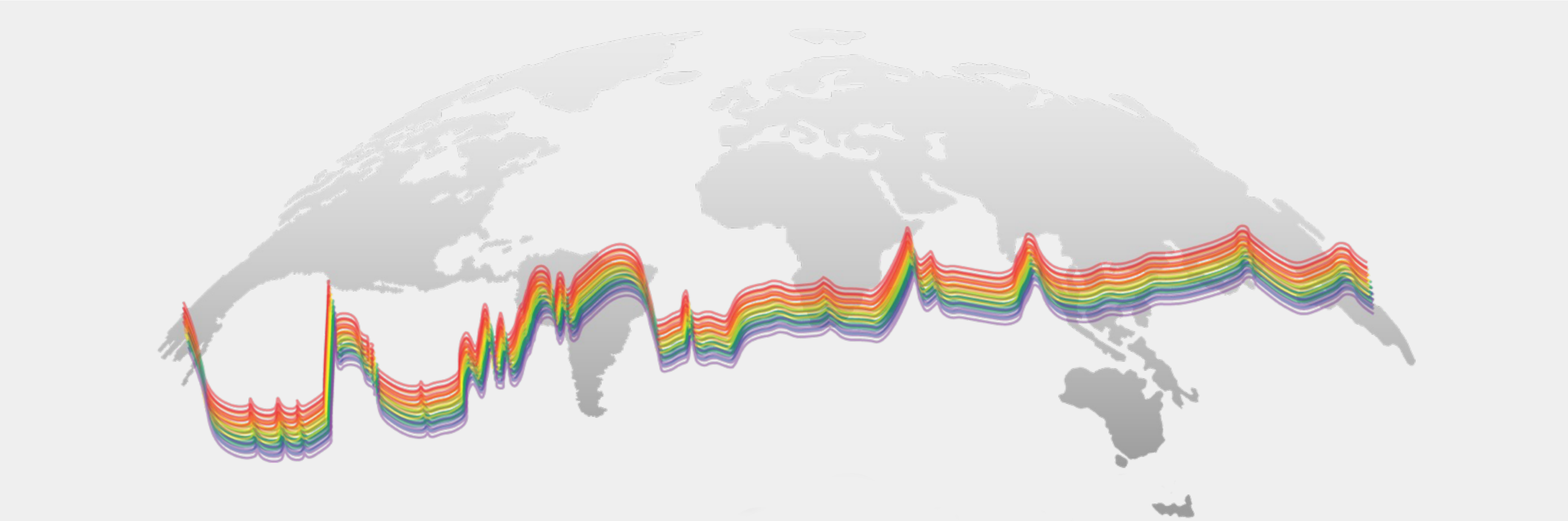


Local Soil Carbon Modelling Using Deep Transfer Learning on Large Soil Spectral Libraries

Zefang Shen and Raphael A. Viscarra Rossel

Soil and Landscape Science
Curtin University, Australia
12/12/2022

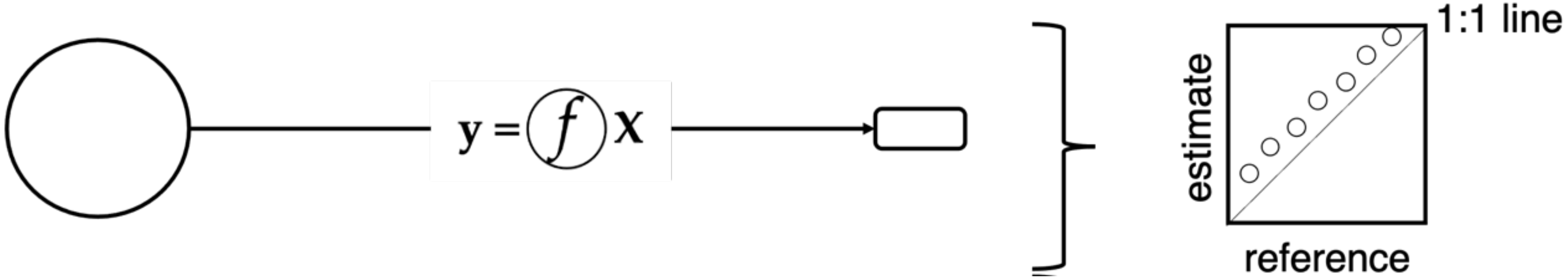
AGU FALL MEETING
SCIENCE LEADS THE FUTURE

soil & landscape science lab
Curtin University

Problem definition

“Global” models built with large and diverse datasets do not generalise well on more homogeneous “local” data.

