activations

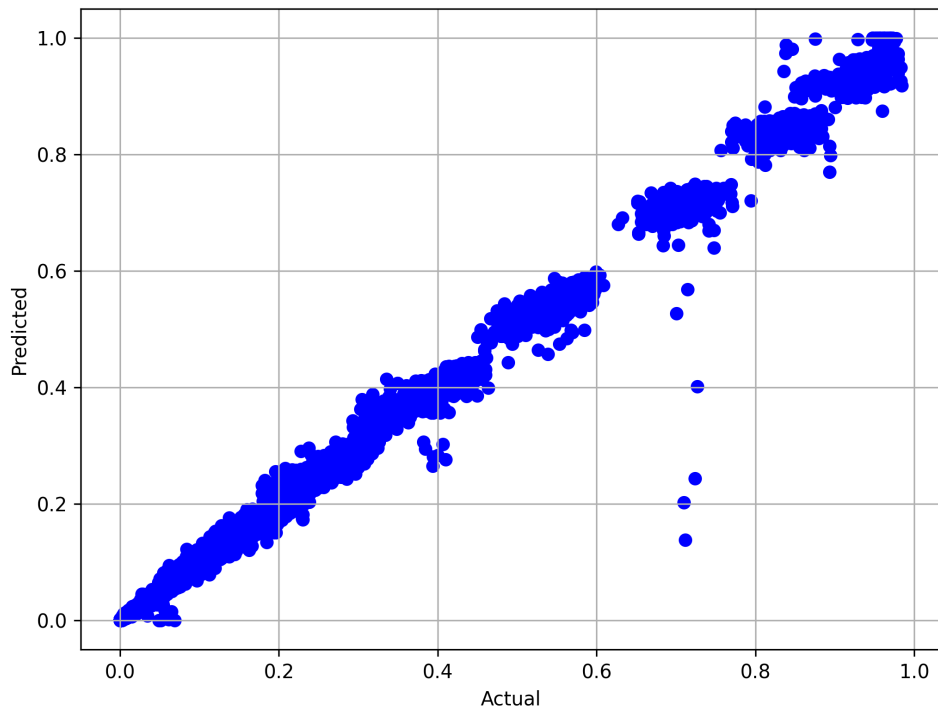


Greenery / vegetation are causing stronger activations

Predictions on the test set are generally quite close to actual values

Results – Model Performance

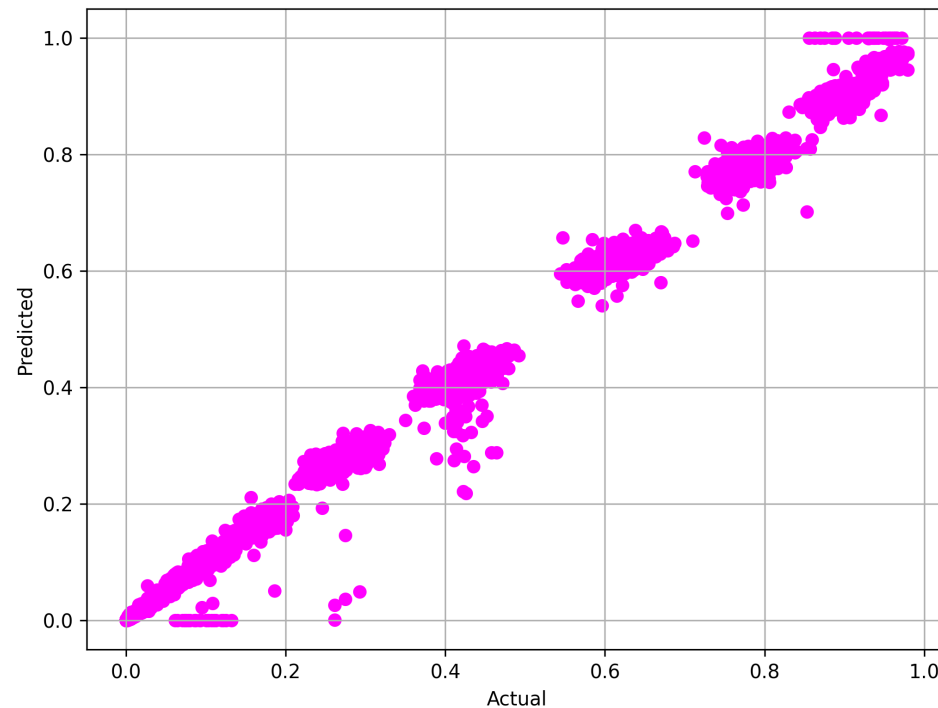
All Male Predictions vs Actual



MAPE (excluding any 0 actual values)	0.116043
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Deviations are generally close but may still be large

