Big Data for Spatial Analysis

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1. What is “big data”?
2. Examples
3. Portals
4. Uses of Big Data
5. Applications
6. How to deal with big (spatio-temporal) data?

What is “big data”?

Often discussed in terms of **volume** (size of data), **velocity** (frequency of data), and **variety** (diversity of data types):

volume data sets that are **too large** to be handled by common processing methods

- e.g., exceed the storage capacity of main memory or even secondary memory

velocity hyper-temporal data sets, or high-bandwidth streams of data

- e.g., social media activity, real-time locations

variety data sets that have too much **complexity** to be handled by common processing methods

- e.g., observations with 100’s to 1000’s of attributes of variable or even unknown data quality

What is different about big data?

- Too **large** to fully understand summaries or identification of unusual cases (“outliers”)
- Too **complex** to fully understand or control modelling
- Generally need **machine-learning methods** to analyze (e.g., random forests, neural nets)
- Generally too **large** to analyze on individual computers, requires cloud computing.

Orders of magnitude

"Kilobytes $2^{10} \approx 10^3$ were stored on floppy disks. Megabytes $2^{20} \approx 10^6$ were stored on hard disks. Terabytes $2^{30} \approx 10^9$ were stored in disk arrays. Petabytes $2^{40} \approx 10^{12}$ are stored in the cloud.

"As we moved along that progression, we went from the *folder* analogy to the *file cabinet* analogy to the *library* analogy to – well, at petabytes we ran out of organizational analogies."

– Anderson, C. (2008, June 23). *The end of theory: the data deluge makes the scientific method obsolete*. **Wired**. https://www.wired.com/2008/06/pb-theory/ [1]

Problems using Big Data

1. **capturing** massive amounts of obserations
   - e.g., real-time sensors, satellite images, monitoring instruments
2. **storage** and data transfer from storage to computation
3. **search**, i.e., query to find/subset/summarize
4. **processing**, i.e., computation (CPU, memory, parallelization)
5. **analysis**: methods and understanding the results
6. **sharing**, information policies, e.g., privacy
   - different parts of the database may have different policies
7. **visualization**
   - summarizing with appropriate graphic design

Sources of big data

- sensor networks with fine temporal resolution
  - e.g., automated weather stations
- mobile devices
  - e.g, geo-located phones
- remote sensors
  - ever-increasing **spatio-temporal resolution**
- digital laboratory instruments
- point-of-sales or service
  - e.g., pharmacies, retail stores
- user contributions
  - social media, citizen science

Examples of large datasets

- NOAA $\approx 50 \cdot 10^9$ multivariate observations of oceans (as of 2018)[1]
  - temperature, salinity, oxygen, nitrates, phosphates and silicates at the particular **location** and **depth** collected at a particular **time**, so 4D
- 23andMe[2] DNA analysis of $5 \cdot 10^6$ individuals
- Twitter has about $500 \cdot 10^6$ tweets per day[3]
- MasterCard processed $74 \cdot 10^9$ transactions per year in 2012[4]

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[1] https://www.ncei.noaa.gov/products/world-ocean-atlas
[2] https://www.23andme.com/en-int/dna-ancestry/, 17-Jan-2021
[3] http://www.internetlivestats.com/twitter-statistics/
[4] http://blog.unibulmerchantservices.com/how-mastercard-processes-74b-transactions-a-year/

Citizen science

- eBird[5] (Cornell Ornithology)
  - $737 \cdot 10^6$ observations (as of end 2019)[6]
  - $169 \cdot 10^6$ new observations in 2020 (“volume”, “velocity”)
  - (semi-)automated quality control[7]