Global dataset | Model | Local site | Validation



Background and aims

Localising soil spectroscopic modelling via data augmentation and transfer learning has been applied with varied performance.

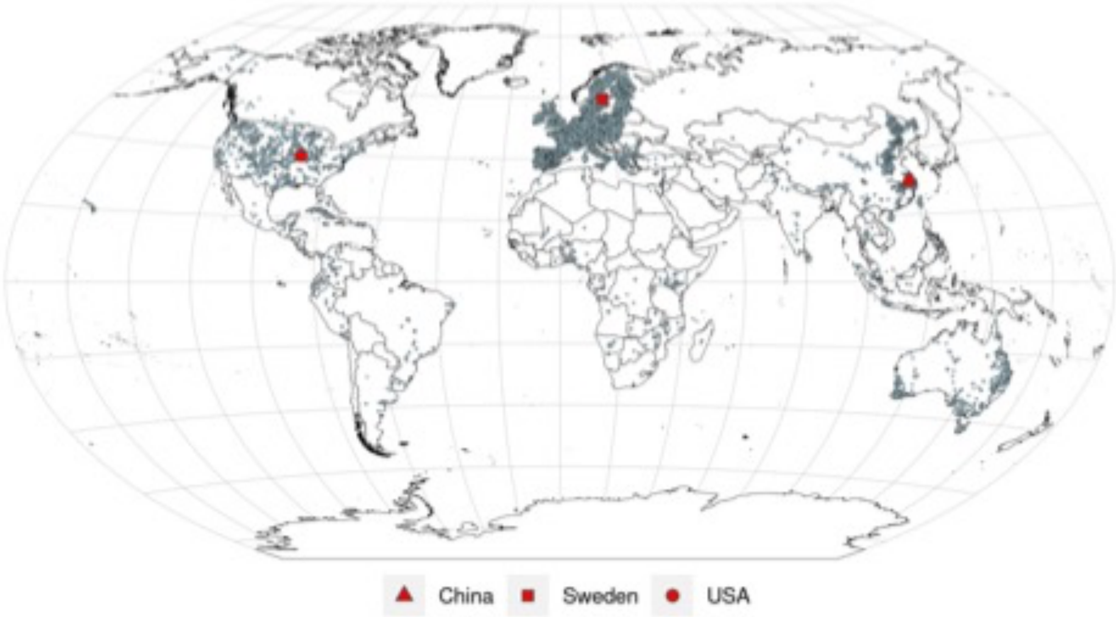
- Spiking
- Memory-based learning
- Transfer learning of representations

Our approach—Deep Transfer Learning (DTL)

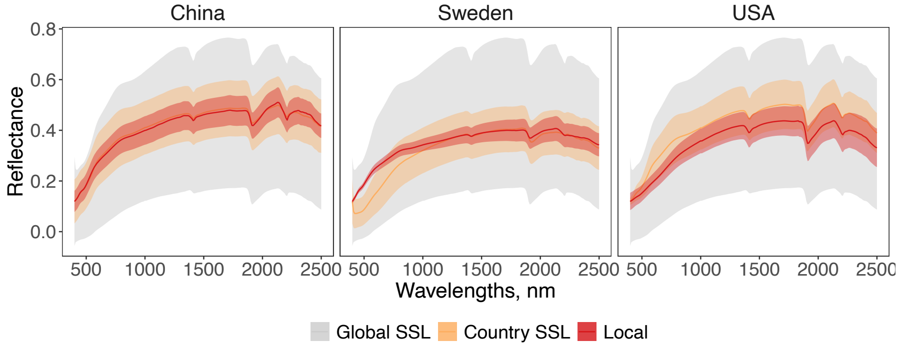
- Deep transfer learning of instances (DTL-I) with RS-Local.
- Deep transfer learning of representations (DTL-R) with one dimensional convolutional neural networks (1D-CNN).
- Combining transfer learning of instances and representations (DTL-IR).