All Female Predictions vs Actual



MAPE (excluding any 0 actual values)	0.128948
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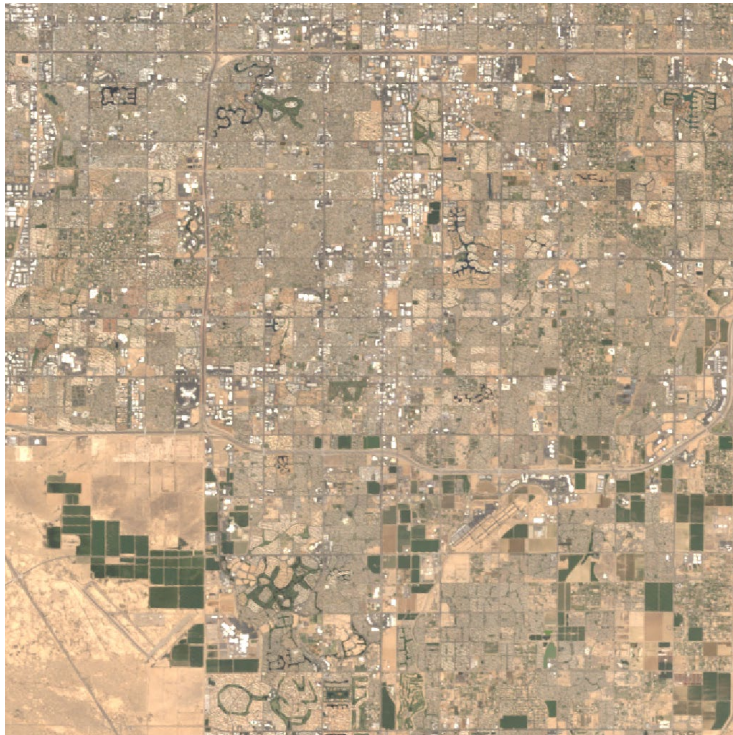
Deviations are generally close but may still be large

Consistent with Jean et al., 2016, years did not have to specified for the model to still make close predictions

Predicted mortality tables can be relatively close to actual mortality tables (1 of 2)

Results – Generated mortality table (Chandler City, AZ, 2011)

Image Used



Chandler City, AZ, 2011
(Natural Colour)

Males

Age Group	Predicted	Actual	% Diff
0	0.0070	0.0061	15%
1-4	0.0011	0.0015	-28%
5-9	0.0009	0.0007	25%
10-14	0.0009	0.0009	-7%
15-19	0.0050	0.0035	44%
20-24	0.0079	0.0072	9%
25-29	0.0083	0.0078	6%
30-34	0.0082	0.0076	8%
35-39	0.0095	0.0091	5%
40-44	0.0155	0.0134	15%
45-49	0.0196	0.0208	-6%
50-54	0.0323	0.0308	5%
55-59	0.0431	0.0440	-2%
60-64	0.0698	0.0591	18%
65-69	0.0853	0.0811	5%
70-74	0.1099	0.1116	-1%
75-79	0.1763	0.1756	0%
80-84	0.3126	0.3038	3%
85-89	0.4894	0.4714	4%
90-94	0.7033	0.6712	5%
95-99	0.8383	0.8363	0%
100-104	0.9143	0.9294	-2%
105-109	0.9644	0.9701	-1%

Females

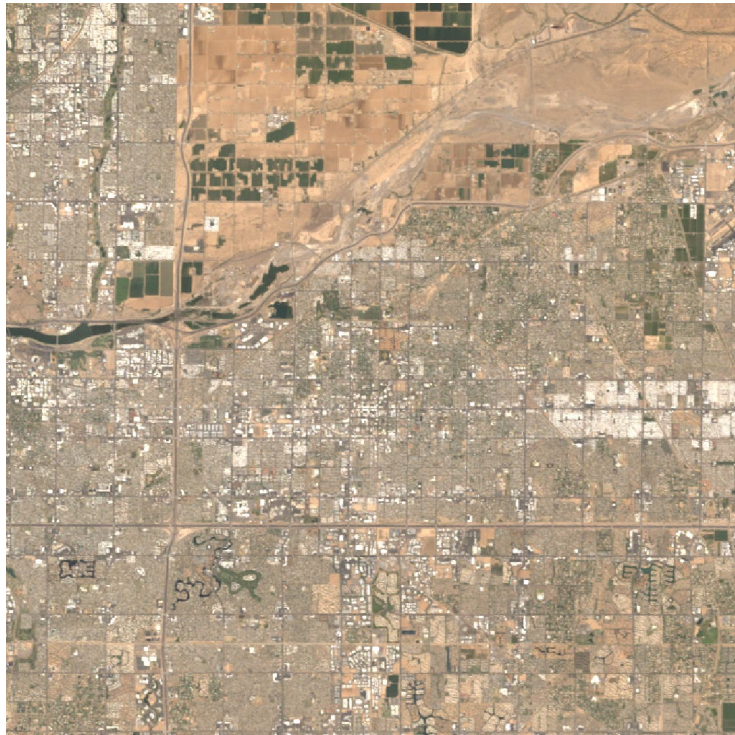
Age Group	Predicted	Actual	% Diff
0	0.0061	0.0056	9%
1-4	0.0012	0.0009	40%
5-9	0.0008	0.0004	97%
10-14	0.0010	0.0007	51%
15-19	0.0022	0.0016	35%
20-24	0.0025	0.0024	5%
25-29	0.0029	0.0026	12%
30-34	0.0042	0.0043	-2%
35-39	0.0058	0.0057	3%
40-44	0.0076	0.0080	-4%
45-49	0.0134	0.0125	7%
50-54	0.0187	0.0177	6%
55-59	0.0269	0.0255	6%
60-64	0.0373	0.0356	5%
65-69	0.0623	0.0488	28%
70-74	0.0893	0.0780	15%
75-79	0.1291	0.1328	-3%
80-84	0.2584	0.2343	10%
85-89	0.3935	0.3971	-1%
90-94	0.6041	0.6081	-1%
95-99	0.7839	0.8003	-2%
100-104	0.8952	0.9169	-2%
105-109	0.9548	0.9673	-1%

