Navigating Privacy and Utility with Multiple Imputation, Satellite Imaging and Deep Learning

Mohammad Kakooei[1], James Bailie[2],
Xiao-Li Meng[2], Adel Daoud[1,3]

[1] Chalmers University of Technology, Sweden.
[2] Harvard University, USA.
[3] Linköping University, Sweden

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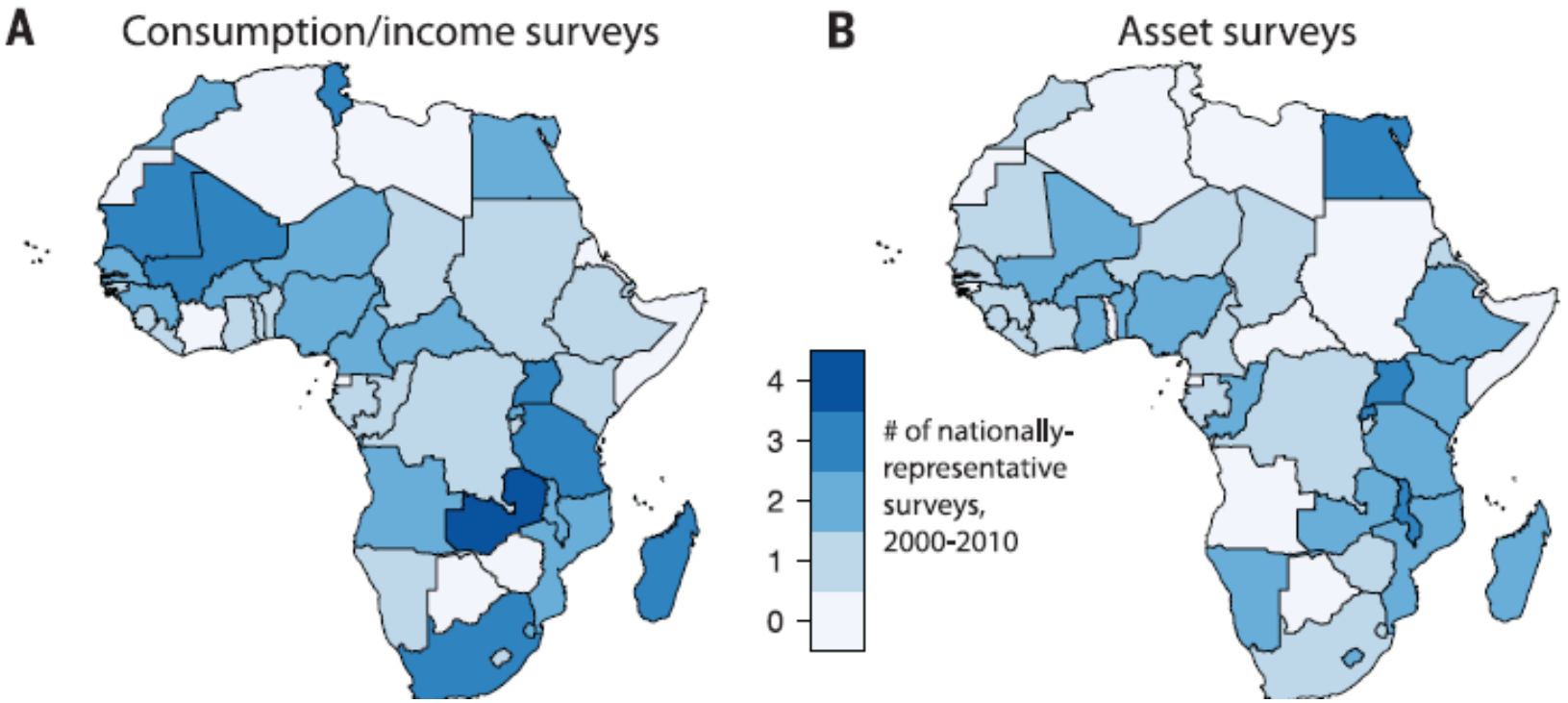
The AI and Global Development Lab

Funded mainly by the Swedish Research Council (SRC)

Because of a lack of high-frequency human-development data across time and space, scholarship on poverty is limited.



Source: Jean et al 2016

Source: Google Earth Timelapse (Google, Landsat, Copernicus)

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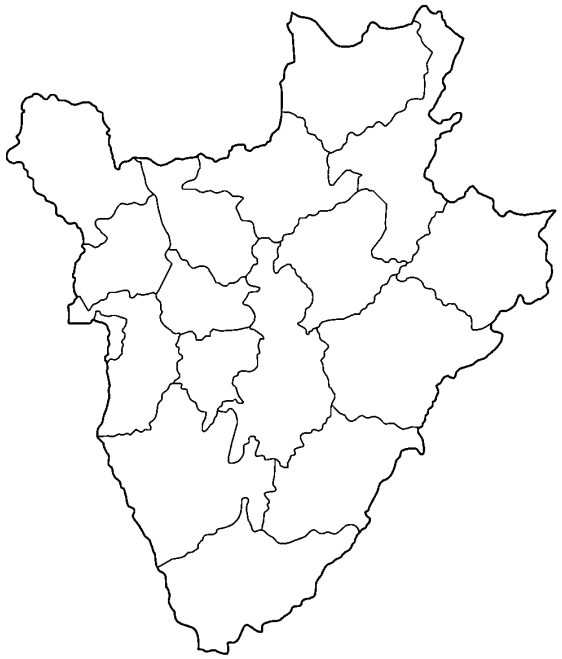
Constructing an Algorithm for Poverty Measurement



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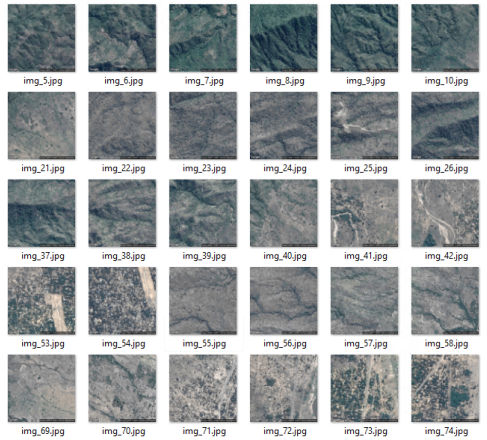

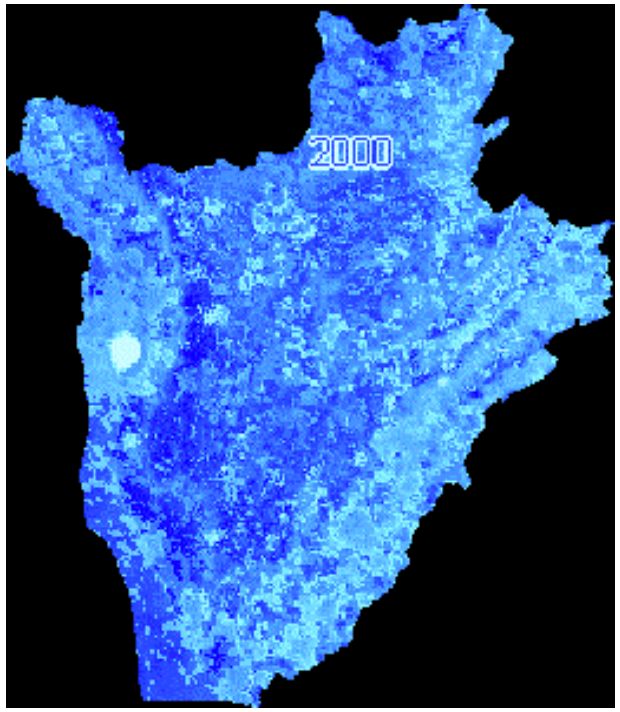

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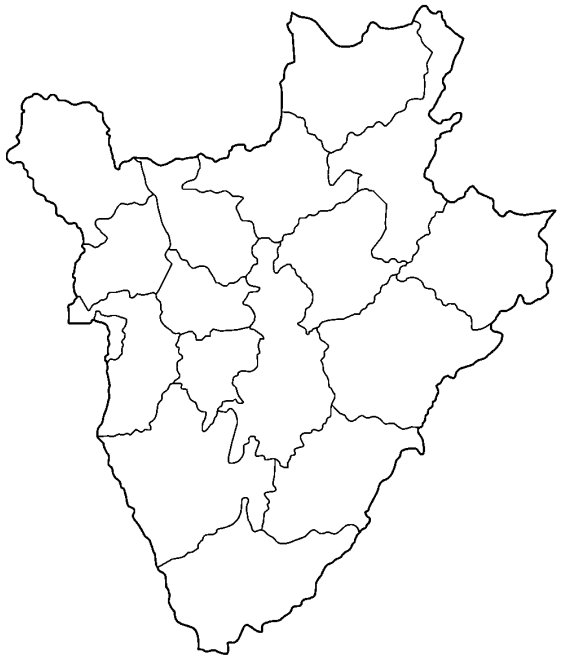

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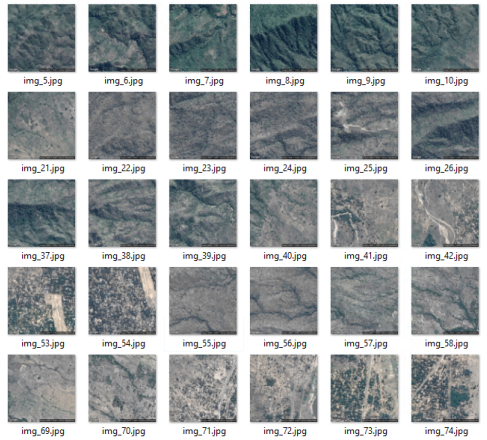
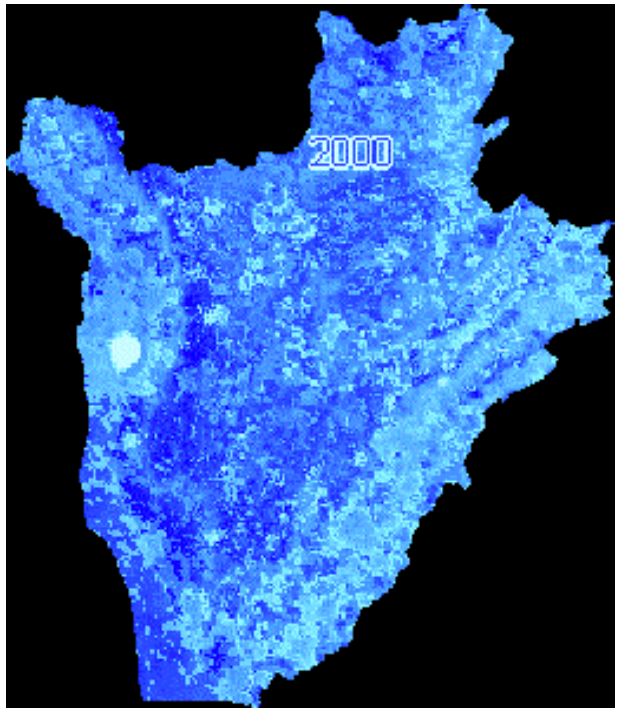
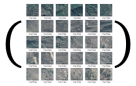