Case study and data

Local soil organic carbon (SOC) modelling
Deep transfer learning for localising spectroscopic estimates of soil organic carbon at the farm-scale with a global soil spectral library (SSL).



	Dataset	# samples
SSL	Global	50,422
	China	5,183
	Sweden	2,319
	USA	4,155
Local	China	135
	Sweden	108
	USA	216

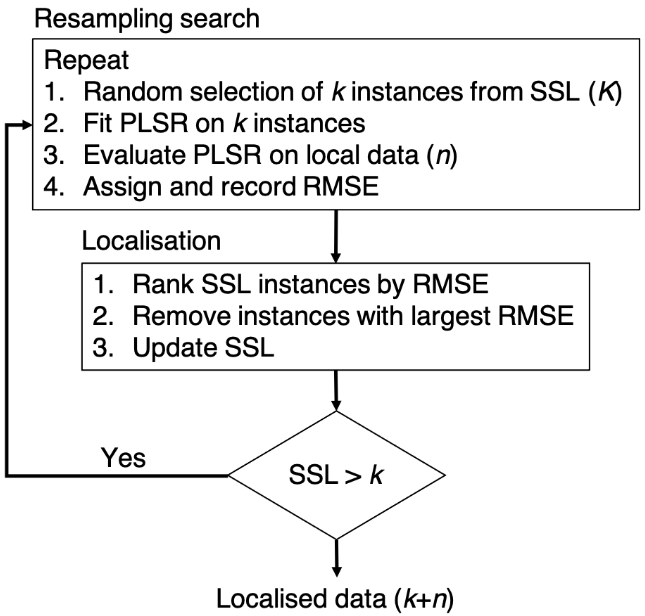


Shen et al. (2022), Viscarra Rossel et al. (2016).

Methods — Deep Transfer Learning

Transferring instances

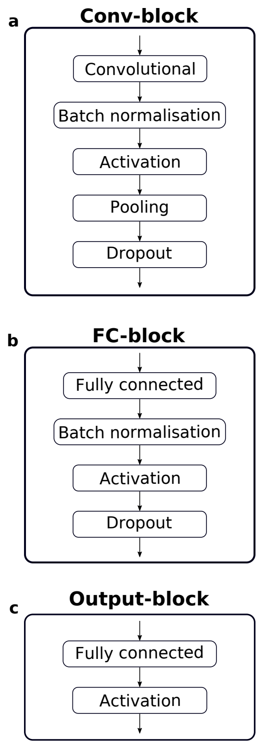
RS-LOCAL-v2.0

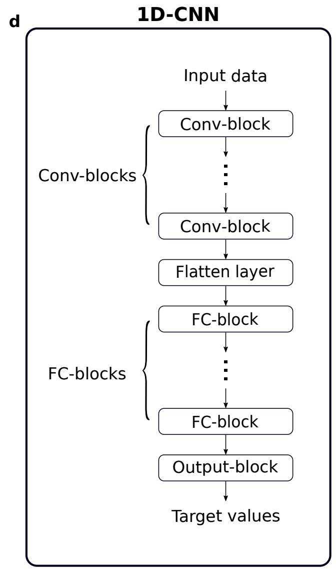


PLSR—partial least square regression;
RMSE—root means squared error.

