Satellite Data and Methodologies for Economists

Fall 2025

Instructor:	Anton Yang	**Date:**	Weekly
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Description: A Ph.D. field course covering the latest research topics in satellite data and machine learning used in economics. Topics include methods, measurements, forecasting, and nowcasting, as well as some applications in economics research.

Motivation: The idea originated from trade economists who use 'counterfactuals' to answer 'what-if' (or policy) questions, which require rigorous parameter estimation. However, the quality of the estimation hinges on the reliability of underlying 'ground-truths,' and poor ground truth is a well-known challenge in trade literature. Meanwhile, advances in satellite data and machine learning have opened new frontiers in economics, allowing researchers to access more reliable, non-recorded data. Inspired by this, economists at the Yale Center for Geospatial Solutions developed the approach outlined in their proposal, "Satellite Data for Measuring Economic Activities" (Ai, Arkolakis, and Yang, 2024), to explore alternative methods for economic theory and measurement. In this course, we will discuss the intersection of economic activities, satellite data, and recent methodologies that address core challenges in economic research.

Requirement: Every group is required to prepare a presentation, followed by discussions. Papers can be chosen from the following list, or students may propose a paper for approval by the instructor. All students enrolled in this course are required to attend each presentation and are expected to participate actively in Q&A sessions and discussions.

Tentative Course Calendar:

(*: suggested readings)

- **Lecture 1: Methods**

  Donaldson, D., & Storeygard, A. (2016). The view from above: Applications of satellite data in economics. Journal of Economic Perspectives, 30(4), 171-198.

  Dell, M. (2024). Deep learning for economists (No. w32768). National Bureau of Economic Research.

  Athey, S., & Imbens, G. W. (2019). Machine learning methods that economists should know about. Annual Review of Economics, 11(1), 685-725.

  Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote sensing of Environment, 202, 18-27.

  (*) Björkegren, D., Blumenstock, J. E., & Knight, S. (2022). (Machine) Learning What Policies Value. *Revision requested (second round), Review of Economic Studies.*

  (*) Ludwig, J., & Mullainathan, S. (2024). Machine learning as a tool for hypothesis generation. The Quarterly Journal of Economics, 139(2), 751-827.

- **Lecture 2: Measurement**

  Henderson, J. V., Storeygard, A., & Weil, D. N. (2012). Measuring economic growth from outer space. American Economic Review, 102(2), 994-1028.

  Chen, X., & Nordhaus, W. D. (2011). Using luminosity data as a proxy for economic statistics. Proceedings of the National Academy of Sciences, 108(21), 8589-8594.

  Mahadevan, M. (2024). The price of power: Costs of political corruption in Indian electricity. American Economic Review, 114(10), 3314-3344.

  Vogel, K. B., Hanson, G. H., Khandelwal, A., Liu, C., & Park, H. (2024). Using Satellite Imagery to Detect the Impacts of New Highways: An Application to India (No. w32047). National Bureau of Economic Research.

  Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., ... & Townshend, J. R. (2013). High-resolution global maps of 21st-century forest cover change. Science, 342(6160), 850-853.

  (*) Jean, N., Burke, M., Xie, M., Davis, W. M., Lobell, D. B., & Ermon, S. (2016). Combining satellite imagery and machine learning to predict poverty. Science, 353(6301), 790-794.

  (*) Paolo, F. S., Kroodsma, D., Raynor, J., Hochberg, T., Davis, P., Cleary, J., ... & Halpin, P. (2024). Satellite mapping reveals extensive industrial activity at sea. Nature, 625(7993), 85-91.

  (*) Greenhill, S., Druckenmiller, H., Wang, S., Keiser, D. A., Girotto, M., Moore, J. K., ... & Shapiro, J. S. (2024). Machine learning predicts which rivers, streams, and wetlands the Clean Water Act regulates. Science, 383(6681), 406-412.

- **Lecture 3: Forecasting, Nowcasting, and Recovery from History**

  Khachiyan, A., Thomas, A., Zhou, H., Hanson, G., Cloninger, A., Rosing, T., & Khandelwal, A. K. (2022). Using neural networks to predict microspatial economic growth. American Economic Review: Insights, 4(4), 491-506.

  Chinn, M. D., Meunier, B., & Stumpner, S. (2023). Nowcasting world trade with machine learning: a three-step approach (No. w31419). National Bureau of Economic Research.

  Keller, W., Shiue, C. H., & Yan, S. (2024). Mining Chinese Historical Sources At Scale: A Machine Learning-Approach to Qing State Capacity (No. w32982). National Bureau of Economic Research.

  Ferguson, J., & Kim, O. (2023). Reassessing China's Rural Reforms: The View from Outer Space. Mimeo. University of California at Berkeley.

  (*) Dell, M., Carlson, J., Bryan, T., Silcock, E., Arora, A., Shen, Z., ... & Heldring, L. (2024). American stories: A large-scale structured text dataset of historical US newspapers. Advances in Neural Information Processing Systems, 36.

(*) Goldblatt, R., You, W., Hanson, G., & Khandelwal, A. K. (2016). Detecting the boundaries of urban areas in India: A dataset for pixel-based image classification in Google Earth Engine. Remote Sensing, 8(8), 634.

(*) Cerdeiro, D. A., Cerdeiro, M. D. A., Komaromi, A., Liu, Y., & Saeed, M. (2020). World seaborne trade in real time: A proof of concept for building AIS-based nowcasts from scratch (No. 20-57). International Monetary Fund.

(*) Chu, B., & Qureshi, S. (2023). Comparing out-of-sample performance of machine learning methods to forecast US GDP growth. Computational Economics, 62(4), 1567-1609.

(*) Nevasalmi, L. (2020). Recession forecasting with big data. Available at SSRN 3630146.

- **Lecture 4: Other Applications**

Kim, J., Kim, K., Park, S., & Sun, C. (2023). The economic costs of trade sanctions: Evidence from North Korea. Journal of International Economics, 145, 103813.

Corral, P., Henderson, H., & Segovia, S. (2025). Poverty mapping in the age of machine learning. Journal of Development Economics, 172, 103377.

Baragwanath, K., Goldblatt, R., Hanson, G., & Khandelwal, A. K. (2021). Detecting urban markets with satellite imagery: An application to India. Journal of Urban Economics, 125, 103173.

Asher, S., Campion, A., Gollin, D., & Novosad, P. (2022). The long-run development impacts of agricultural productivity gains: Evidence from irrigation canals in India. London, UK: Centre for Economic Policy Research.

Cengiz, D., Dube, A., Lindner, A., & Zentler-Munro, D. (2022). Seeing beyond the trees: Using machine learning to estimate the impact of minimum wages on labor market outcomes. Journal of Labor Economics, 40(S1), S203-S247.

(*) Knittel, C. R., & Stolper, S. (2021, May). Machine learning about treatment effect heterogeneity: The case of household energy use. In AEA Papers and Proceedings (Vol. 111, pp. 440-444). 2014 Broadway, Suite 305, Nashville, TN 37203: American Economic Association.

(*) Chi, G., Fang, H., Chatterjee, S., & Blumenstock, J. E. (2022). Microestimates of wealth for all low- and middle-income countries. Proceedings of the National Academy of Sciences, 119(3), e2113658119.

(*) Jeong, I., & Yang, H. (2021). Using maps to predict economic activity. arXiv preprint arXiv:2112.13850.