Notes: % Diff = (Pred. – Actual) / Actual

Predicted mortality tables can be relatively close to actual mortality tables (2 of 2)

Results – Generated mortality table (Mesa City, AZ, 2011)

Image Used



Mesa City, AZ, 2011
(Natural Colour)

Males

Age Group	Predicted	Actual	% Diff
0	0.0047	0.0061	-23%
1-4	0.0017	0.0015	17%
5-9	0.0013	0.0007	77%
10-14	0.0008	0.0009	-12%
15-19	0.0052	0.0035	51%
20-24	0.0085	0.0072	18%
25-29	0.0085	0.0078	9%
30-34	0.0064	0.0076	-15%
35-39	0.0086	0.0091	-6%
40-44	0.0134	0.0134	0%
45-49	0.0210	0.0208	1%
50-54	0.0315	0.0308	2%
55-59	0.0424	0.0440	-4%
60-64	0.0690	0.0591	17%
65-69	0.0889	0.0811	10%
70-74	0.1170	0.1116	5%
75-79	0.1839	0.1756	5%
80-84	0.3295	0.3038	8%
85-89	0.4951	0.4714	5%
90-94	0.7043	0.6712	5%
95-99	0.8420	0.8363	1%
100-104	0.9177	0.9294	-1%
105-109	0.9665	0.9701	0%

Females

Age Group	Predicted	Actual	% Diff
0	0.0054	0.0056	-2%
1-4	0.0012	0.0009	36%
5-9	0.0007	0.0004	68%
10-14	0.0006	0.0007	-8%
15-19	0.0021	0.0016	29%
20-24	0.0035	0.0024	47%
25-29	0.0030	0.0026	17%
30-34	0.0036	0.0043	-16%
35-39	0.0068	0.0057	19%
40-44	0.0083	0.0080	4%
45-49	0.0135	0.0125	8%
50-54	0.0177	0.0177	0%
55-59	0.0263	0.0255	3%
60-64	0.0371	0.0356	4%
65-69	0.0632	0.0488	30%
70-74	0.0924	0.0780	19%
75-79	0.1393	0.1328	5%
80-84	0.2806	0.2343	20%
85-89	0.3993	0.3971	1%
90-94	0.6067	0.6081	0%
95-99	0.7857	0.8003	-2%
100-104	0.8954	0.9169	-2%
105-109	0.9539	0.9673	-1%

Notes: % Diff = (Pred. – Actual) / Actual

Taking the average of the predicted rates may yield closer results

Results – Generated mortality table (Arizona, 2011)

Findings

Cities Used

1. Chandler City
2. Gilbert Town
3. Mesa City

Results:

1. Male table average predictions are better
2. Female table average predictions have slight improvements for some age groups

Analysis:

1. Incorporating a weighted average by population may be worth examining

Males

Females

Age	Chandler	Gilbert	Mesa	Avg	Actual	% Diff	Chandler	Gilbert	Mesa	Avg	Actual	% Diff
0	0.0070	0.0072	0.0047	0.0063	0.0061	4%	0.0061	0.0057	0.0054	0.0057	0.0056	3%
1-4	0.0011	0.0013	0.0017	0.0014	0.0015	-8%	0.0012	0.0015	0.0012	0.0013	0.0009	49%
5-9	0.0009	0.0010	0.0013	0.0010	0.0007	46%	0.0008	0.0008	0.0007	0.0008	0.0004	82%
10-14	0.0009	0.0008	0.0008	0.0008	0.0009	-12%	0.0010	0.0007	0.0006	0.0008	0.0007	16%
15-19	0.0050	0.0043	0.0052	0.0048	0.0035	40%	0.0022	0.0019	0.0021	0.0020	0.0016	26%
20-24	0.0079	0.0070	0.0085	0.0078	0.0072	8%	0.0025	0.0031	0.0035	0.0030	0.0024	27%
25-29	0.0083	0.0088	0.0085	0.0086	0.0078	9%	0.0029	0.0031	0.0030	0.0030	0.0026	17%
30-34	0.0082	0.0067	0.0064	0.0071	0.0076	-6%	0.0042	0.0037	0.0036	0.0038	0.0043	-11%
35-39	0.0095	0.0089	0.0086	0.0090	0.0091	-1%	0.0058	0.0056	0.0068	0.0061	0.0057	7%
40-44	0.0155	0.0147	0.0134	0.0145	0.0134	8%	0.0076	0.0076	0.0083	0.0079	0.0080	-2%
45-49	0.0196	0.0192	0.0210	0.0199	0.0208	-4%	0.0134	0.0126	0.0135	0.0132	0.0125	5%
50-54	0.0323	0.0308	0.0315	0.0315	0.0308	2%	0.0187	0.0174	0.0177	0.0179	0.0177	1%
55-59	0.0431	0.0433	0.0424	0.0430	0.0440	-2%	0.0269	0.0258	0.0263	0.0263	0.0255	3%
60-64	0.0698	0.0763	0.0690	0.0717	0.0591	21%	0.0373	0.0376	0.0371	0.0373	0.0356	5%
65-69	0.0853	0.0922	0.0889	0.0888	0.0811	10%	0.0623	0.0626	0.0632	0.0627	0.0488	28%
70-74	0.1099	0.1126	0.1170	0.1132	0.1116	1%	0.0893	0.0890	0.0924	0.0902	0.0780	16%
75-79	0.1763	0.1746	0.1839	0.1782	0.1756	1%	0.1291	0.1306	0.1393	0.1330	0.1328	0%
80-84	0.3126	0.3195	0.3295	0.3205	0.3038	5%	0.2584	0.2663	0.2806	0.2684	0.2343	15%
85-89	0.4894	0.4880	0.4951	0.4908	0.4714	4%	0.3935	0.3859	0.3993	0.3929	0.3971	-1%
90-94	0.7033	0.6905	0.7043	0.6994	0.6712	4%	0.6041	0.5995	0.6067	0.6035	0.6081	-1%
95-99	0.8383	0.8373	0.8420	0.8392	0.8363	0%	0.7839	0.7778	0.7857	0.7825	0.8003	-2%
100-104	0.9143	0.9143	0.9177	0.9154	0.9294	-2%	0.8952	0.8974	0.8954	0.8960	0.9169	-2%
105-109	0.9644	0.9642	0.9665	0.9650	0.9701	-1%	0.9548	0.9560	0.9539	0.9549	0.9673	-1%