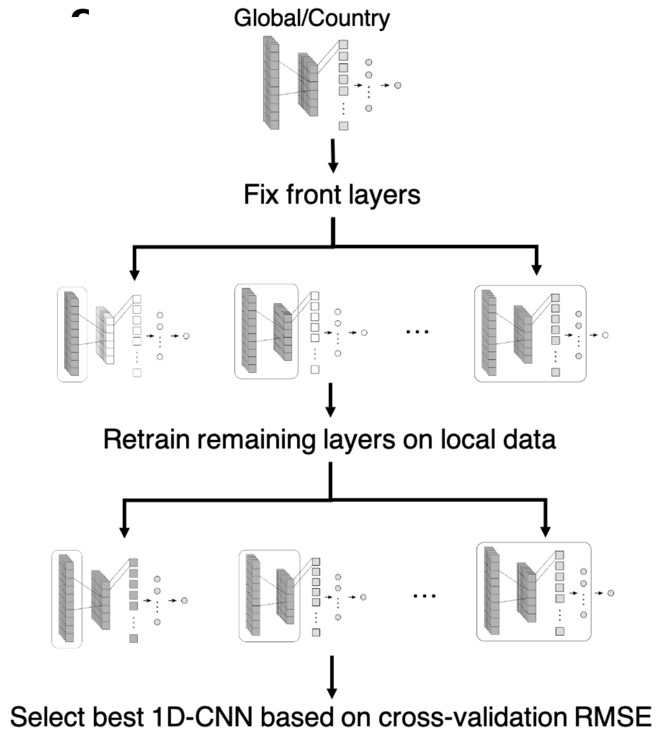
RS-Local-v2.0 selects relevant samples from SSL to augment local data for modelling.

1D-CNN and transferring representations



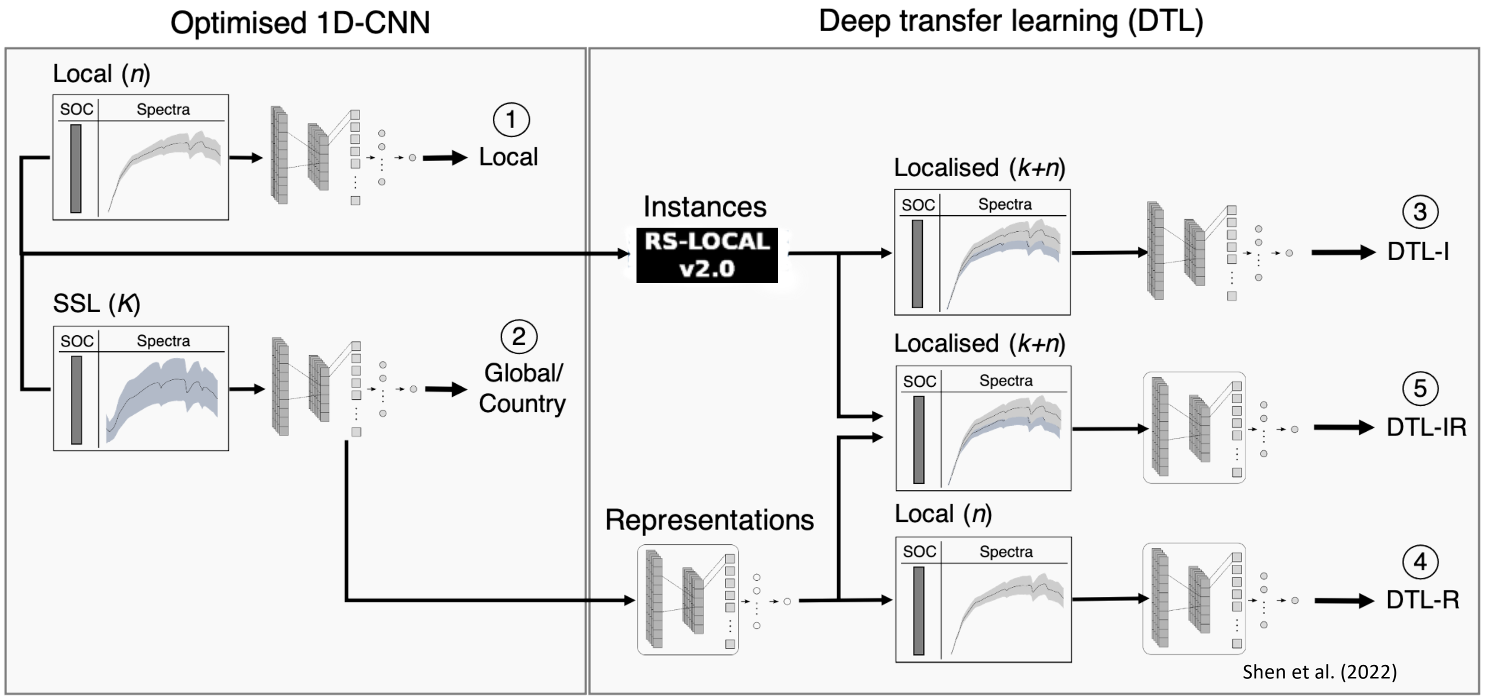


Building blocks are optimsed for best cross-validation performance using Bayesian optimisation.