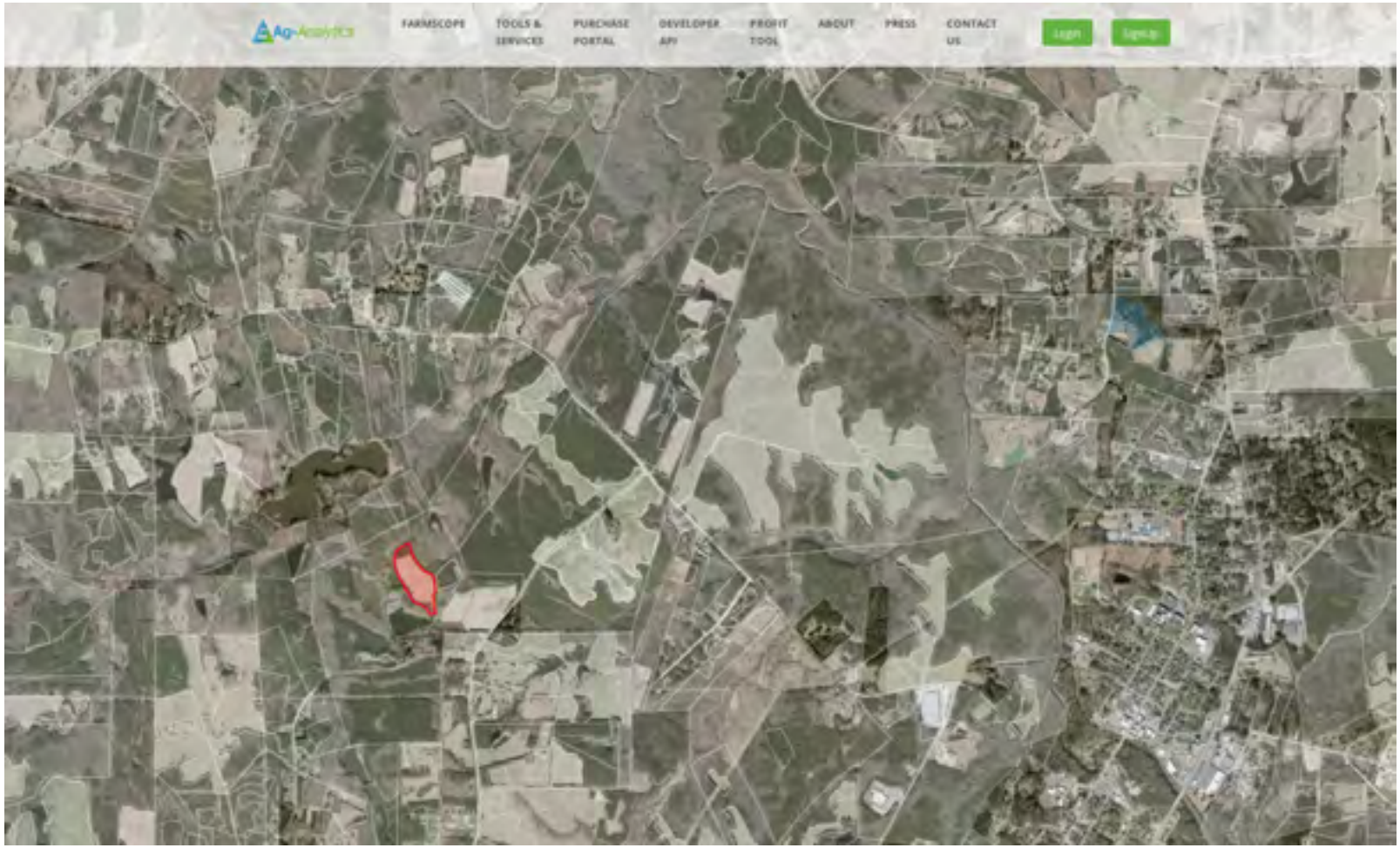
[5] http://www.ebird.org
[6] https://ebird.org/news/ebird-2019-year-in-review
[7] https://support.ebird.org/en/support/solutions/articles/48000795278

Agriculture

- Ag-Analytics[8]
  - zoom in, click on individual fields: insurance, revenue, yield forecast
  - combines multiple open layers, with own analytics
- Gro Intelligence[9]
  - “leading the modern agricultural revolution using data and technology, driven by advances in parallel processing, remote sensing, machine learning, and AI”

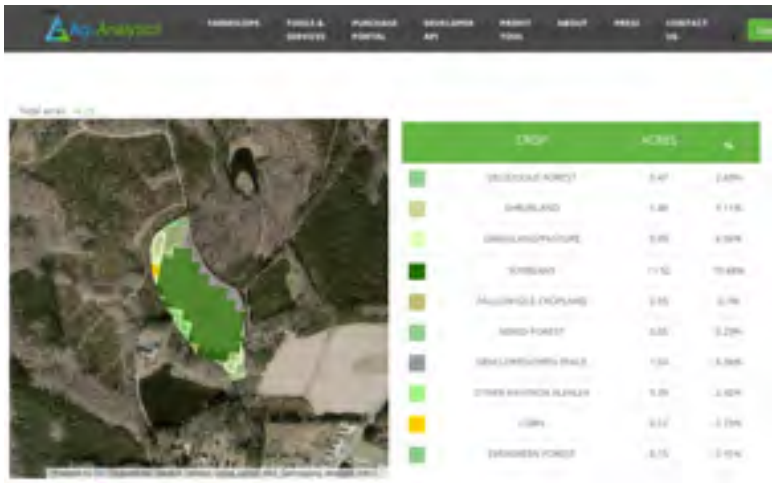
[8] https://app.profit.ag/app
[9] https://www.gro-intelligence.com