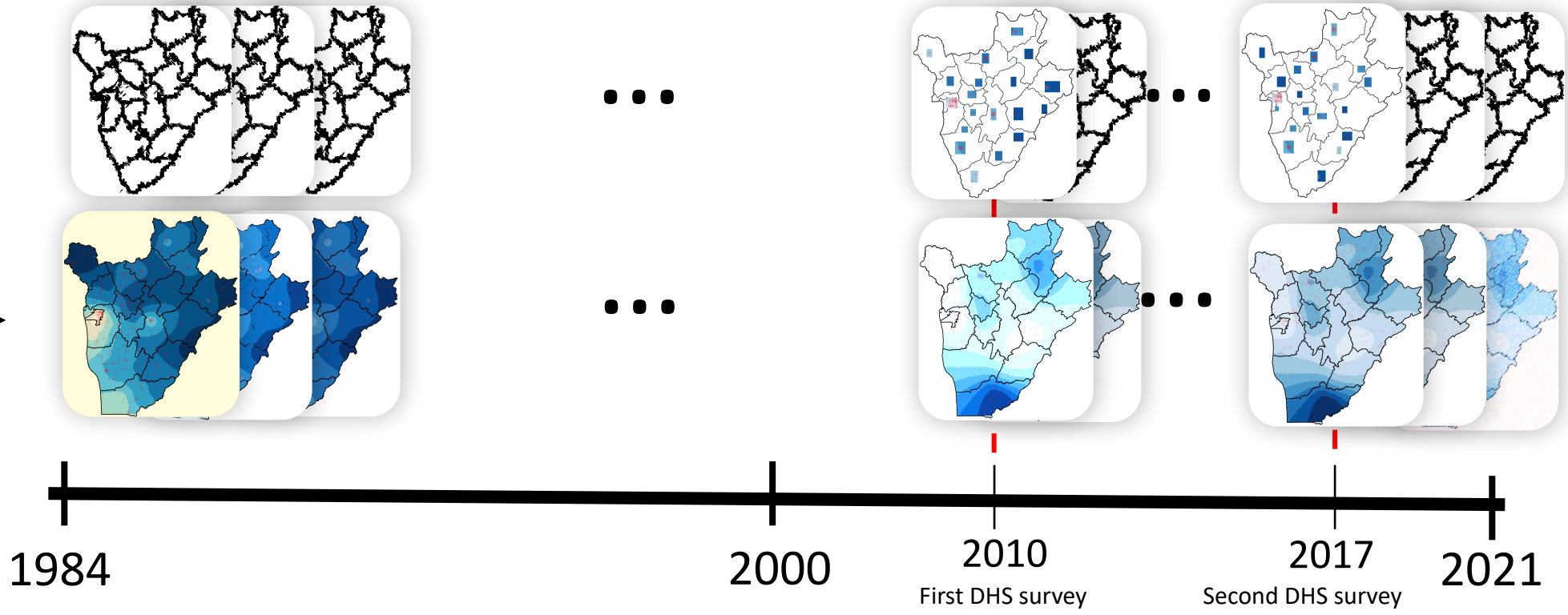


Our Data Product

Without our data

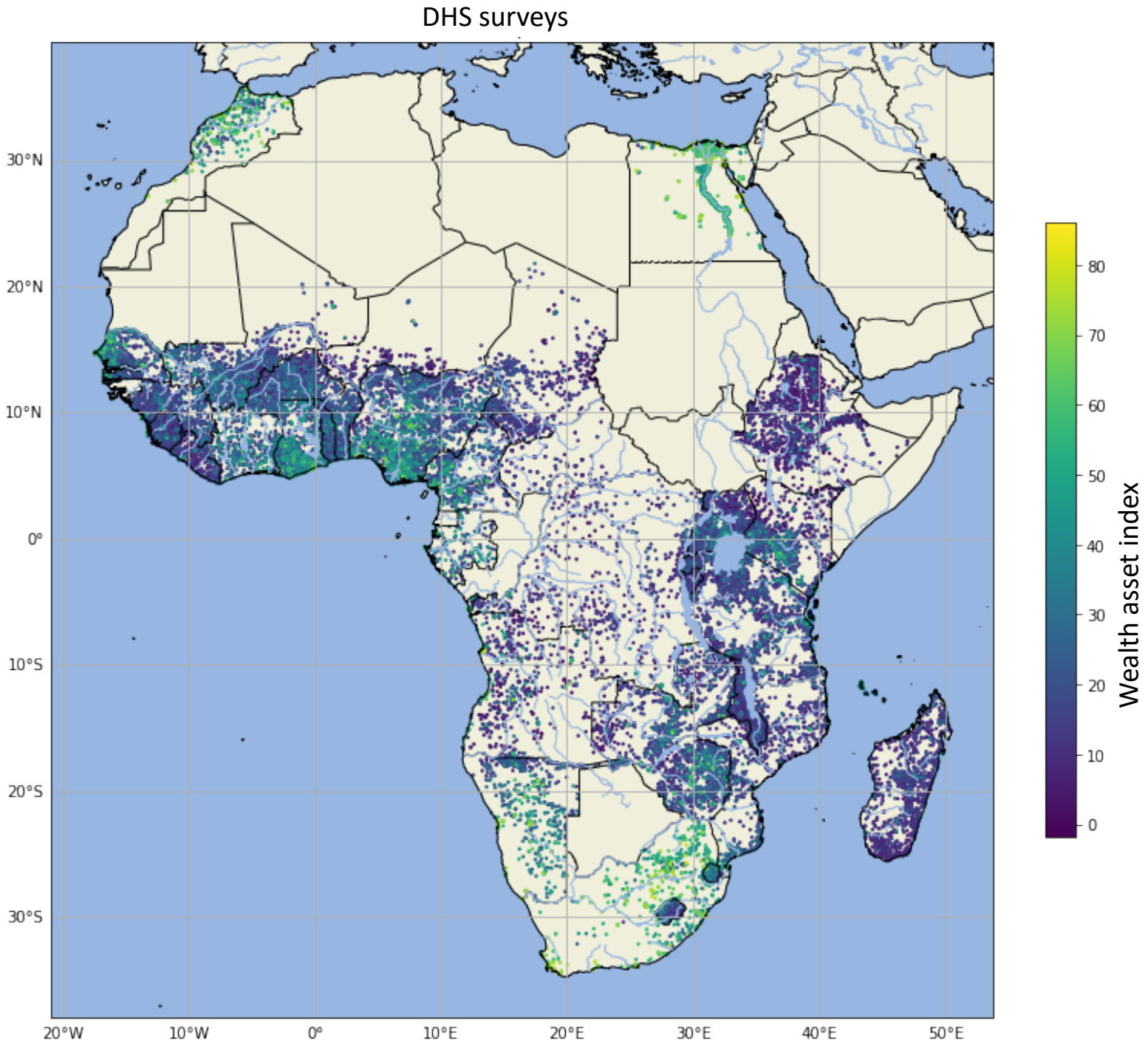
With our data

$f($  $)$ →



Ground "truth"

- International wealth index (material assets)
- ≈57 000 DHS survey units ("clusters")
- From 36 countries
- 1984 – 2019
- Unit of analysis: clusters consisting of about 20-30 households



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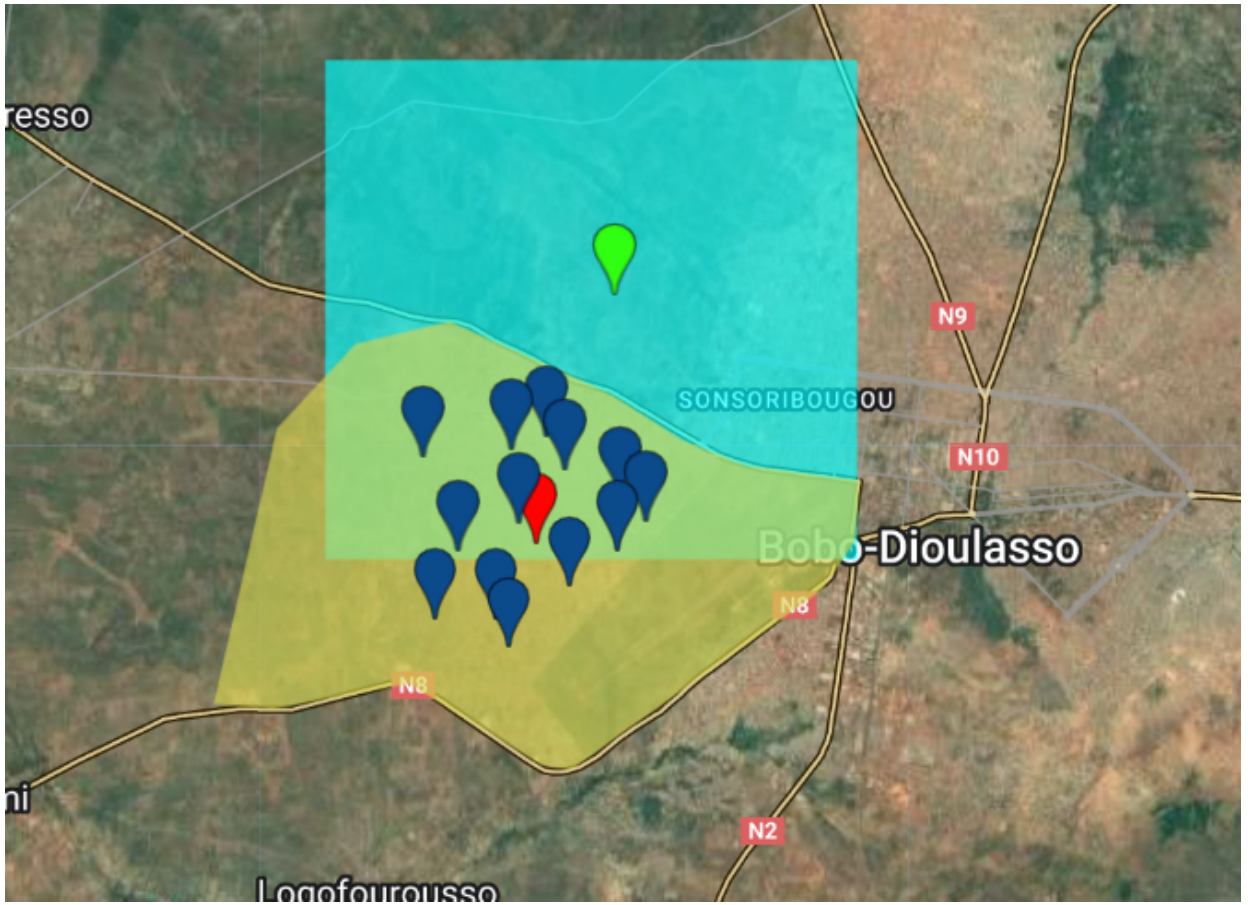

- Households
- Cluster center
- Displaced location (released coordinates)

Correcting For Privacy Using Multiple Imputation?

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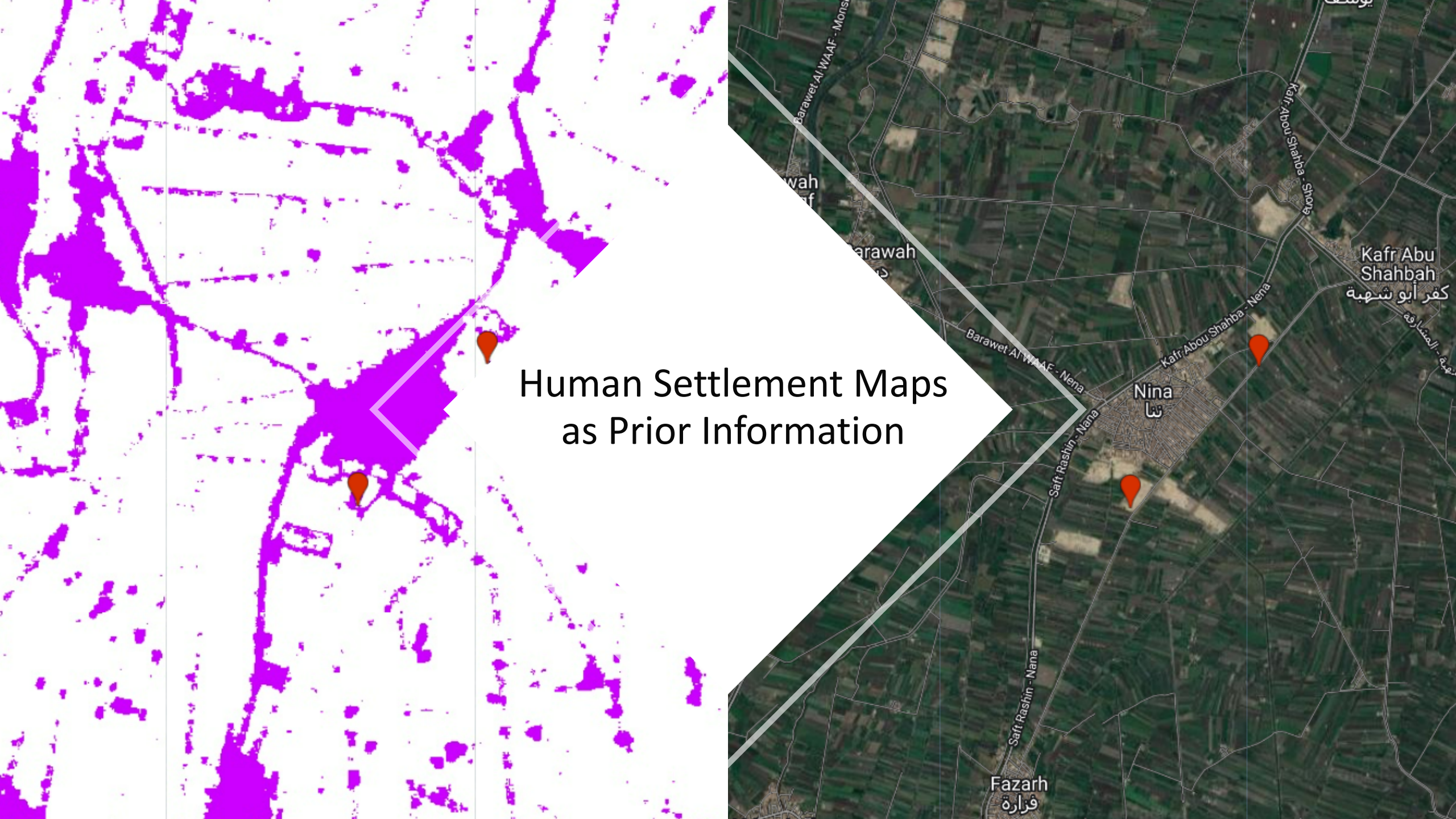
- Train and test model using the satellite images at the imputed locations $\hat{L}_i$.


Human Settlement Maps
as Prior Information
Barawet Al WAAF - Monsh
Kafr Abou Shahba - Shorb
Kafr Abu
Shahbah
كفر أبو شهبة
Barawet Al WAAF - Nena
Kafr Abou Shahba - Nena
Nina
نينا
Saft Rashin - Nana
Fazarh
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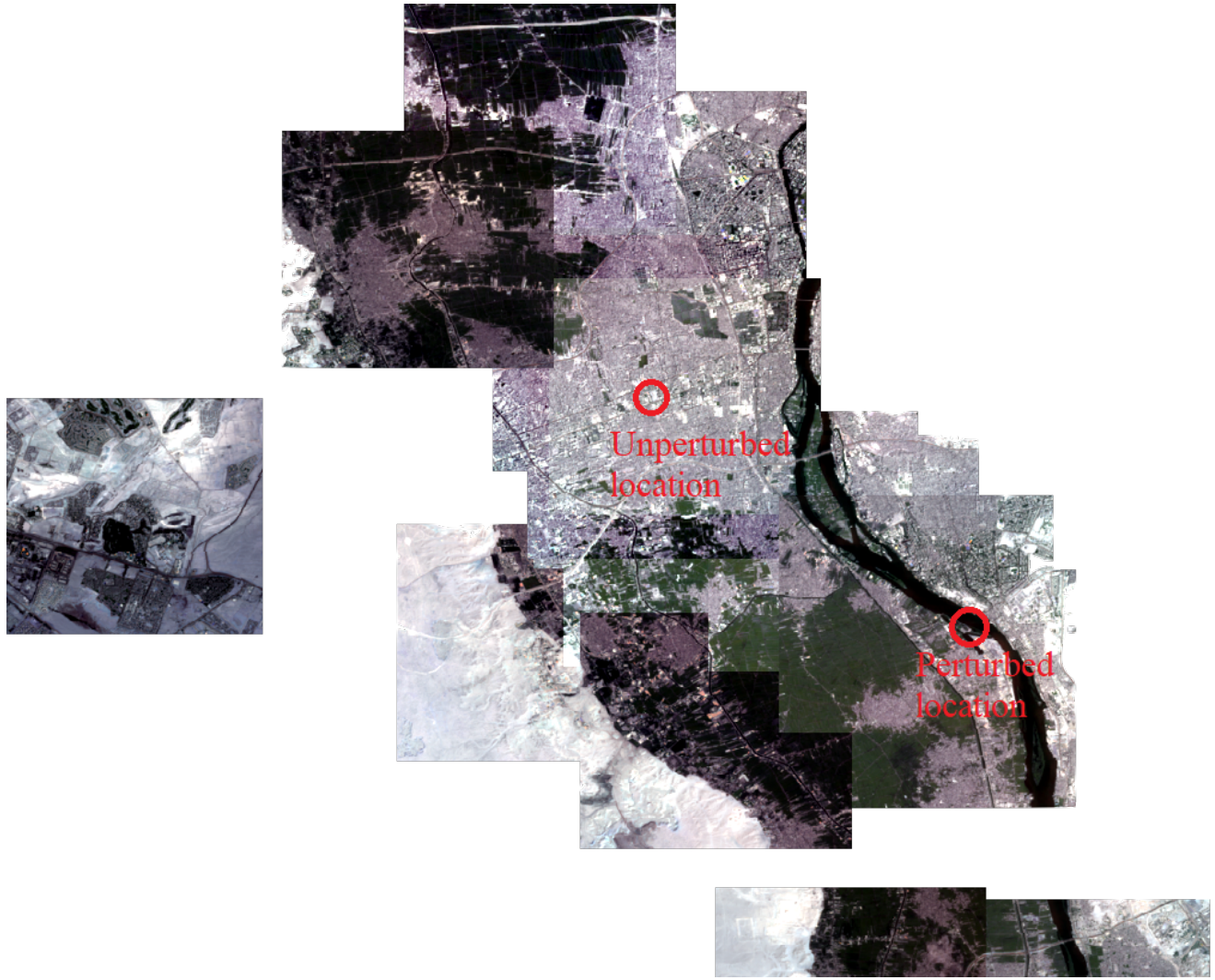