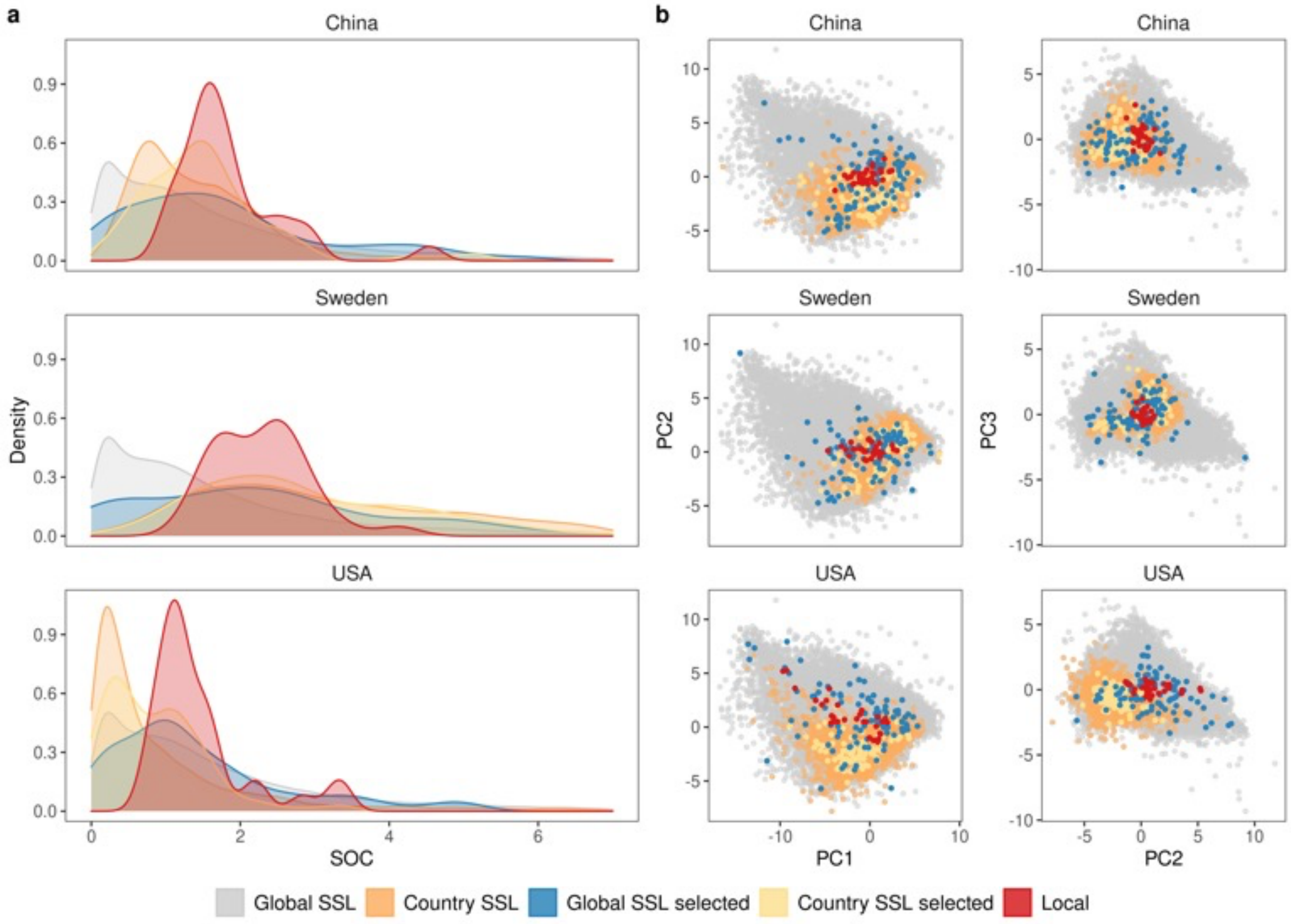
Lobsey et al., (2017),
Shen and Viscarra Rossel (2021),
Shen et al. (2022)