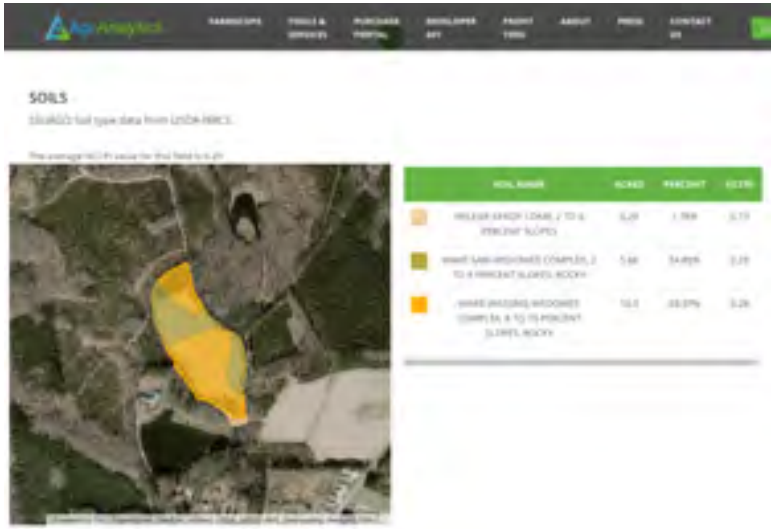
Ag-Analytics – location

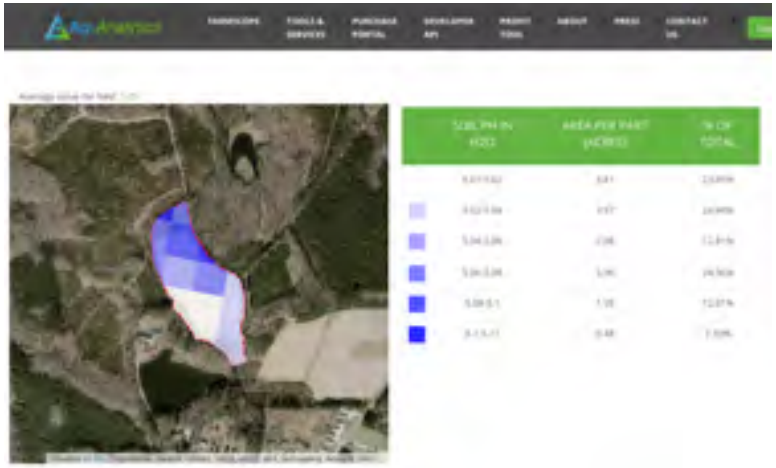


near Franklinton, North Carolina
field at (36.1068N, -78.3530E)