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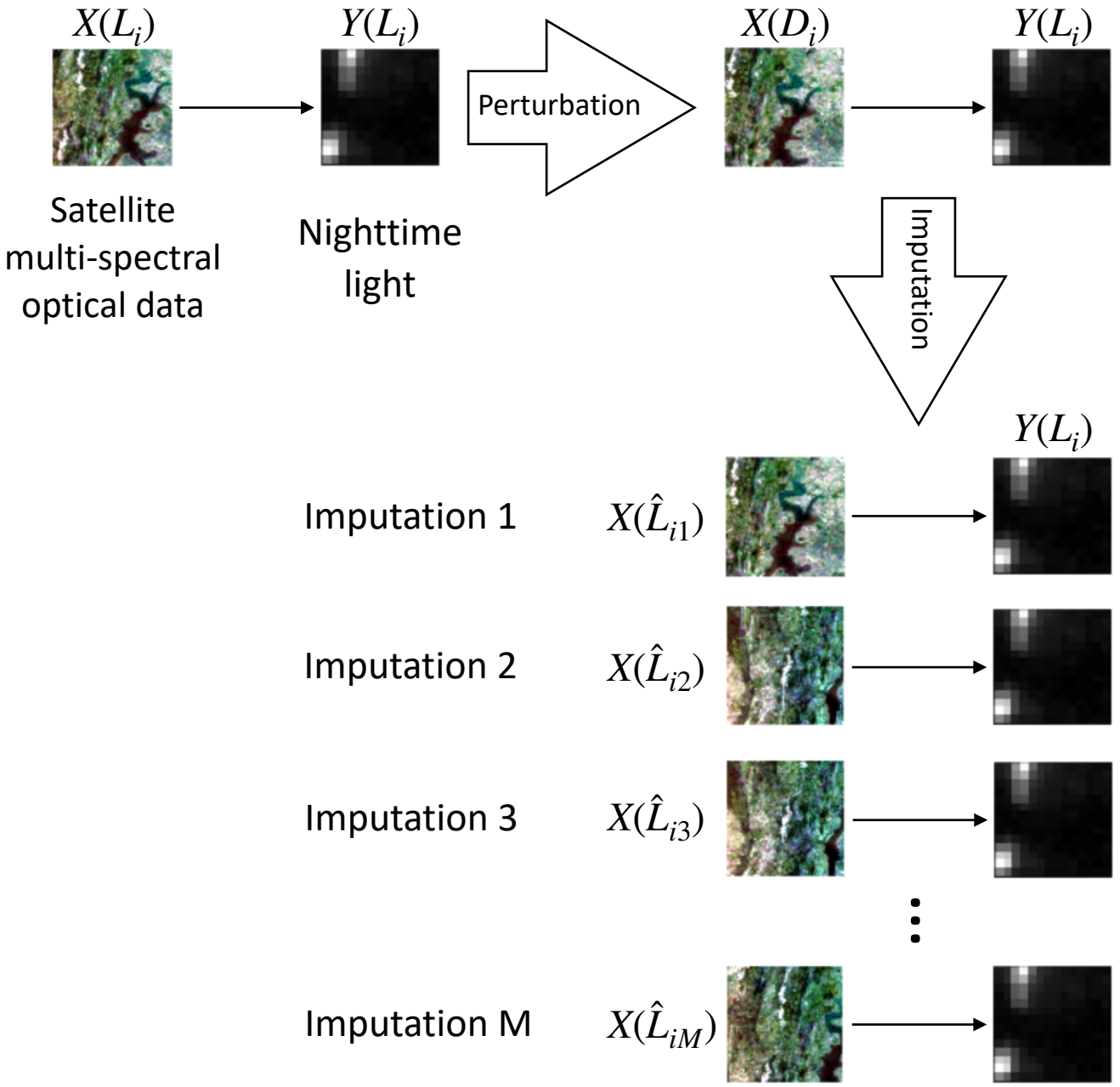

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- With some simple algebra, $R^2 = R^2_{\text{Syn}} + (1 - R^2_{\text{Syn}})f_{\text{Syn}}$, where

$$f_{\text{Syn}} = \frac{RSS_{\text{Syn}}/RSS - TSS_{\text{Syn}}/TSS}{RSS_{\text{Syn}}/RSS}$$

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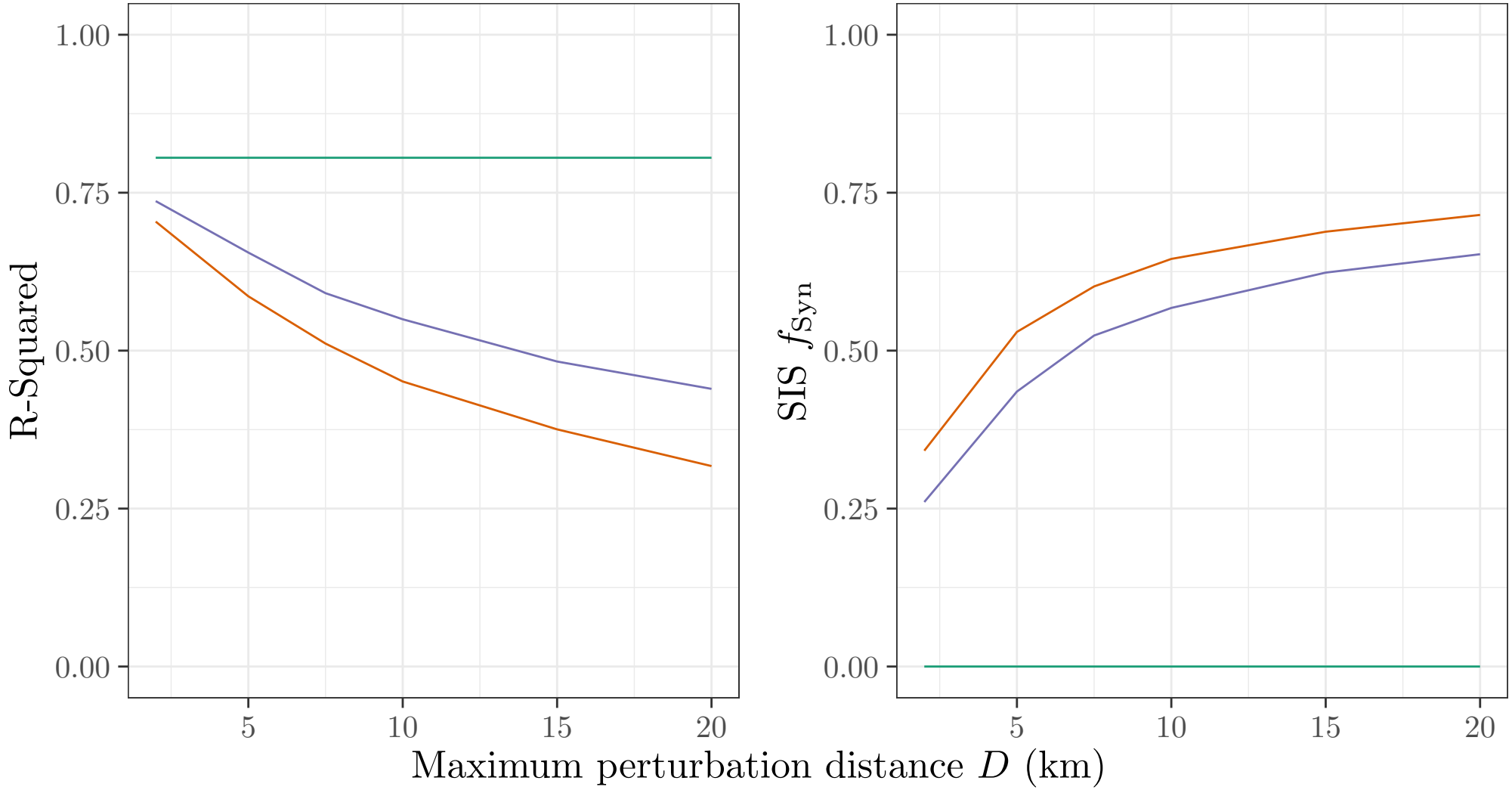

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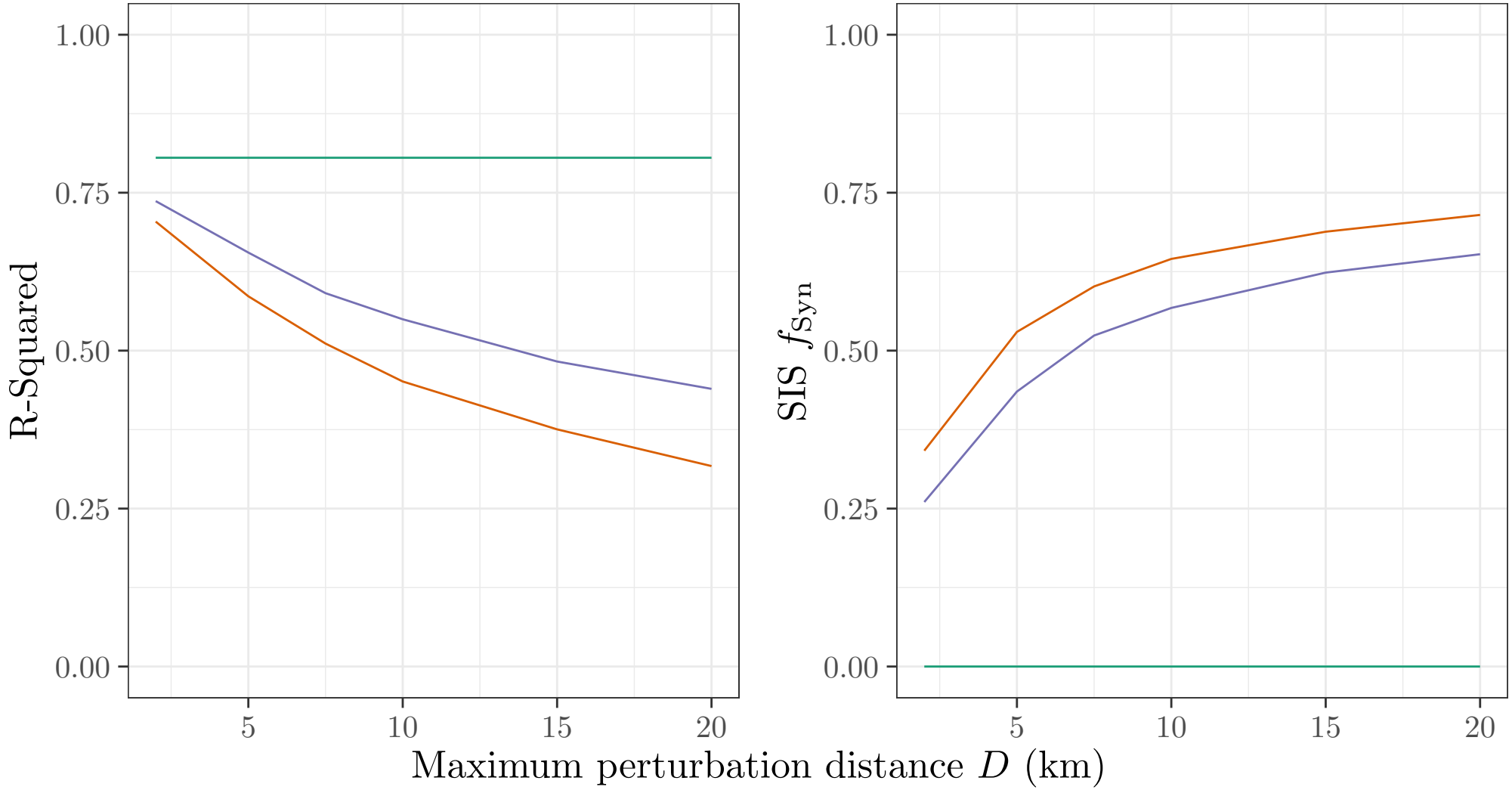

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- I.e. R^2_{Syn} is a lower bound as long as δ_i is not informative of r_i.