Methods — Study design



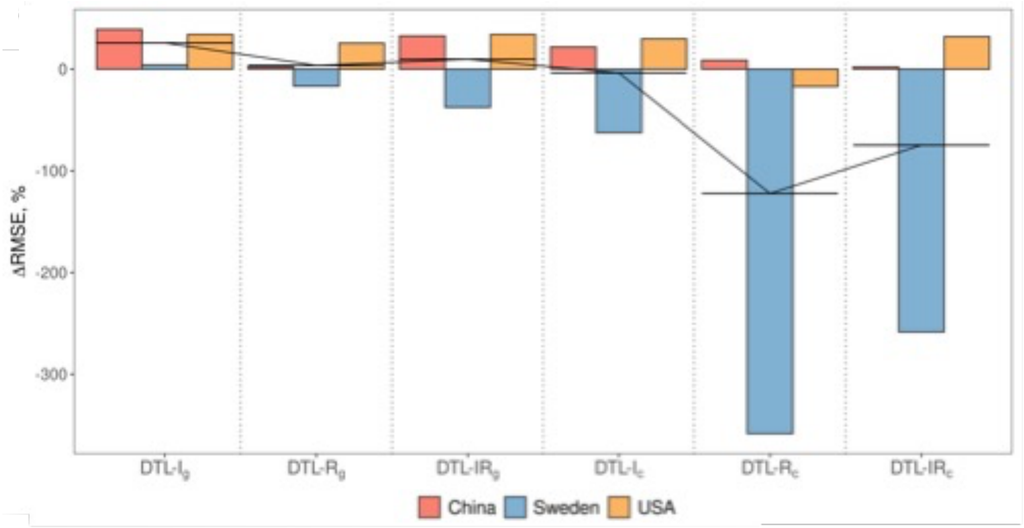
① Local: 1D-CNN developed on local data (*n*=30).
② Global/Country: 1D-CNN developed on Global/Country SSL(s)
③ DTL-I: Deep transfer learning of Instances
④ DTL-R: Deep transfer learning of Representations
⑤ DTL-IR: Deep transfer learning of Instances and Representations.

Results—Transferring instances



- Transferring instances using RS-Local minimised the difference between the conditional distributions of the SSLs and the local data.
- RS-Local aligned the marginal distributions of the global/country SSLs and the local data.