Ag-Analytics – field static information

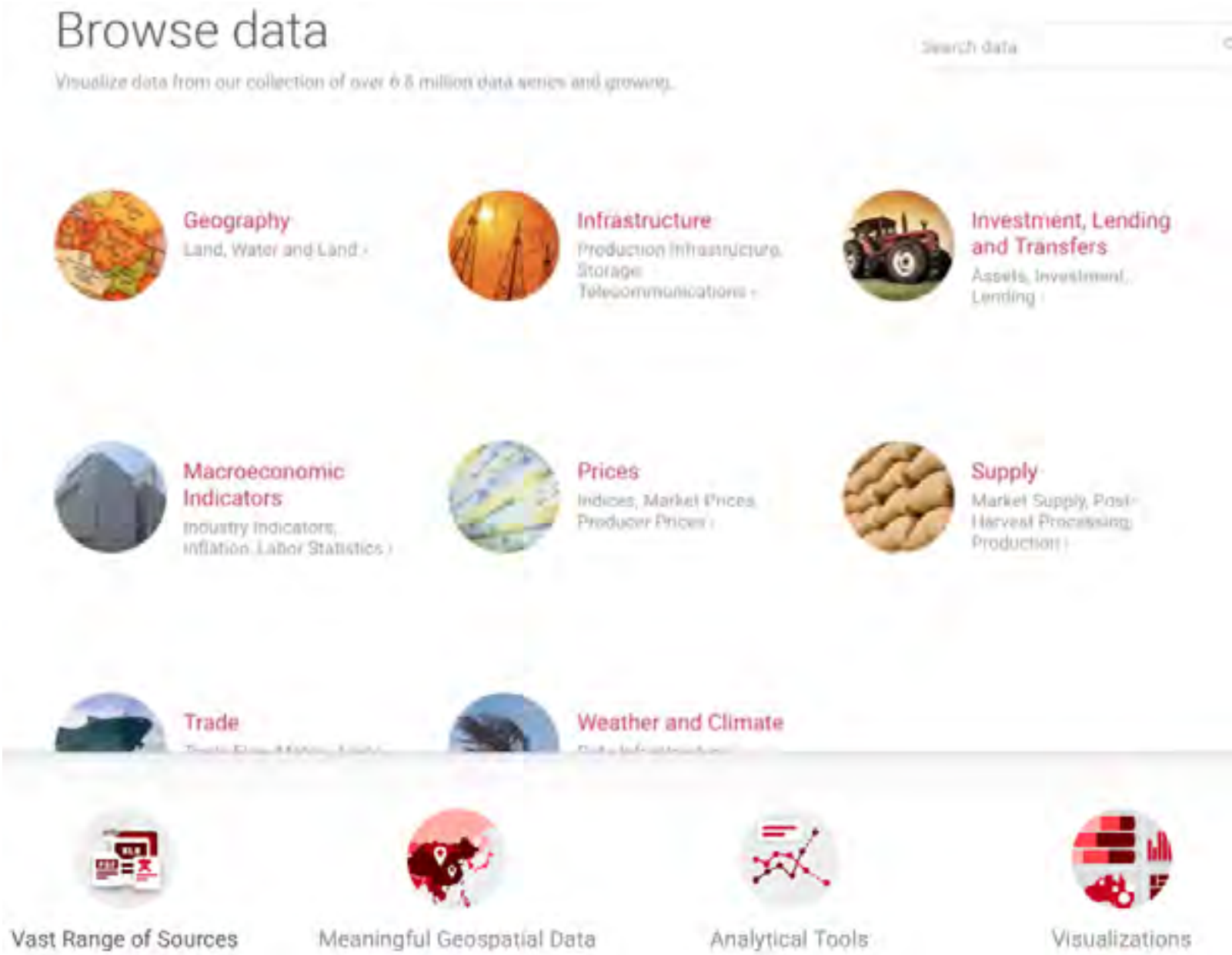






Ag-Analytics – field dynamic information

Gro Intelligence



Soils – SoilGrids

- Reference: [10]
- Global predictions for numeric soil properties: OC, bulk density, Cation Exchange Capacity (CEC), pH, soil texture fractions and coarse fragments at seven standard depths (0, 5, 15, 30, 60, 100 and 200 cm; total 280 raster layers
- based on $\approx$ 150k profiles, 158 gridded covariates
- Maps for on-line view or download[10]