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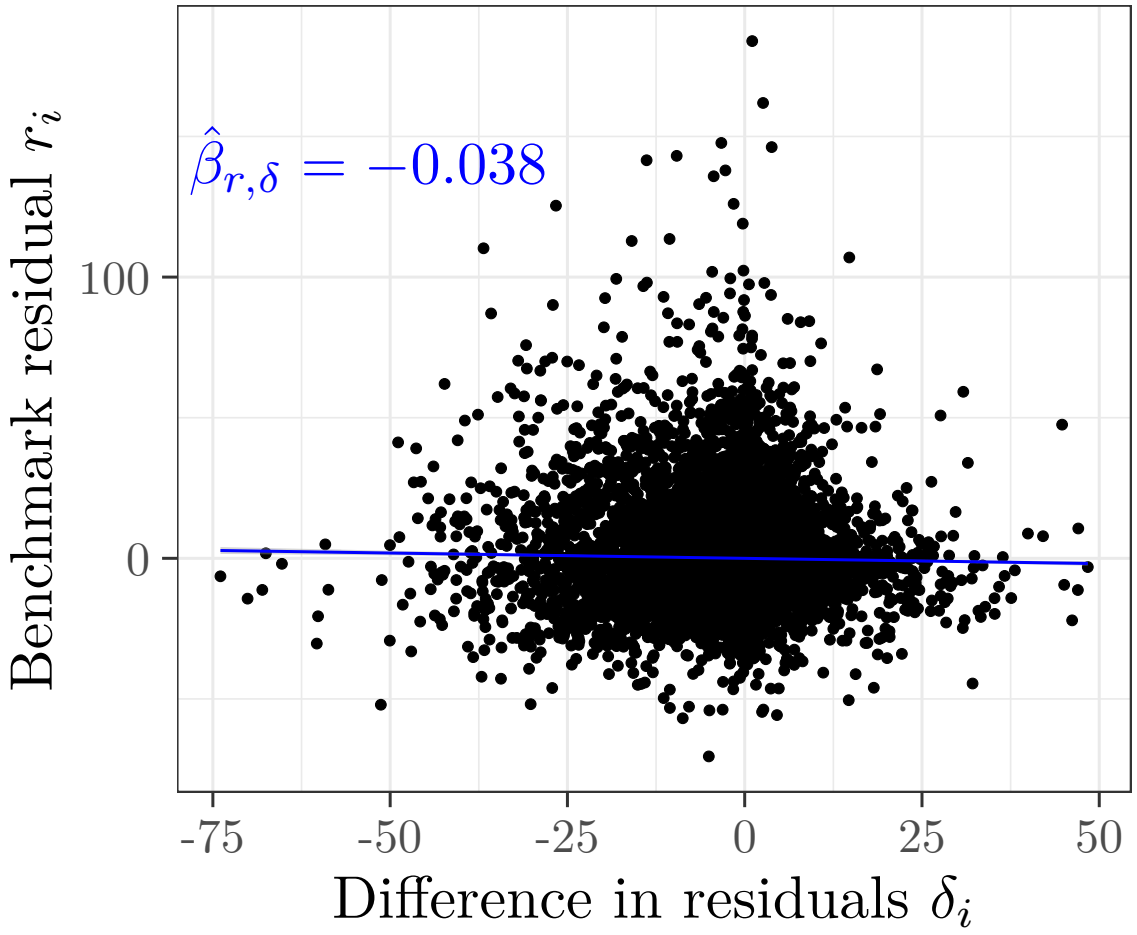

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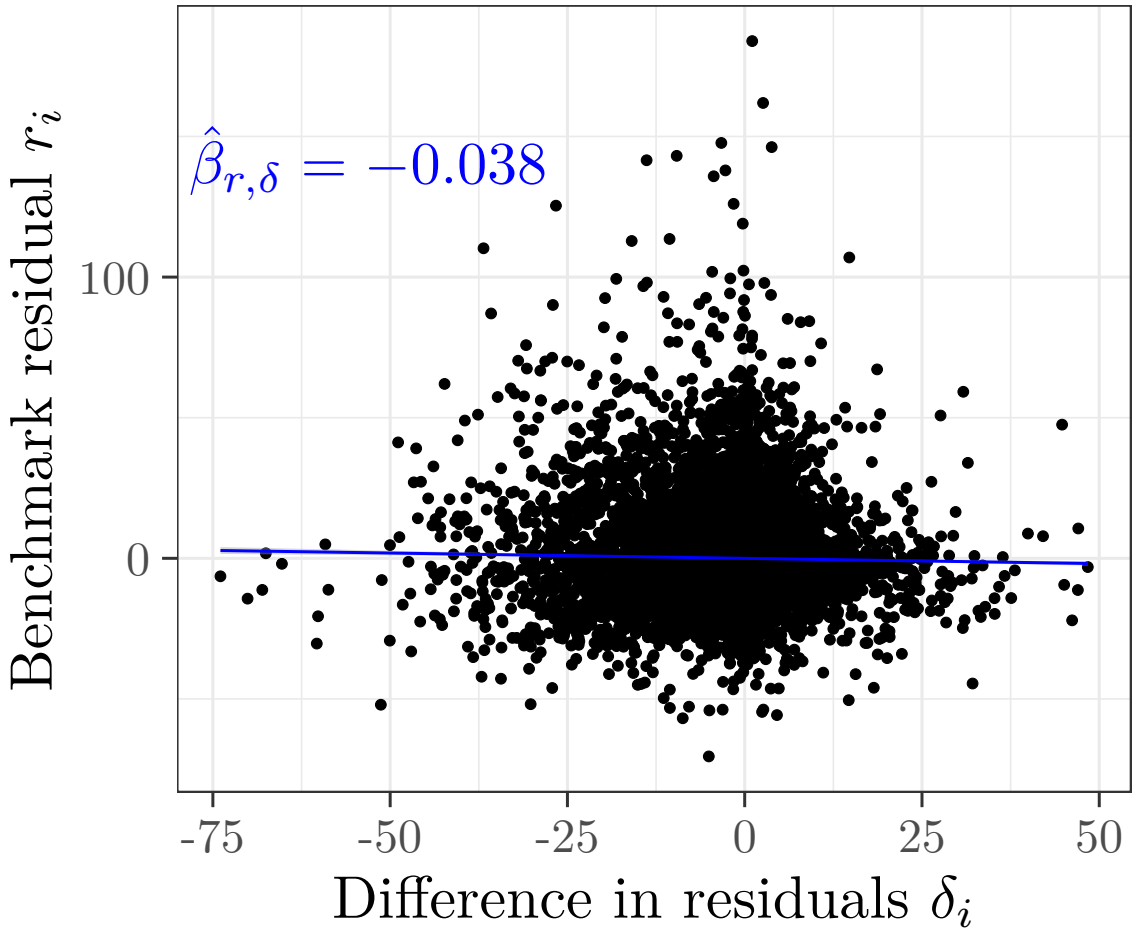

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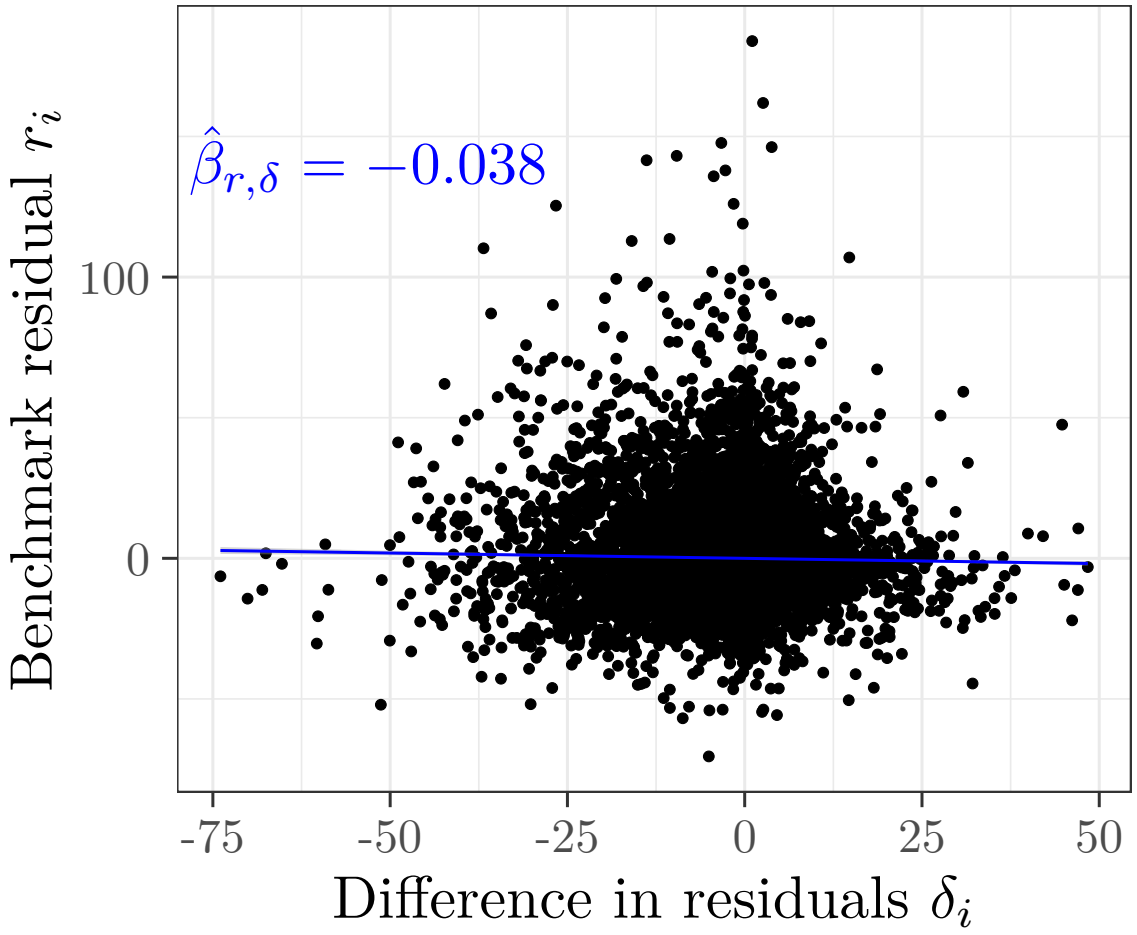

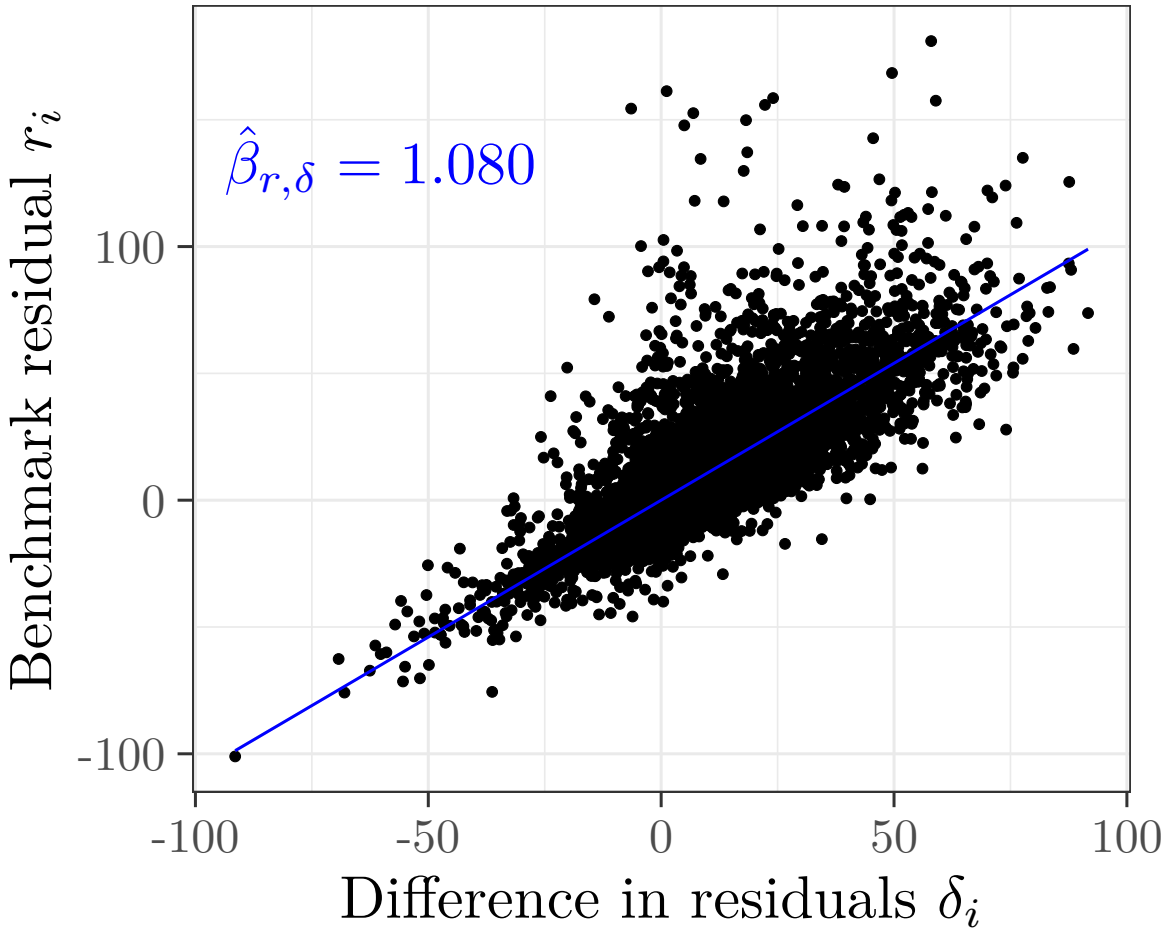

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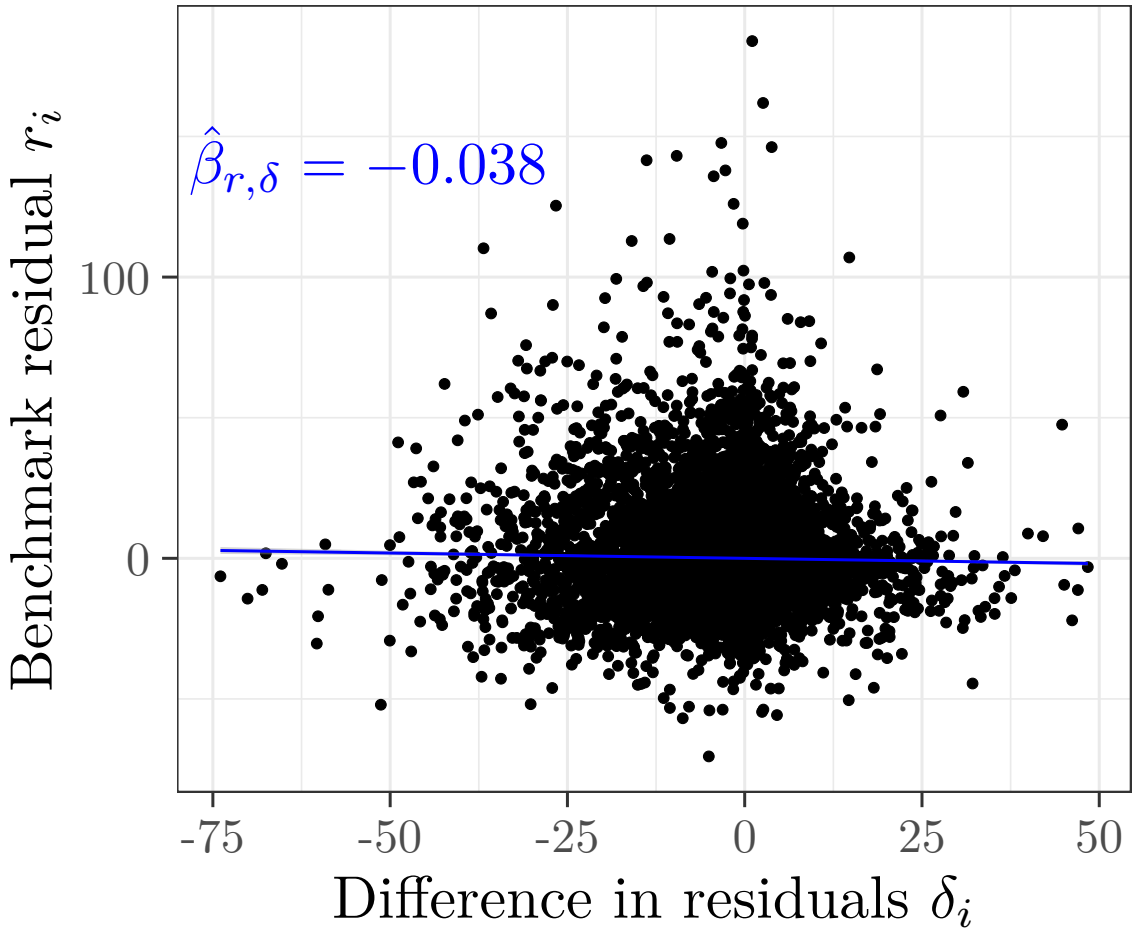