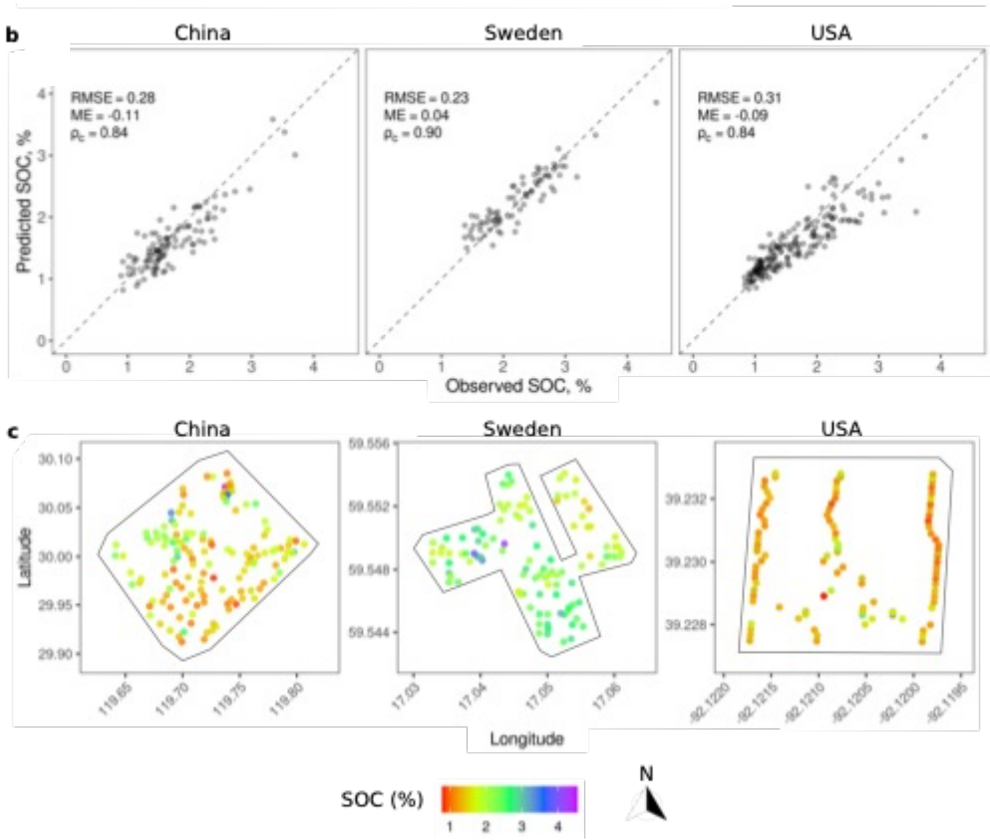
Results—Model performance



$$\Delta RMSE = (RMSE_{Local} - RMSE_{Other}) \times 100$$

- DTL-I from global SSL improved local SOC prediction accuracy by 25.8% on average.

- DTL-R and DTL-IR did not show consistent improvement.



ME—Mean error;

ρ_c—Concordance correlation coefficient.

Results—DTL-I_g 1D-CNN architectures

Local site	Block	Layer	Kernel/Pool size	Filters/Nodes	Padding	Strides	Activation
China	Conv-block	Convolutional	3 x 1	232	Valid	2 x 1	Swish
		Dropout (0.001)					
		Flatten					
	FC-block	Fully-connected		22			ELU
		Dropout (0.38)					
	Output-block	Fully-connected		1			Linear
Sweden	Conv-block	Convolutional	10 x 1	214	Same	6x1	SELU
		Dropout (0.20)					
		Flatten					
	FC-block 1	Fully-connected		446			LeakyReLU
		Batch Normalisation					
	FC-block 2	Fully-connected		208			Swish
		Dropout (0.48)					
	Output-block	Fully-connected		1			Linear
USA	Conv-block	Convolutional	7 x 1	212	Same	3x1	Swish
		Dropout (0.16)					
		Flatten					
	FC-block 1	Fully-connected		1005			Swish
	FC-block 2	Fully-connected		1015			SELU
	Output-block	Fully-connected		1			Linear

Conclusions

- DTL-I improved local modelling of SOC and the method could help more accurately monitor SOC changes any where in the world.
- Large/Global datasets, e.g. SSLs contain helpful information that can be transferred 'locally' to improve the modelling. There is value in developing and maintaining these large/global datasets.
- More research is needed to understand and improve DTL to further improve local modelling.

When modelling soil and environmental data,
we need to think global but act (fit) locally

References

- Shen, Z. and Viscarra Rossel, R.A., 2021. Automated spectroscopic modelling with optimised convolutional neural networks. Scientific Reports, 11(1), pp.1-12.

- Shen, Z., Ramirez-Lopez, L., Behrens, T., Cui, L., Zhang, M., Walden, L., Wetterlind, J., Shi, Z., Sudduth, K.A., Baumann, P., Song, Y., Catambay, K., Viscarra Rossel, R.A., 2022. Deep transfer learning of global spectra for local soil carbon monitoring. *ISPRS Journal of Photogrammetry and Remote Sensing*, *188*, pp.190-200.

- Viscarra Rossel, R.A., Behrens, T., Ben-Dor, E., Brown, D.J., Demattê, J.A.M., Shepherd, K.D., Shi, Z., Stenberg, B., Stevens, A., Adamchuk, V. and Aïchi, H., 2016. A global spectral library to characterize the world's soil. Earth-Science Reviews, 155, pp.198-230.

- Lobsey, C.R., Viscarra Rossel, R.A., Roudier, P. and Hedley, C.B., 2017. RS-Local data-mines information from spectral libraries to improve local calibrations. European Journal of Soil Science, 68(6), pp.840-852.

Thank you!

Dr. Zefang Shen

Research Associate

Soil & Landscape Science

Curtin University, Australia

Email: zefang.shen@curtin.edu.au

Curtin University