[10] https://soilgrids.isric.org

SoilGrids processing flow

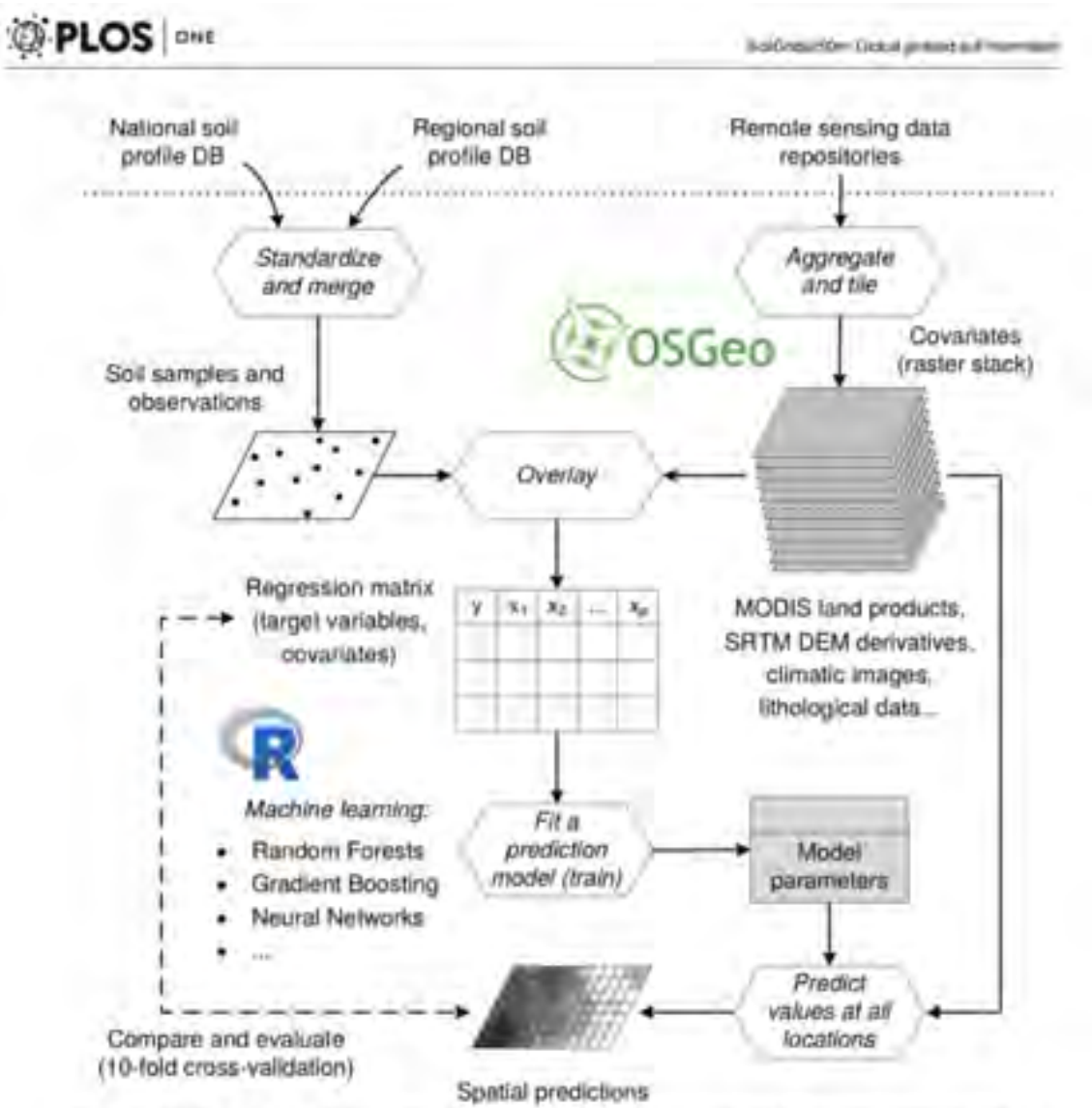
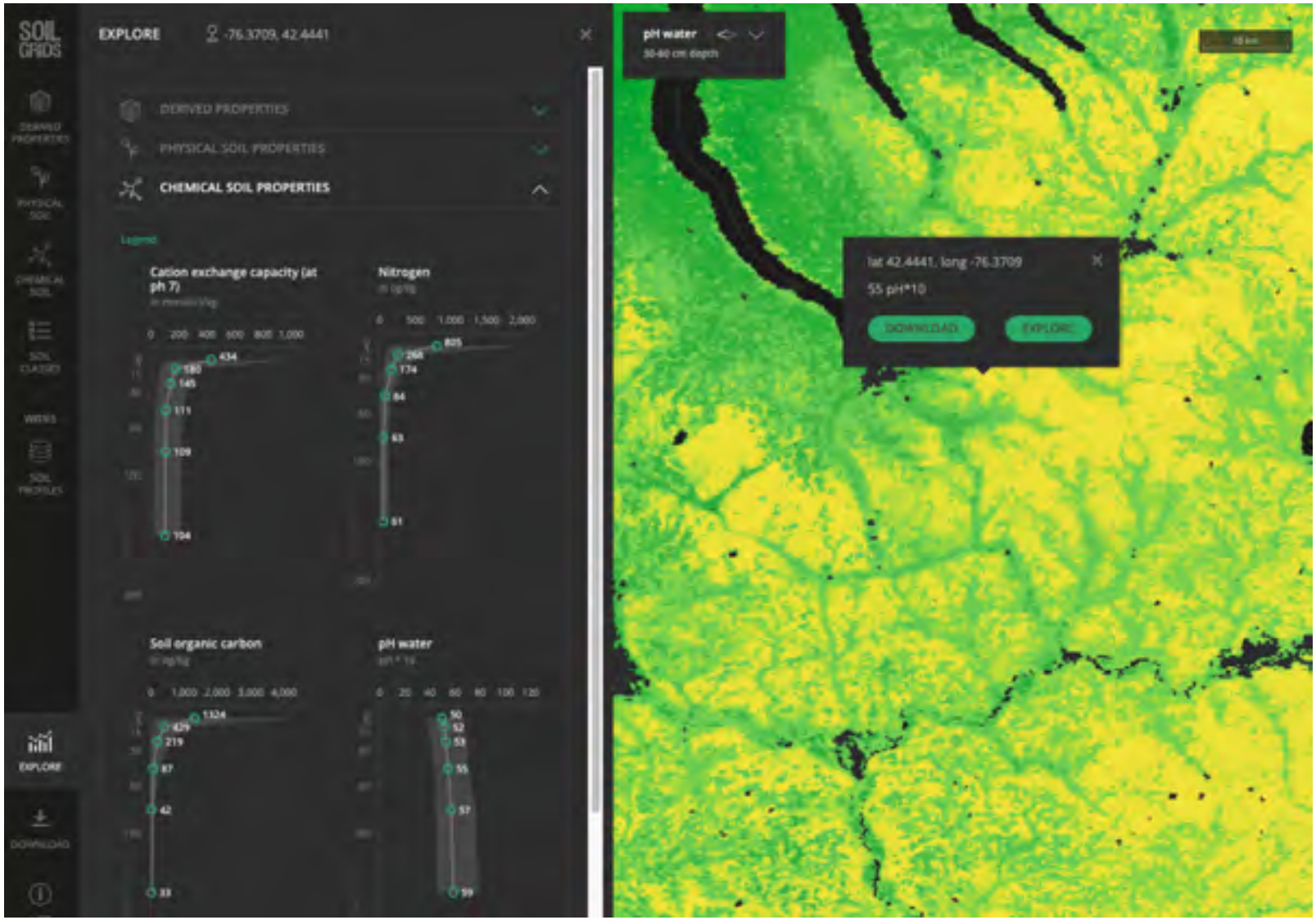