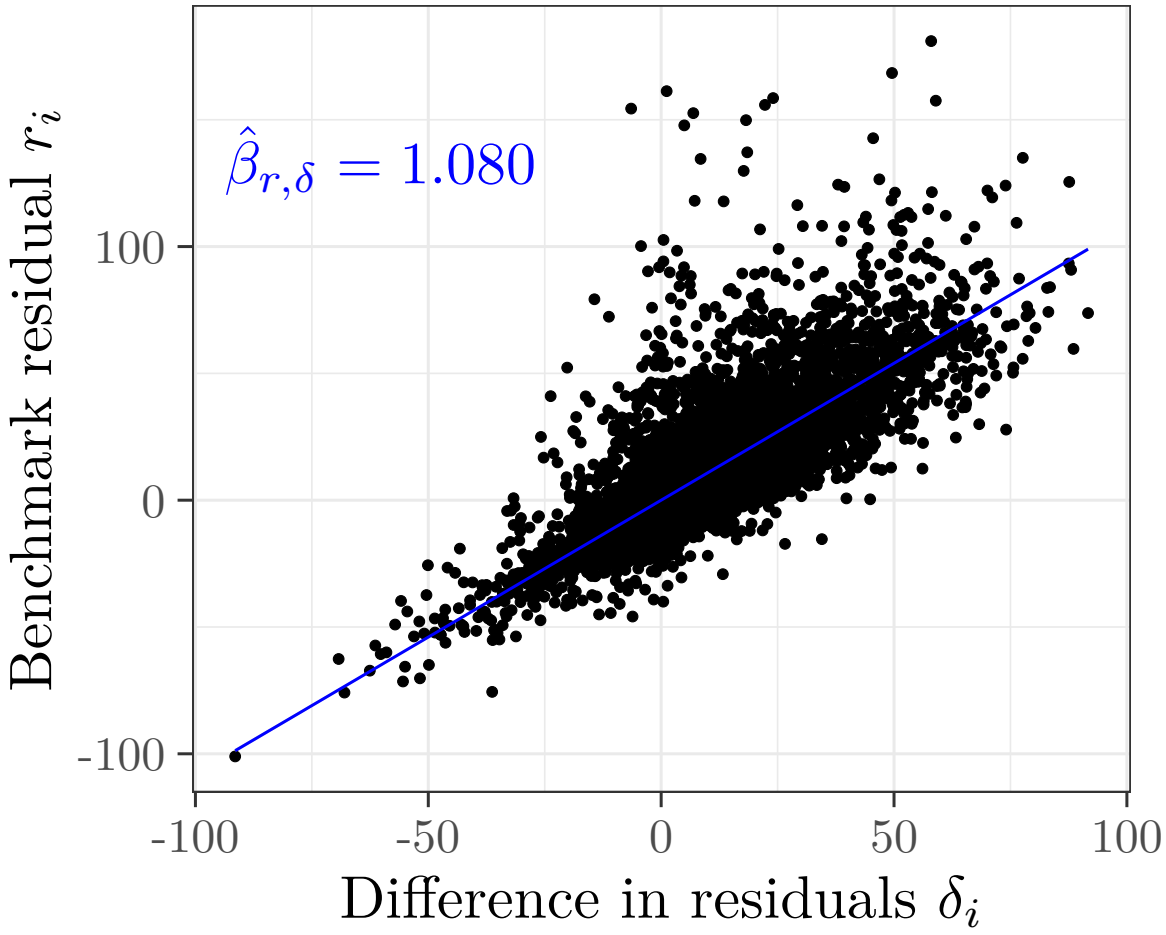

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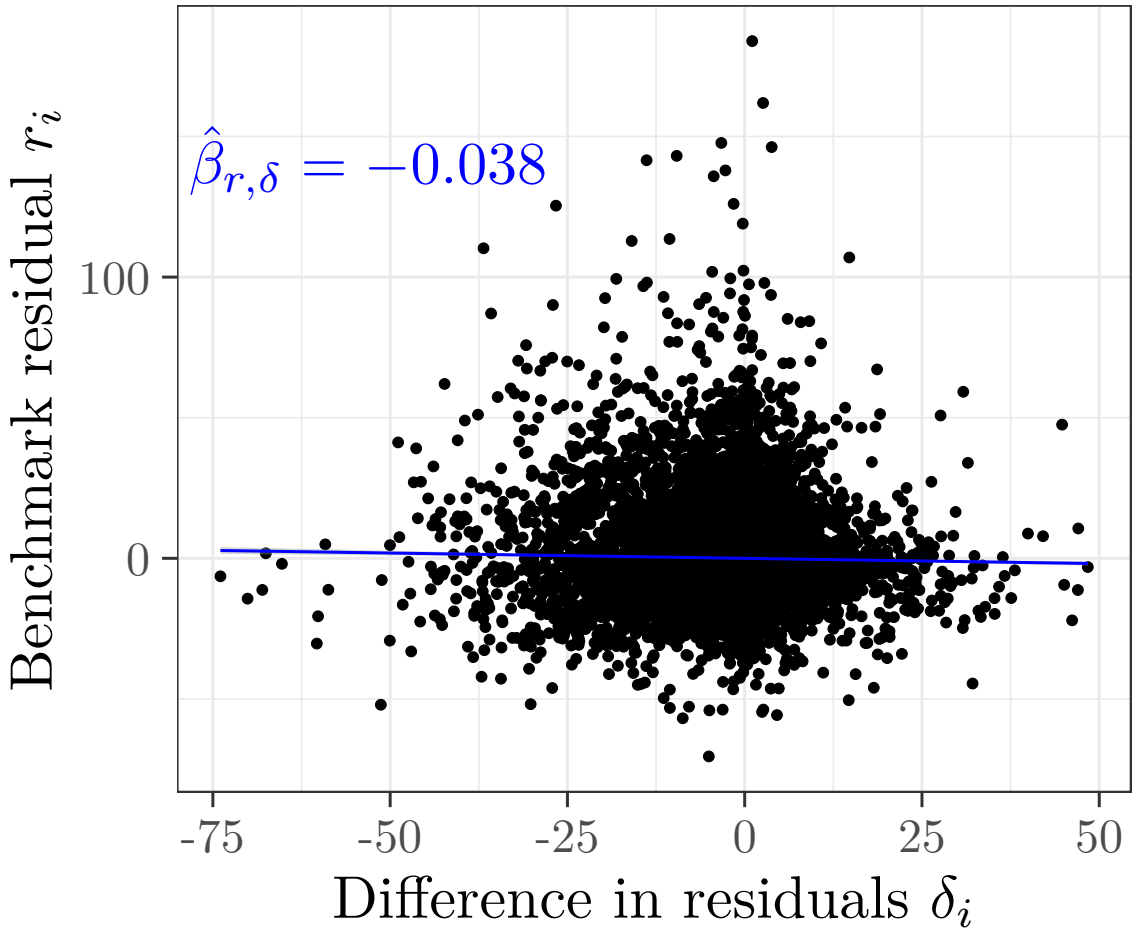
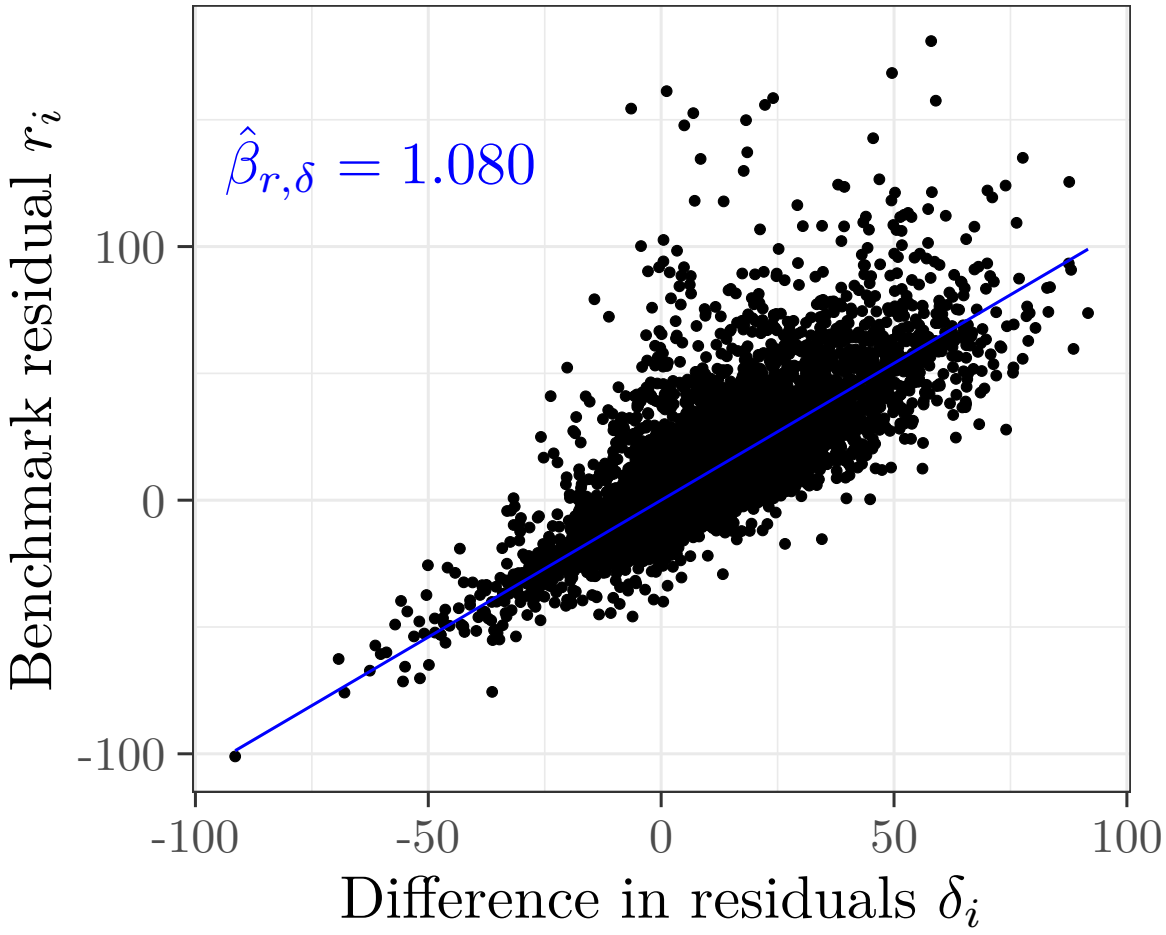
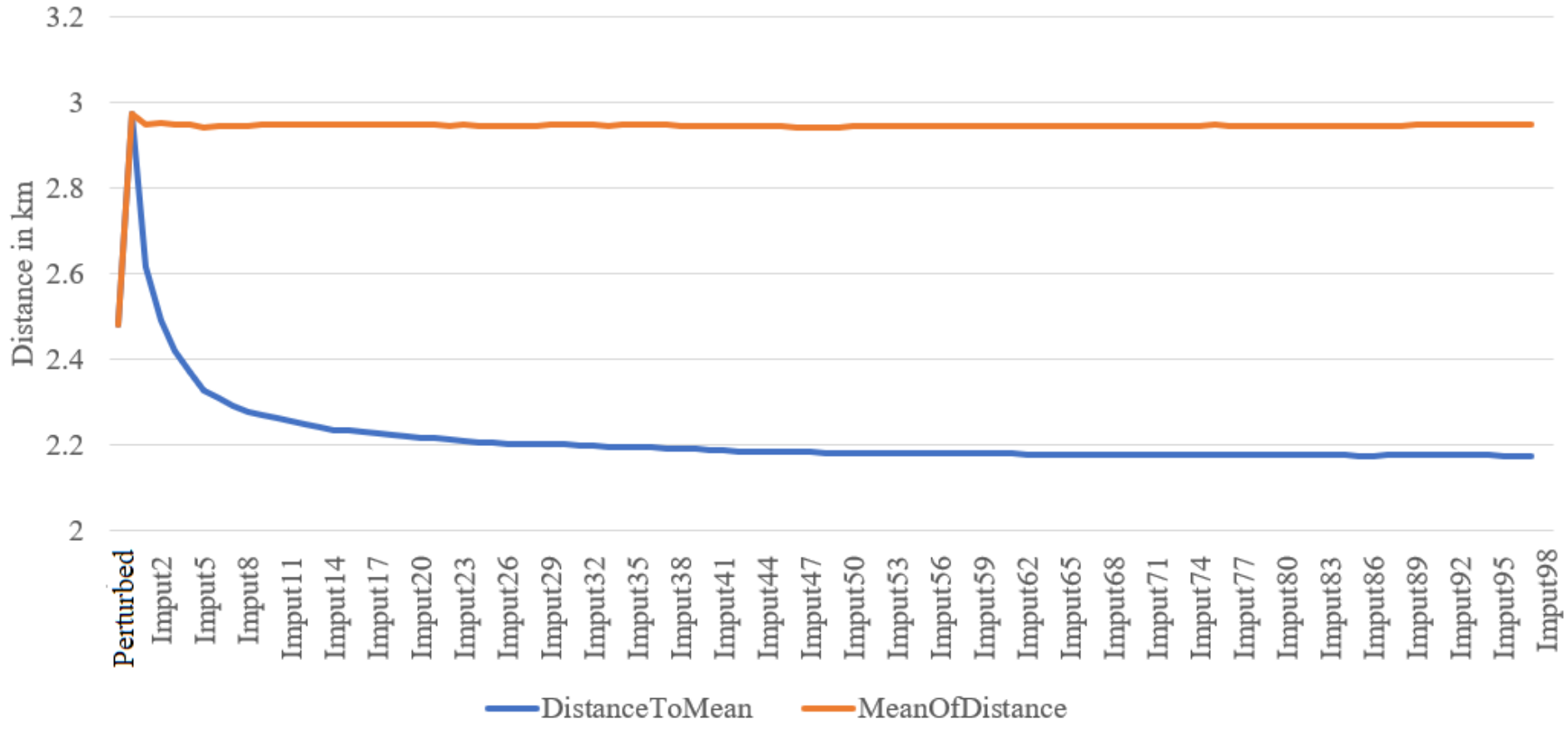