Notes: % Diff = (Pred. – Actual) / Actual

We applied the trained models to Wales and Scotland (UK) for 2011 images (1 of 2)

Result – Applying to areas outside dataset (Cardiff, Wales, 2011)

Findings



Cardiff,
Wales,
2011

Comparison:

Based off 2009 - 2011 actual experience VS 2011 prediction

Analysis:

- Poorer predictions may be due to different patterns in mortality between US and UK
- Model may be too heavily trained on US data

Males

Age Group	Predicted	Actual	% Diff
0	0.0063	0.0047	34%
1-4	0.0015	0.0005	205%
5-9	0.0009	0.0006	58%
10-14	0.0027	0.0006	317%
15-19	0.0054	0.0025	120%
20-24	0.0078	0.0034	125%
25-29	0.0086	0.0040	116%
30-34	0.0080	0.0058	39%
35-39	0.0115	0.0074	56%
40-44	0.0146	0.0104	41%
45-49	0.0194	0.0143	35%
50-54	0.0263	0.0211	25%
55-59	0.0462	0.0334	38%
60-64	0.0753	0.0506	49%
65-69	0.1056	0.0810	30%
70-74	0.1697	0.1318	29%
75-79	0.1528	0.2080	-27%
80-84	0.3651	0.3352	9%
85-89	0.5040	0.5190	-3%
90-94	0.7050	0.6936	2%
95-99	0.8424	0.8335	1%
100-104			
105-109			

Females

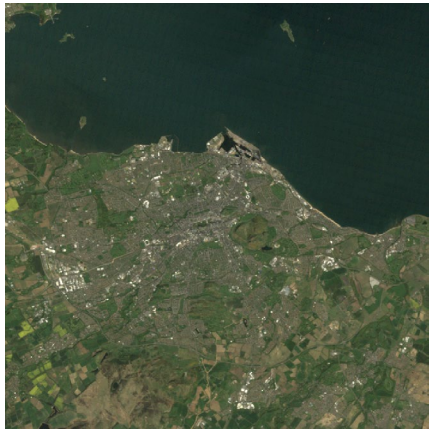
Age Group	Predicted	Actual	% Diff
0	0.0068	0.0037	82%
1-4	0.0011	0.0006	74%
5-9	0.0009	0.0003	200%
10-14	0.0007	0.0005	40%
15-19	0.0017	0.0008	116%
20-24	0.0026	0.0011	133%
25-29	0.0035	0.0018	95%
30-34	0.0034	0.0027	26%
35-39	0.0054	0.0038	39%
40-44	0.0112	0.0059	91%
45-49	0.0120	0.0094	27%
50-54	0.0190	0.0149	27%
55-59	0.0300	0.0216	39%
60-64	0.0444	0.0346	29%
65-69	0.0616	0.0530	16%
70-74	0.1022	0.0888	15%
75-79	0.1522	0.1477	3%
80-84	0.2609	0.2545	3%
85-89	0.4018	0.4092	-2%
90-94	0.5983	0.6051	-1%
95-99	0.7813	0.7905	-1%
100-104			
105-109			

Notes: % Diff = (Pred. – Actual) / Actual

We applied the trained models to Wales and Scotland (UK) for 2011 images (2 of 2)

Result – Applying to areas outside dataset (Edinburgh, Scotland, 2011)

Findings



Edinburgh,
Scotland,
2011

Comparison:

Based off 2009 - 2011 actual experience VS 2011 prediction

Analysis:

- Poorer predictions may be due to different patterns in mortality between US and UK
- Model may be too heavily trained on US data