Fig 5. The (data-driven) statistical framework used for generating SoilGrids.

SoilGrids processing results



Soils – POLARIS

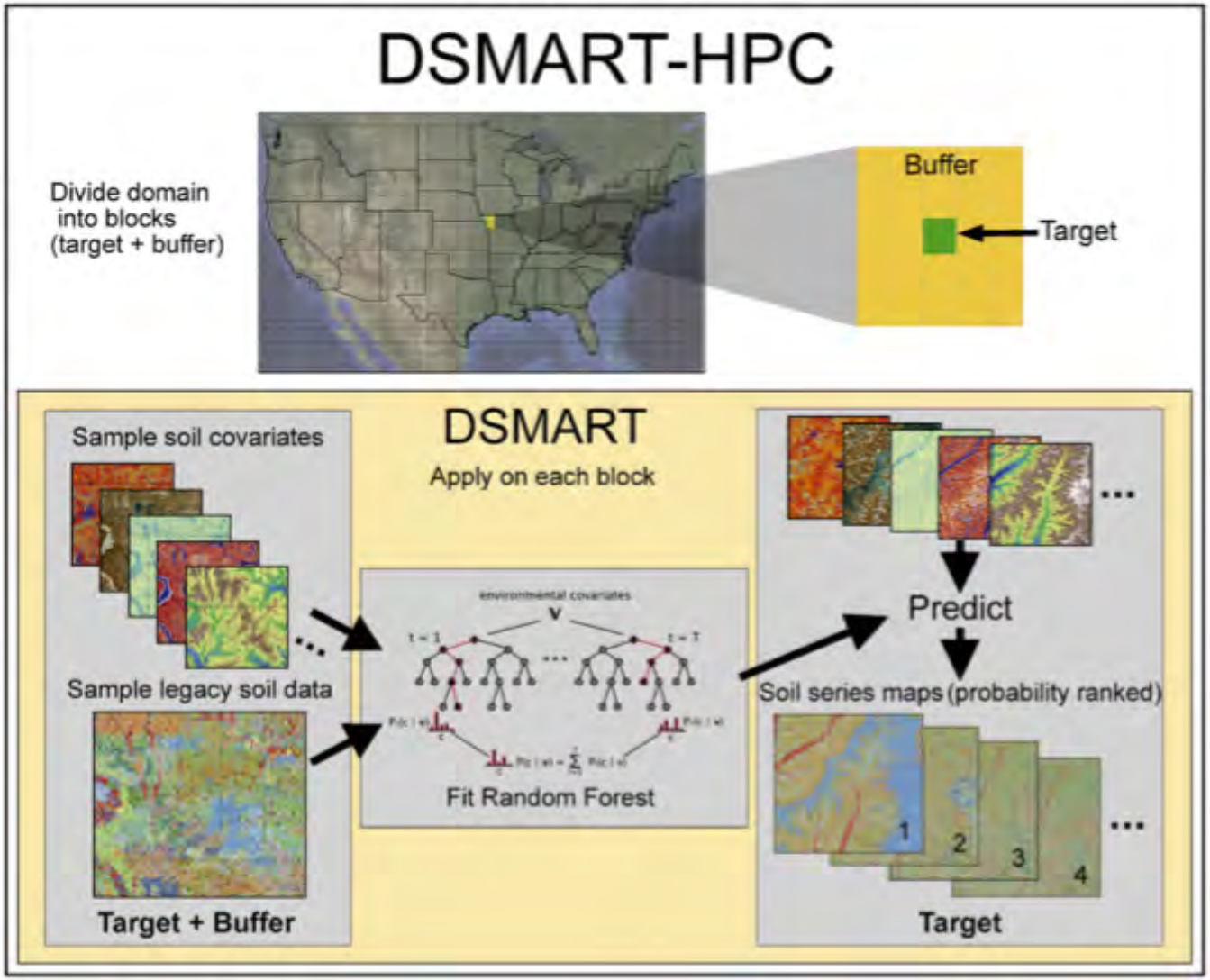
POLARIS [3]