Compare MI average distance with distance to average of MI



Comparing 5 DL models

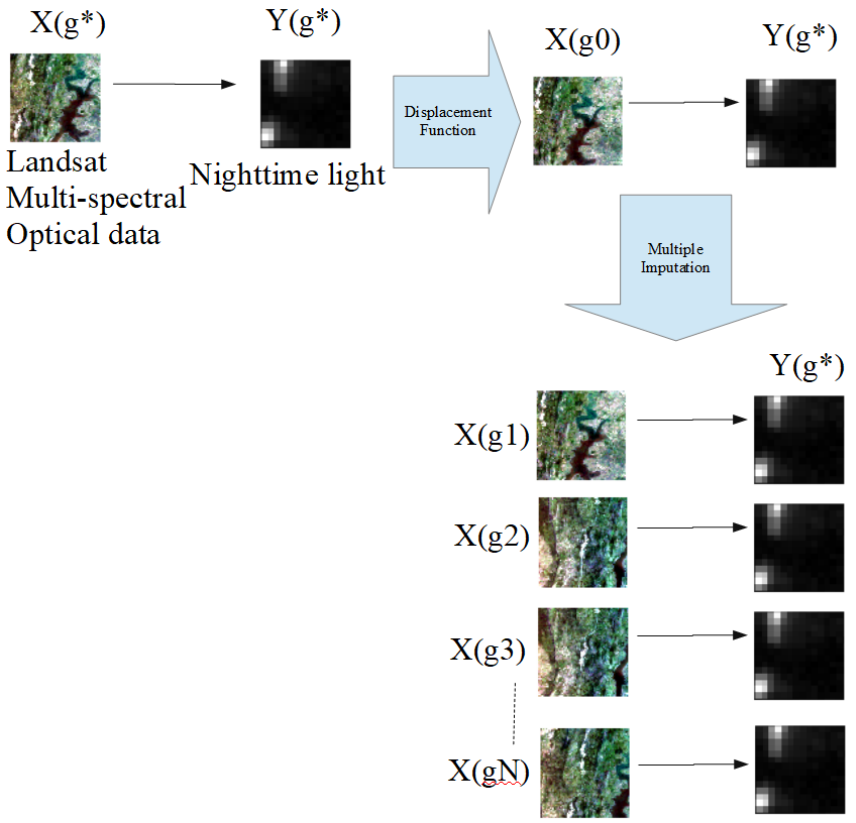
(1) DL trained on confidential data

(2) DL on released data

(3.a) DL on each imputation and than taking average

(3.b) DL on the average location of the imputed data

(3.c) DL on all imputed data collectively



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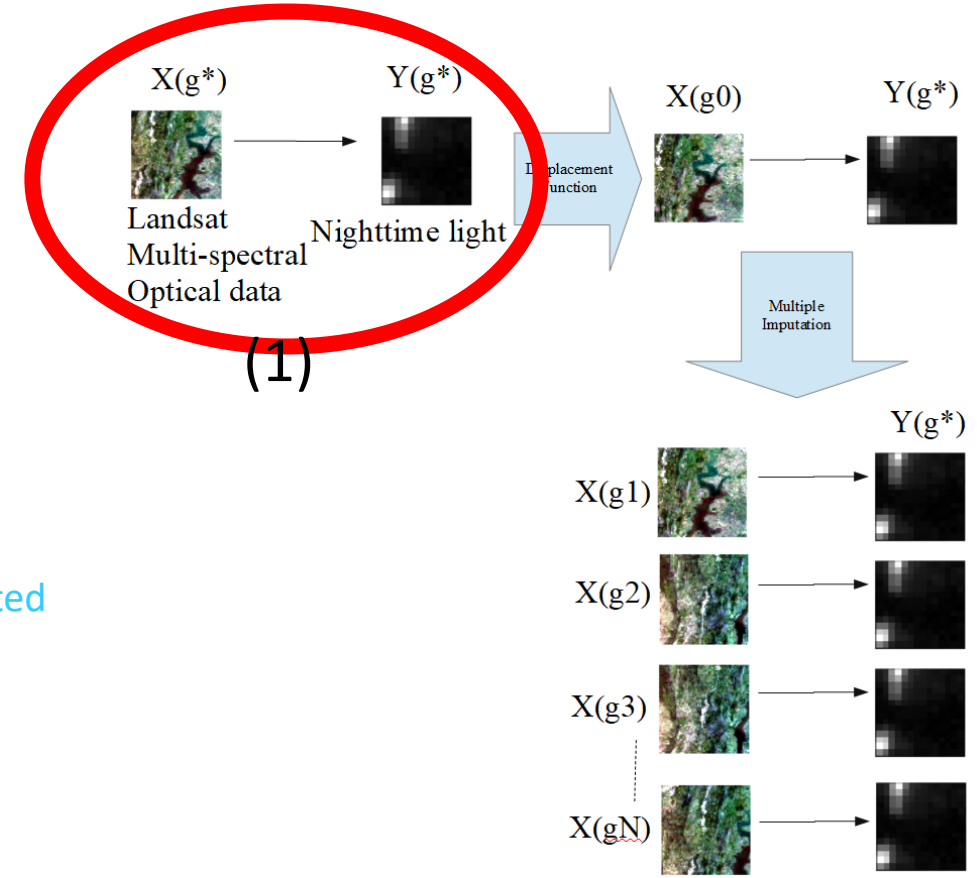

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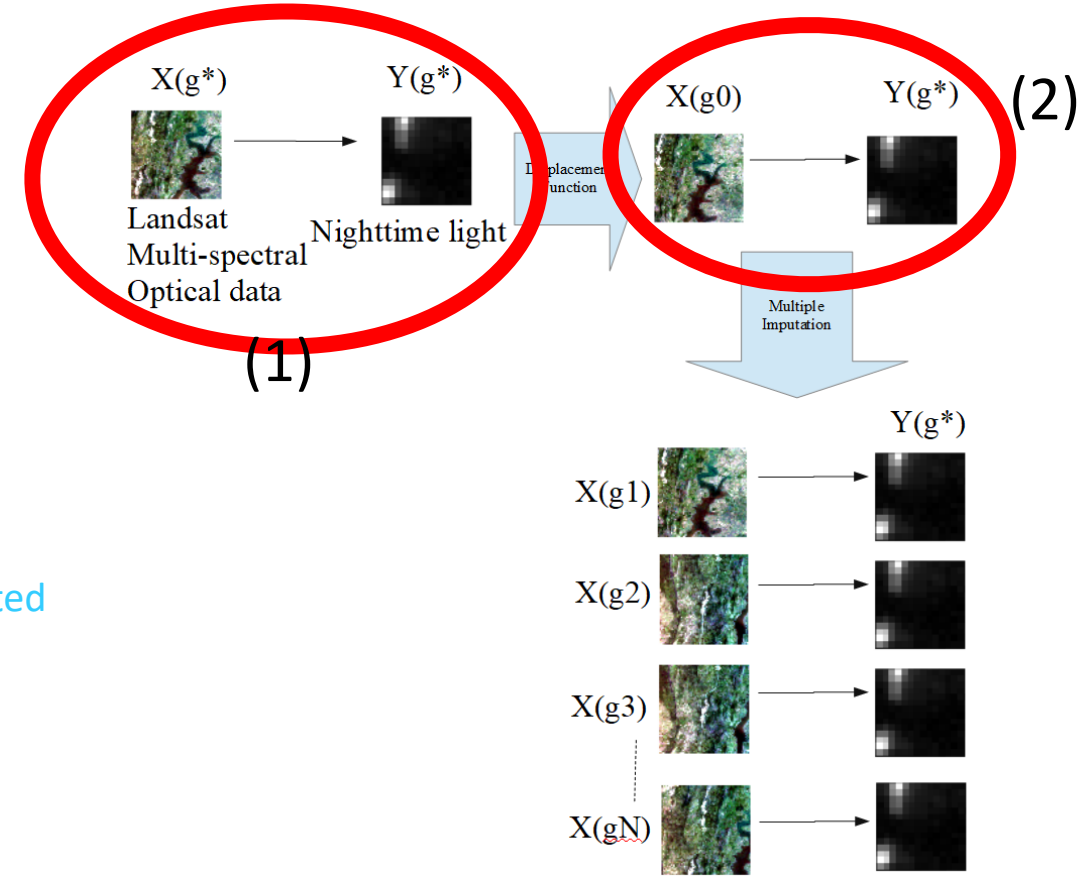

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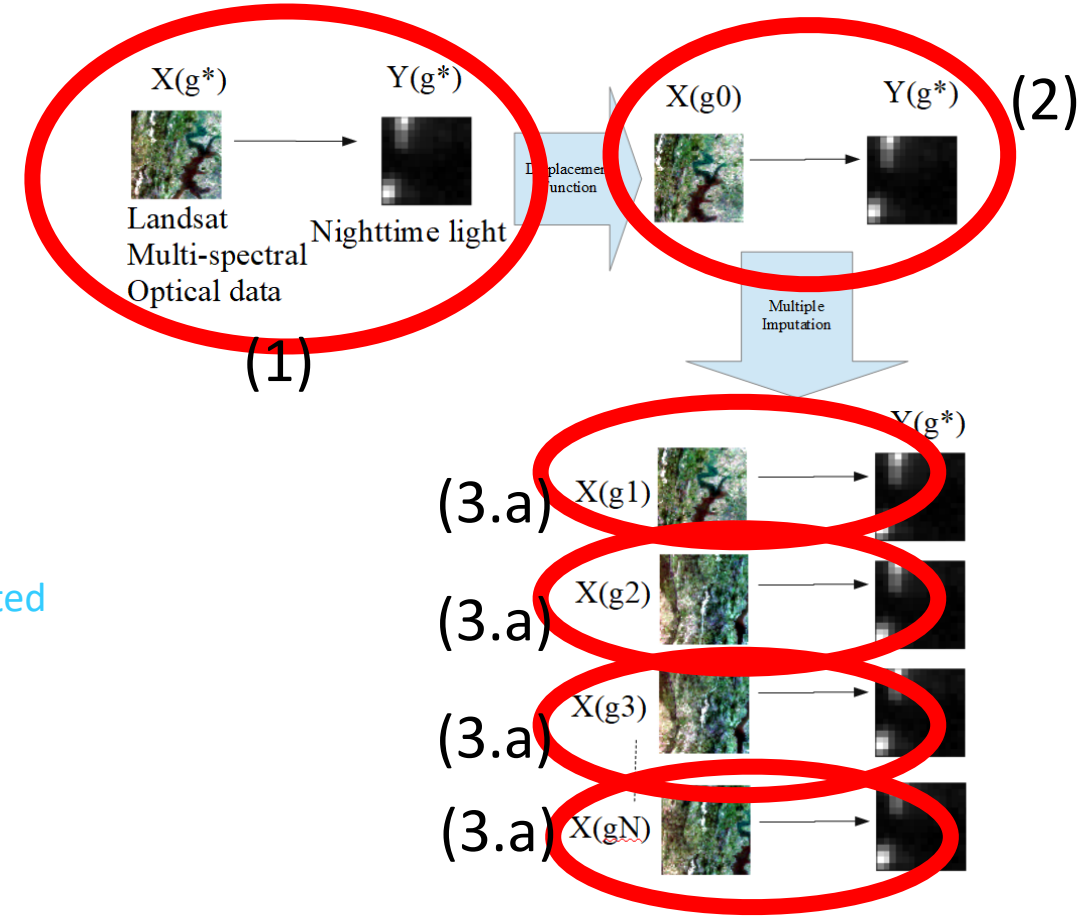

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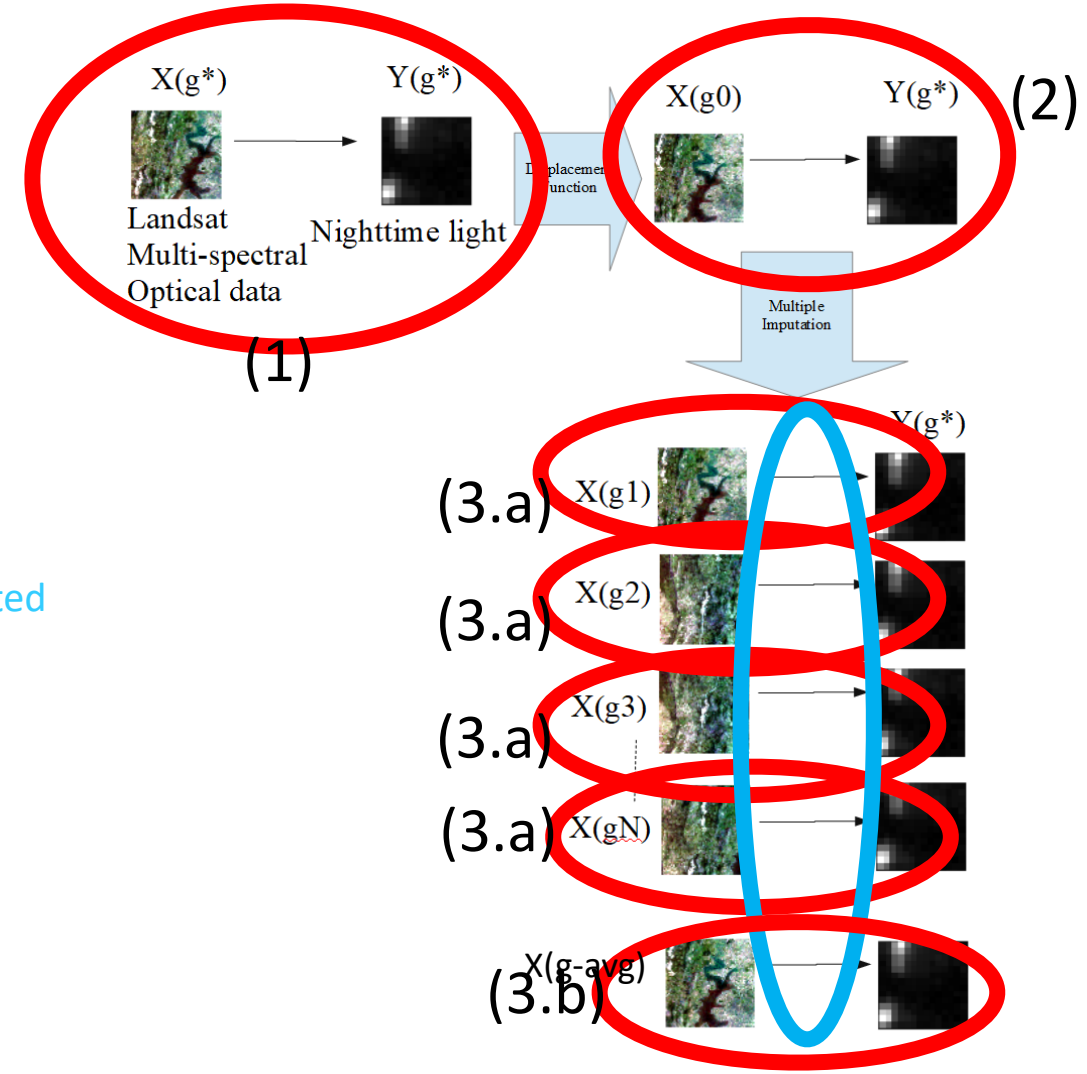