Males

Age Group	Predicted	Actual	% Diff
0	0.0083	0.0044	88%
1-4	0.0030	0.0007	319%
5-9	0.0009	0.0006	47%
10-14	0.0015	0.0004	255%
15-19	0.0070	0.0027	158%
20-24	0.0071	0.0043	67%
25-29	0.0068	0.0060	14%
30-34	0.0101	0.0076	33%
35-39	0.0083	0.0097	-15%
40-44	0.0163	0.0132	23%
45-49	0.0204	0.0164	24%
50-54	0.0321	0.0255	26%
55-59	0.0524	0.0394	33%
60-64	0.0821	0.0605	36%
65-69	0.1158	0.0968	20%
70-74	0.1562	0.1510	3%
75-79	0.2298	0.2299	0%
80-84	0.3591	0.3652	-2%
85-89	0.5034	0.5225	-4%
90-94	0.7027	0.7075	-1%
95-99	0.8517	0.8602	-1%
100-104			
105-109			

Females

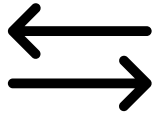
Age Group	Predicted	Actual	% Diff
0	0.0071	0.0034	110%
1-4	0.0027	0.0007	300%
5-9	0.0006	0.0003	65%
10-14	0.0008	0.0005	63%
15-19	0.0017	0.0014	22%
20-24	0.0034	0.0016	106%
25-29	0.0022	0.0022	0%
30-34	0.0038	0.0035	9%
35-39	0.0064	0.0050	29%
40-44	0.0086	0.0071	20%
45-49	0.0141	0.0107	32%
50-54	0.0200	0.0176	14%
55-59	0.0315	0.0253	24%
60-64	0.0477	0.0405	18%
65-69	0.0728	0.0643	13%
70-74	0.1099	0.1022	7%
75-79	0.1812	0.1682	8%
80-84	0.2743	0.2789	-2%
85-89	0.2799	0.4323	-35%
90-94	0.6005	0.6431	-7%
95-99	0.7550	0.8099	-7%
100-104			
105-109			

Notes: % Diff = (Pred. – Actual) / Actual

The research has its own limitations, mostly related to the choice of data

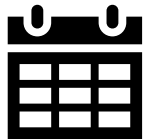
Summary and Limitations of Work

Conclusion



Satellite images can be a **starting point** for trying to incorporate environment effects on mortality

- Suggests some environment features can be decent predictors of mortality



“**Year**” variable is still a very important **covariate** in mortality prediction and should be included somehow



Further tests are required to determine if such models can be “transferrable” between different regions

Limitations of Research

01

Period of Analysis

Would be interesting to note how **additional data in recent years** affect the results

02

Data Filtering

Data may not always be “complete” due to unusable images

03

City Choices

A **question of how many cities are required to be used** for large countries

04

Satellite Bands

“**Natural colour**” is the only type of images we are using now

The work may be further improved via one of these directions...

Future Work

Next Steps

01

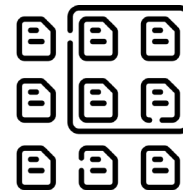
The “Year” is still an important predictor variable

- Use the satellite images to account for the mortality improvement instead
- Incorporate Longitude and Latitude to aid during out-of-sample prediction



02

Using NDVI, NDWI images to capture greenery and moisture which may have other effects



03

Using images as proxies for climate factors instead of mortality rates directly to overcome mortality patterns



Many other directions are available which may contribute to the improvement of the methodology