- Purpose: map **probability** of **soil series** at **every grid cell** in the lower 48 (USA) States; total $\approx 1.25 \cdot 10^9$ grid cells
- algorithm: DSMART (Disaggregation and Harmonization of Soil Map Units Through Resampled Classification Trees)
- supercomputer "Blue Waters"; 12 474 nodes 30 x 30 km, with 60 km buffer to ensure continuity
- 30 m horizontal spatial resolution, so 1000 x 1000 = 10^6 per 1° tile[11]
- required 450 000 core-hours = 5 wall-clock hours
- "This is negligible computer time at current HPC facilities that can handle 10 million ($\approx$ 1100 years) core-hour tasks."

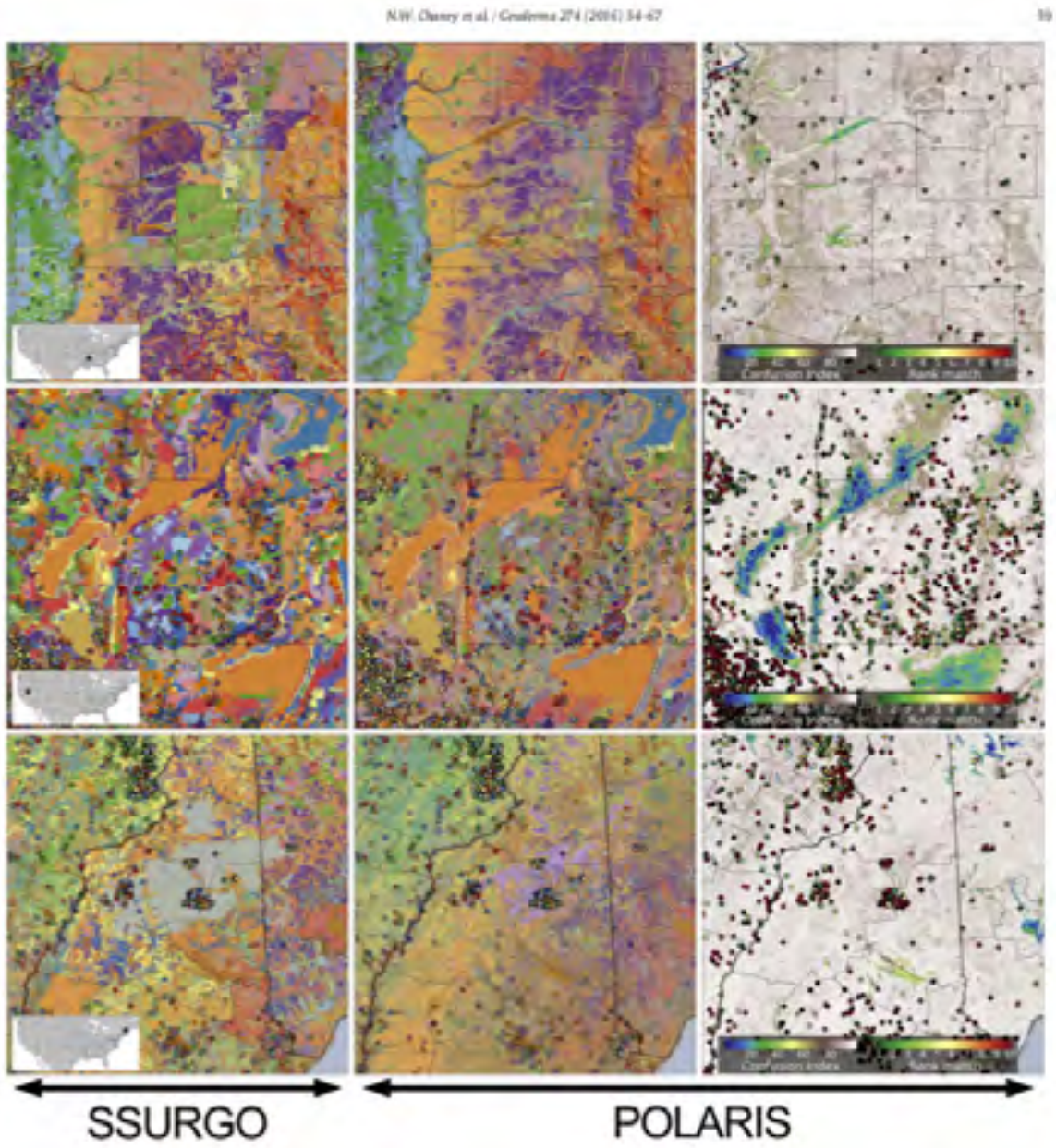
[11] http://hydrology.cee.duke.edu/POLARIS/