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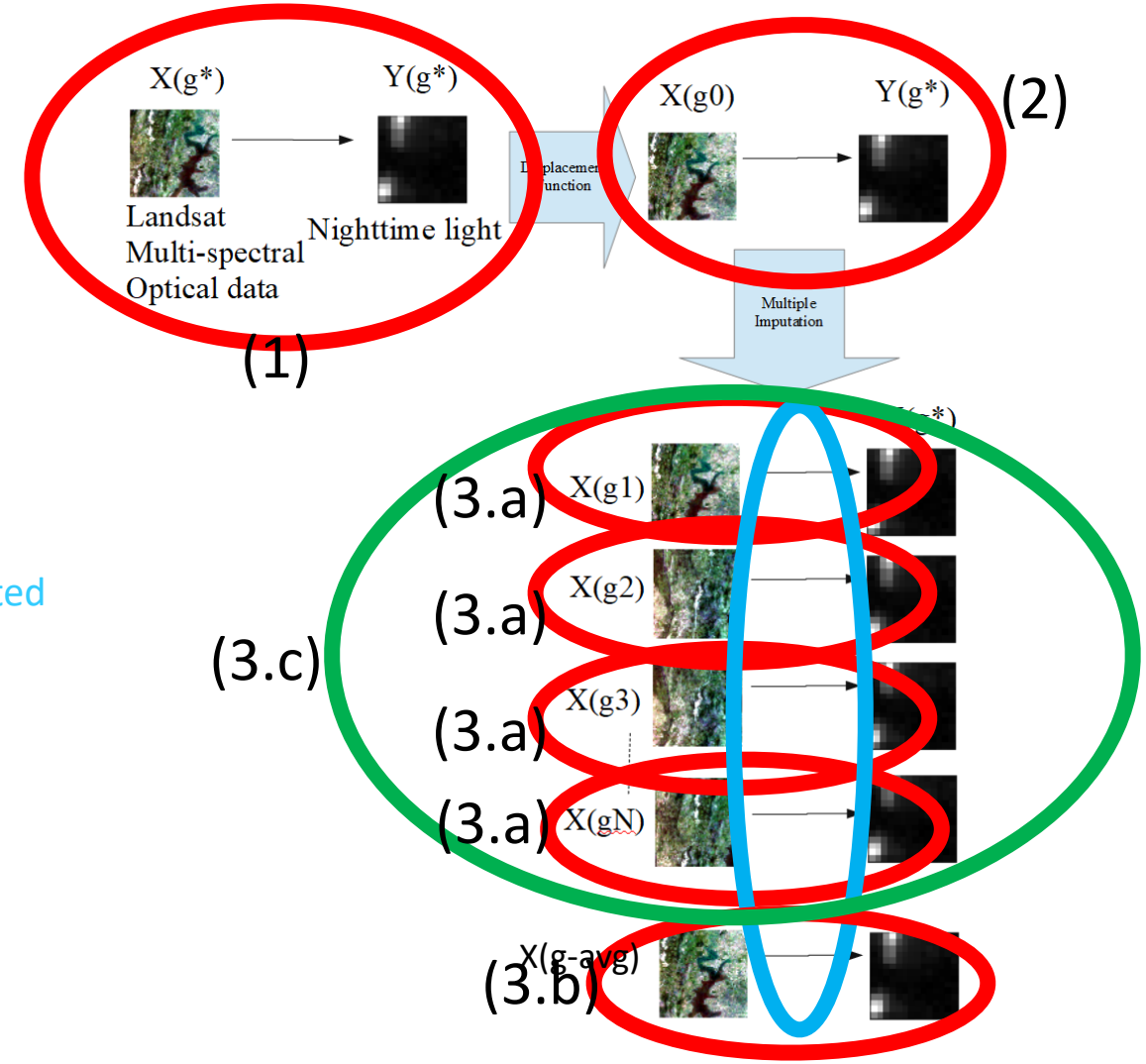

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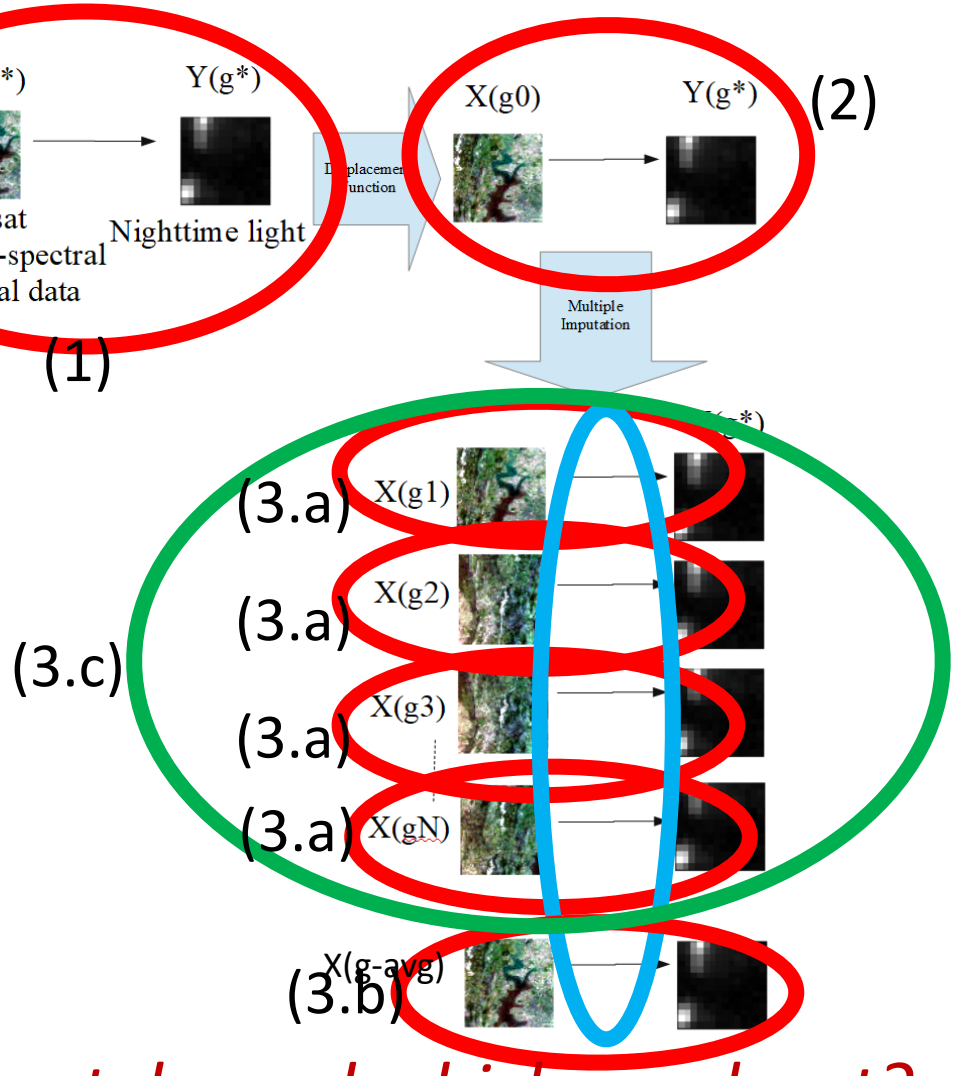

Which one predicts most accurately, and which one least?

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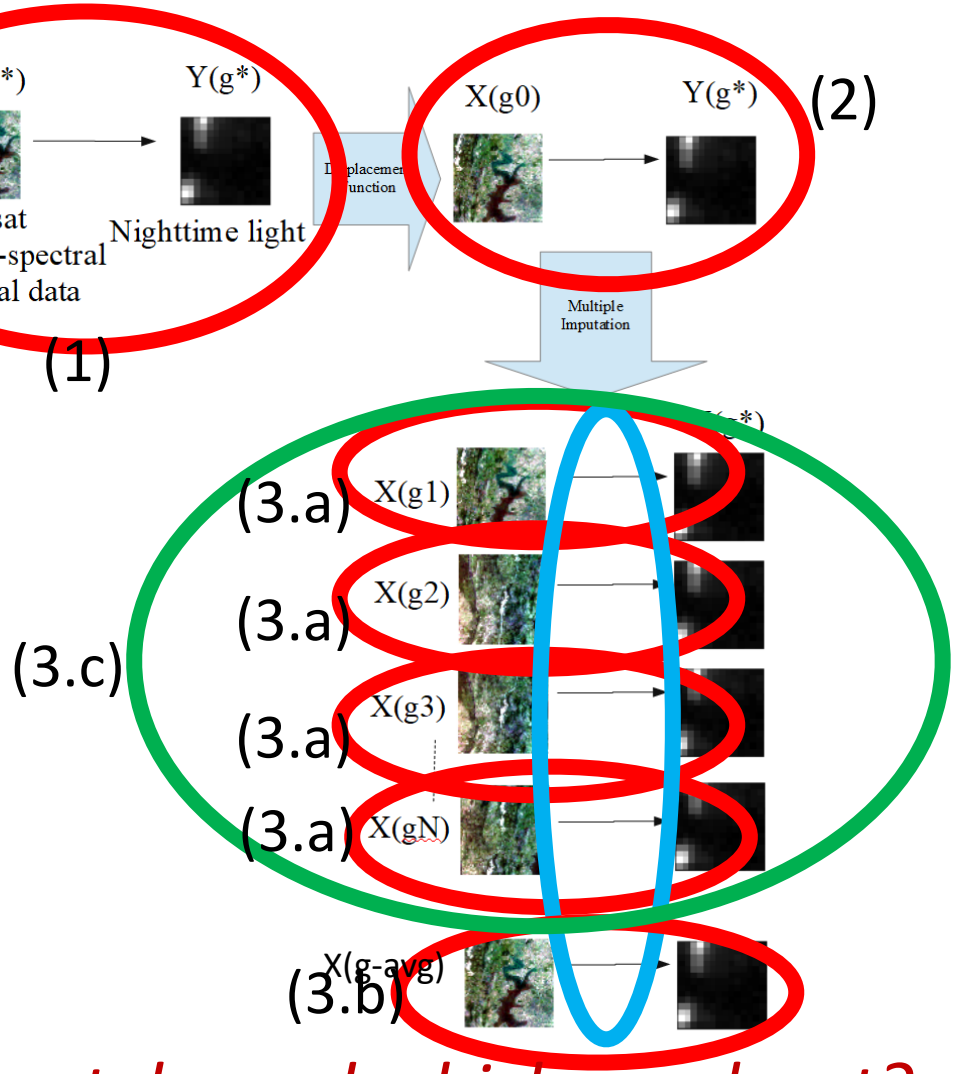

Which one predicts most accurately, and which one least?
When measuring accuracy against what benchmark?

Evaluating the 5 DL models on five different test datasets

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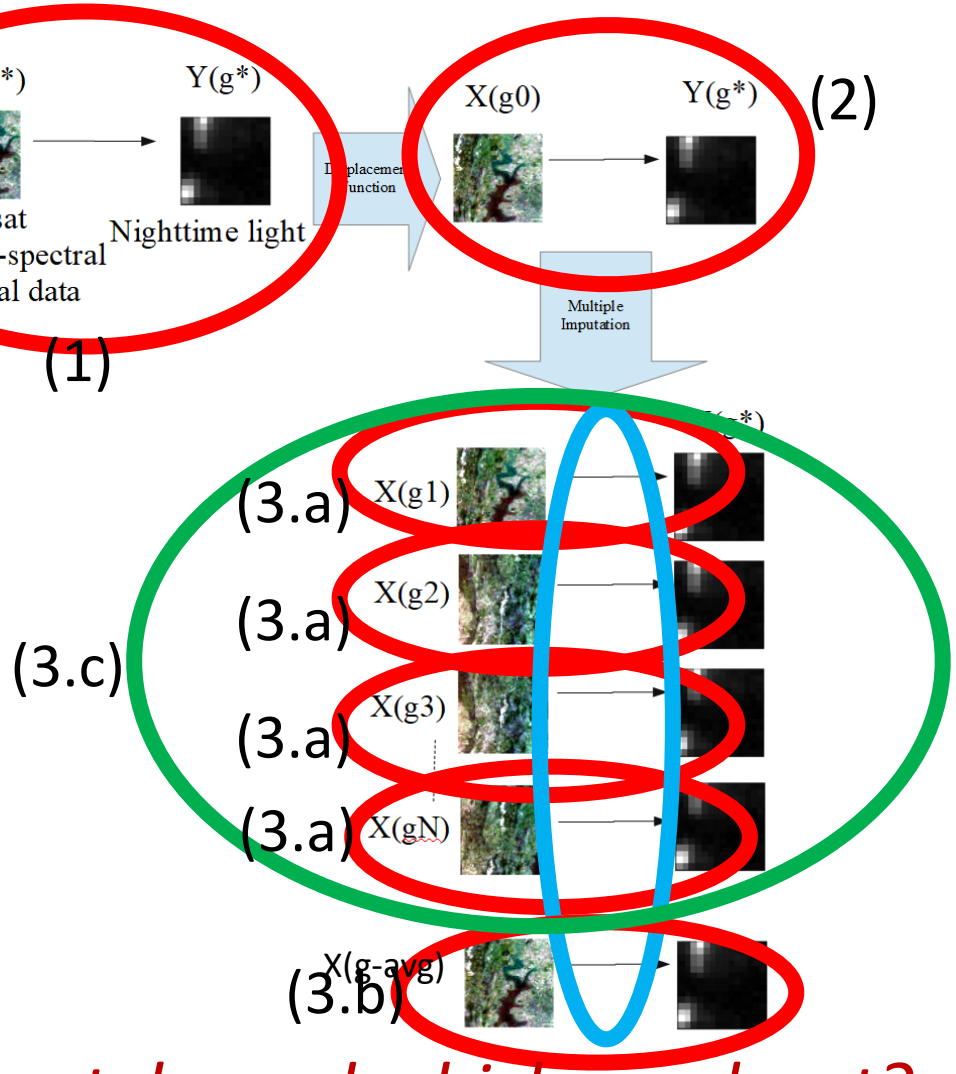

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(4) Test on a single imputed data

Training dataset(s) $\mathscr{D}^{\text{Tr}}$			Test dataset(s) $\mathscr{D}^{\text{Te}}$					
			Single					Multiple
			(1)	(2)	(4)	(3b)	(3c)	(3a)
Single		(1)	0.77	0.56	0.58	0.62	0.58	0.69
		(2)	0.69	0.64	0.62	0.64	0.62	0.66
		(4)	0.70	0.64	0.64	0.66	0.63	0.68
		(3b)	0.72	0.63	0.62	0.67	0.63	0.68
		(3c)						
Multiple	w/ diff. seeds	(3a)	0.73	0.67	0.69	0.69	0.63	0.69
		(1)	0.81	0.59	0.61	0.66	0.57	0.70
		(2)	0.70	0.65	0.63	0.66	0.59	0.66
		(4)	0.72	0.66	0.66	0.68	0.62	0.68
		(3b)	0.74	0.65	0.65	0.69	0.62	0.69
		(3c)						

Which one predicts most accurately, and which one least?
When measuring accuracy against what benchmark?