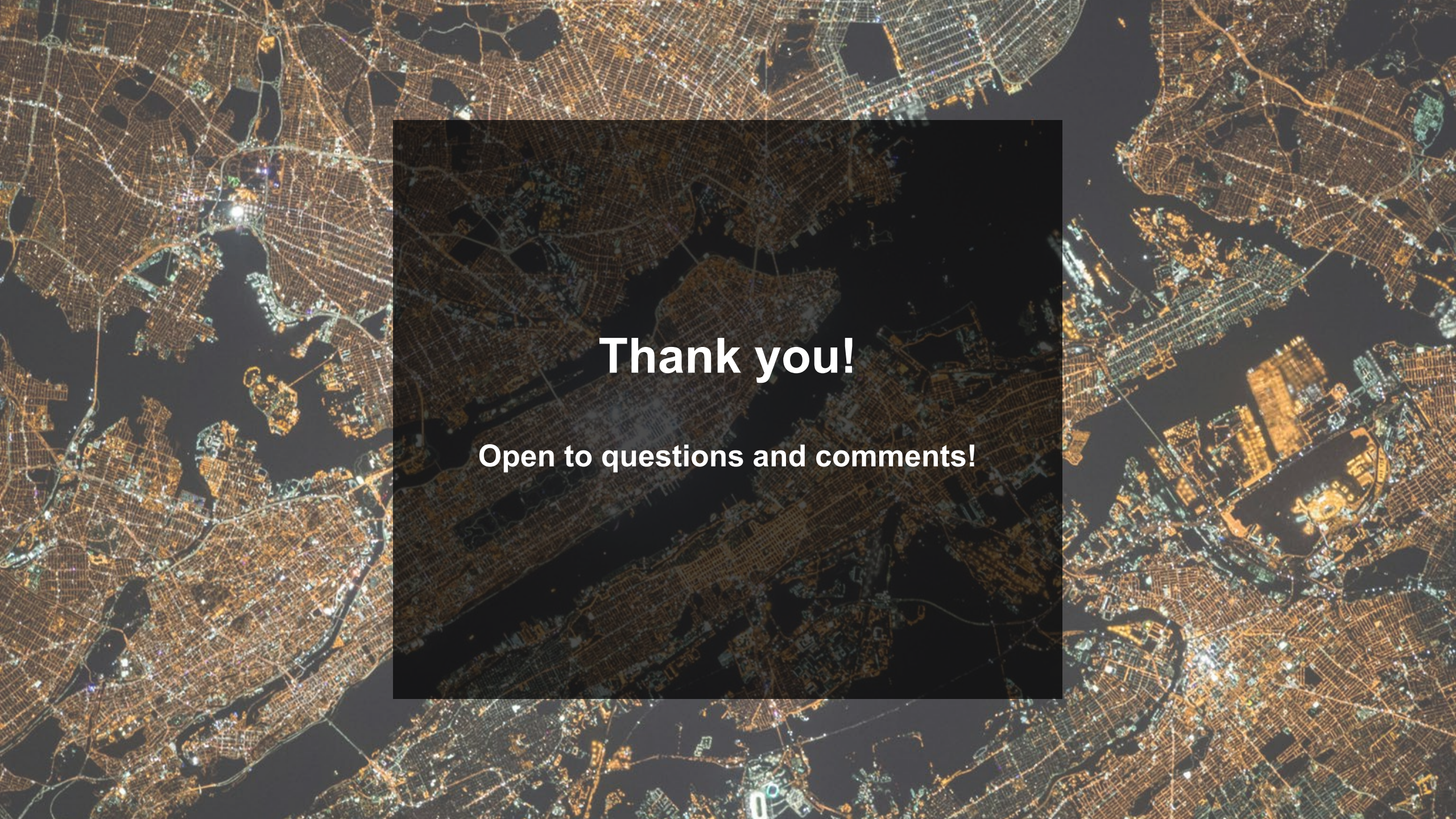
Research Acknowledgements

Acknowledgements



URECA
Undergraduate Research Programme

**We would like to
acknowledge the funding
support from Nanyang
Technological University -
URECA Undergraduate
Research Programme for this
research project.**



Thank you!

Open to questions and comments!

Appendix A1: Satellite Images Dataset

No. of Images By States

State	No.	State	No.	State	No.
MO	110	WY	80	NV	53
KS	103	NH	79	IN	51
CO	102	AL	79	MA	50
WA	99	GA	76	FL	49
NM	95	VA	75	ND	48
OR	93	OH	71	MI	47
CT	92	DE	70	NE	46
IA	91	AR	69	KY	45
UT	91	WI	67	VT	45
IL	90	MS	66	MN	45
CA	89	LA	64	OK	40
MT	88	PA	63	WV	36
MD	88	AZ	59	ME	27
SD	84	SC	57	DC	23
ID	84	AK	55		
TX	84	NJ	55		
RI	81	TN	55		
NY	80	NC	53		