International Wealth Index (IWI)

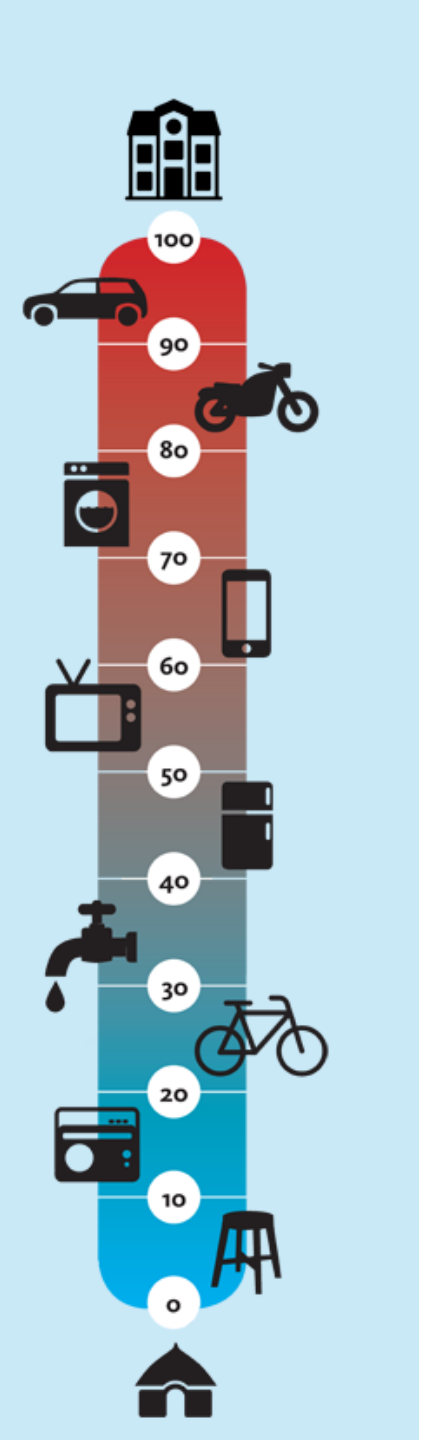
Does the household own or have a:

TV:	(●) Yes	( ) No	( ) Unknown
Refrigerator:	( ) Yes	(●) No	( ) Unknown
Phone:	( ) Yes	(●) No	( ) Unknown
Bike:	( ) Yes	(●) No	( ) Unknown
Car:	( ) Yes	(●) No	( ) Unknown
Cheap utensils (<$50):	(●) Yes	( ) No	( ) Unknown
Expensive utensil (>$300):	( ) Yes	(●) No	( ) Unknown
Electricity:	( ) Yes	(●) No	( ) Unknown

What is the quality of the...

Main source drinking water?:	(●) Low	( ) Middle	( ) High	( ) Unknown
Toilet facility usually used?:	(●) Low	( ) Middle	( ) High	( ) Unknown
Main floor material?:	(●) Low	( ) Middle	( ) High	( ) Unknown
Nr. of rooms used for sleeping:	(●) One	( ) Two	( ) Three+	( ) Unknown

The household's IWI score is: **12.73**



https://globaldatalab.org/iwi/form/

International Wealth Index (IWI)

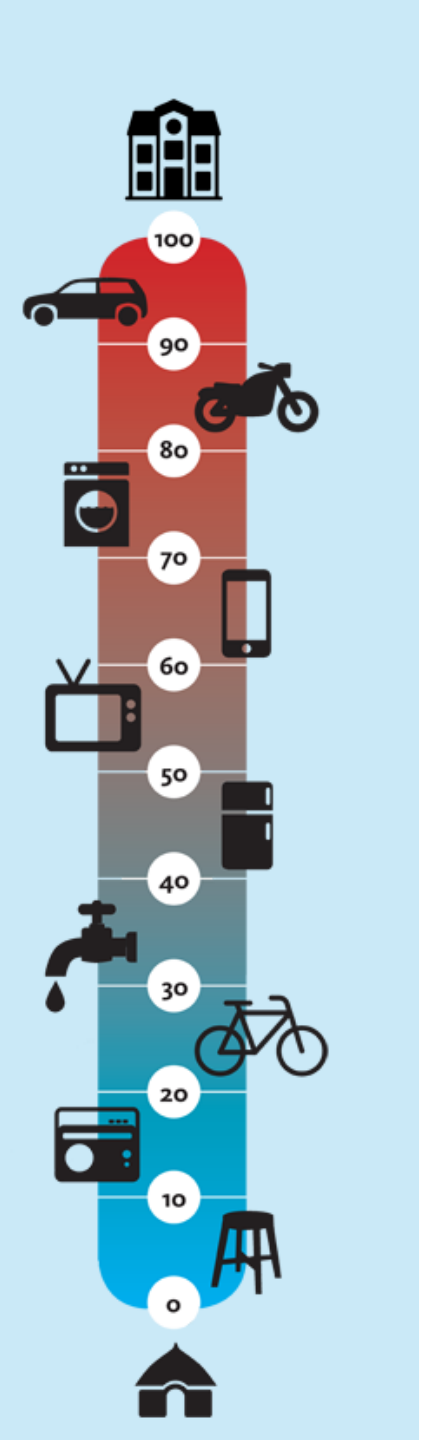
Does the household own or have a:

TV:	◉ Yes	○ No	○ Unknown
Refrigerator:	○ Yes	◉ No	○ Unknown
Phone:	○ Yes	◉ No	○ Unknown
Bike:	○ Yes	◉ No	○ Unknown
Car:	○ Yes	◉ No	○ Unknown
Cheap utensils (<$50):	◉ Yes	○ No	○ Unknown
Expensive utensil (>$300):	○ Yes	◉ No	○ Unknown
Electricity:	○ Yes	◉ No	○ Unknown

What is the quality of the...

Main source drinking water?:	◉ Low	○ Middle	○ High	○ Unknown
Toilet facility usually used?:	◉ Low	○ Middle	○ High	○ Unknown
Main floor material?:	◉ Low	○ Middle	○ High	○ Unknown
Nr. of rooms used for sleeping:	◉ One	○ Two	○ Three+	○ Unknown

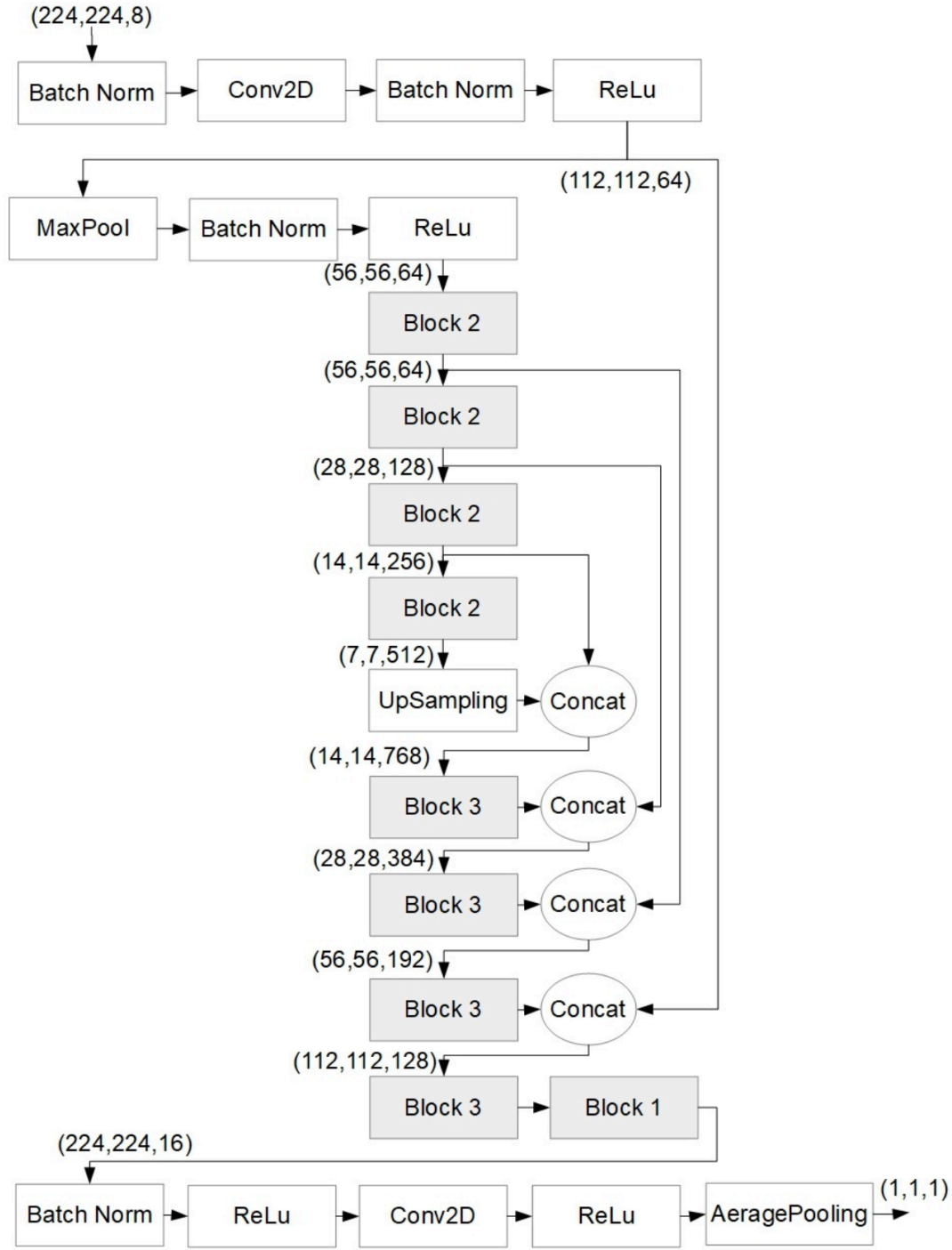
The household's IWI score is: **12.73**



<u>With TV</u> =12.73

<u>Without TV</u> = 4.12

https://globaldatalab.org/iwi/form/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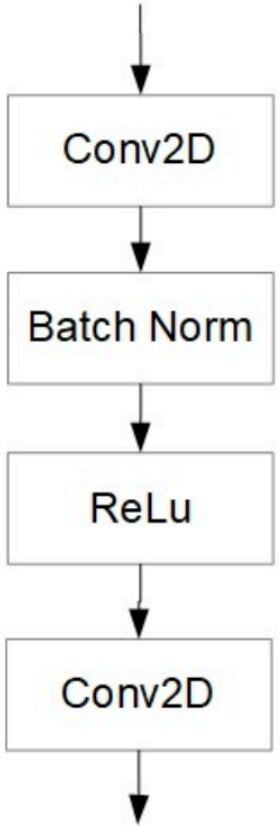
Batch Norm
Conv2D
Batch Norm
ReLu
(112,112,64)
MaxPool
Batch Norm
ReLu
(56,56,64)
Block 2
(56,56,64)
Block 2
(28,28,128)
Block 2
(14,14,256)
Block 2
(7,7,512)
UpSampling
Concat
(14,14,768)
Block 3
Concat
(28,28,384)
Block 3
Concat
(56,56,192)
Block 3
Concat
(112,112,128)
Block 3
Block 1
(224,224,16)
Batch Norm
ReLu
Conv2D
ReLu
AeragePooling
(1,1,1)



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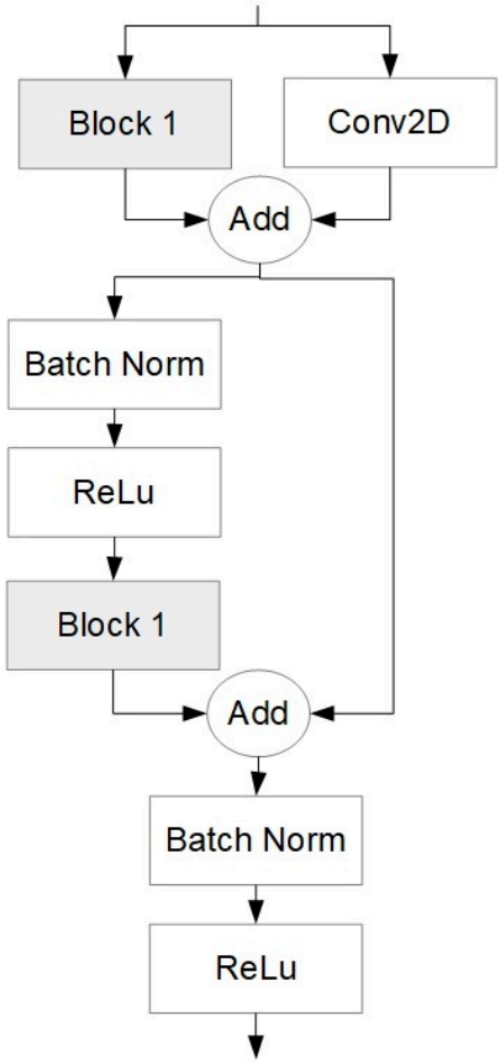

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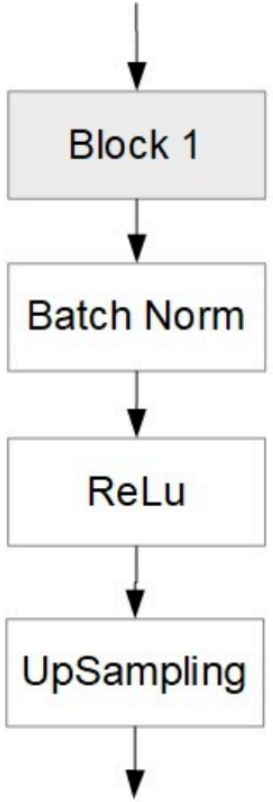

Block 3