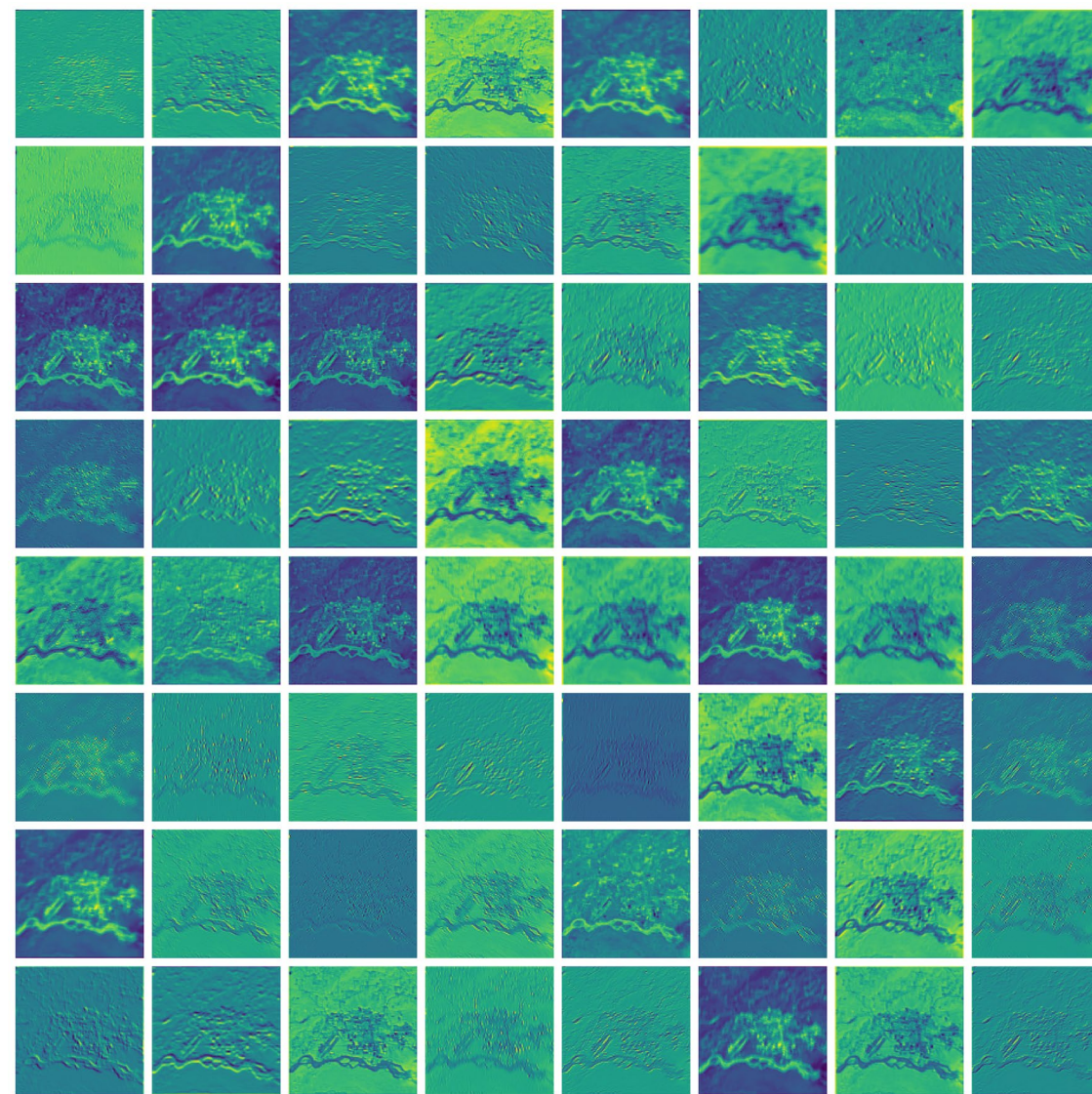
No. of Images By Year

State	No.	State	No.
1984 (dropped)	91	2001	126
1985	108	2002	132
1986	137	2003	136
1987	144	2004	127
1988	112	2005	132
1989	122	2006	140
1990	105	2007	123
1991	108	2008	142
1992	89	2009	125
1993	119	2010	135
1994	125	2011	127
1995	136		
1996	111		
1997	118		
1998	140		
1999	130		
2000	102		

Appendix B1: Feature Maps (Conv1)



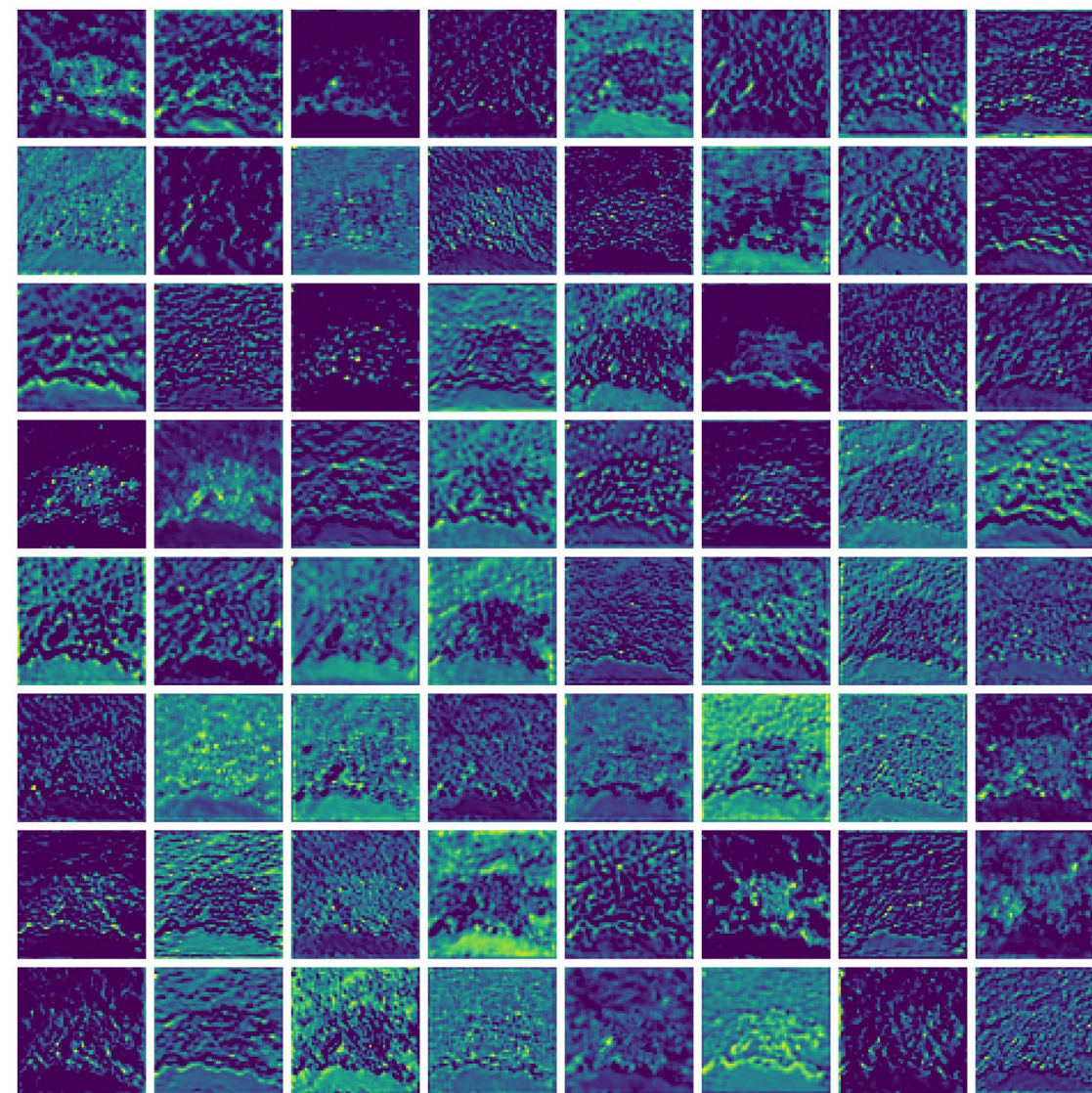
Fairbanks, AK, 2003
(Natural Colour)



Appendix B2: Feature Maps (Layer 1)



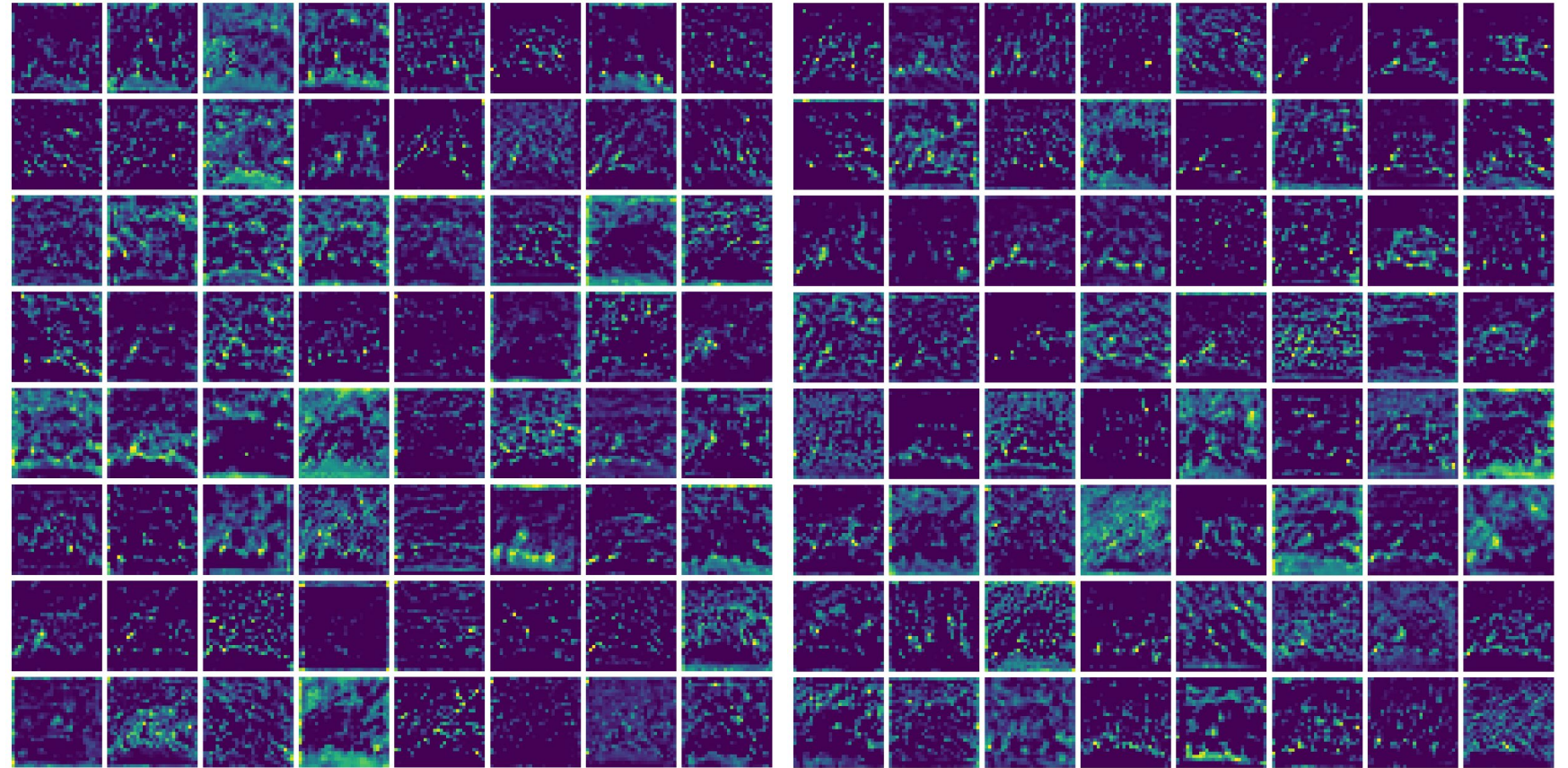
Fairbanks, AK, 2003
(Natural Colour)



Appendix B3: Feature Maps (Layer 2)



Fairbanks, AK, 2003
(Natural Colour)



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