POLARIS methods

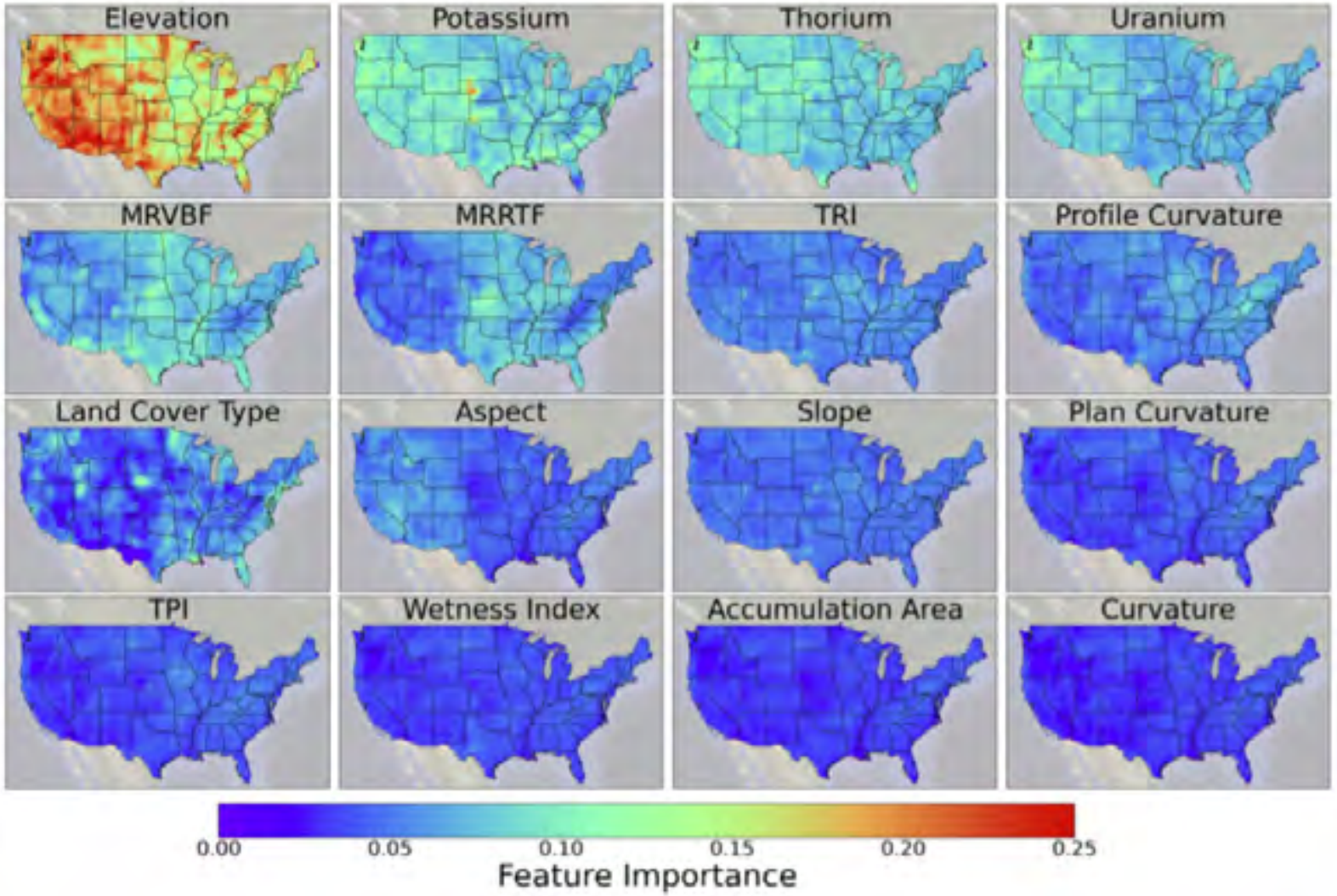
N.W. Chaney et al. / Geoderma 274 (2016) 54–67



POLARIS results



POLARIS covariate importance



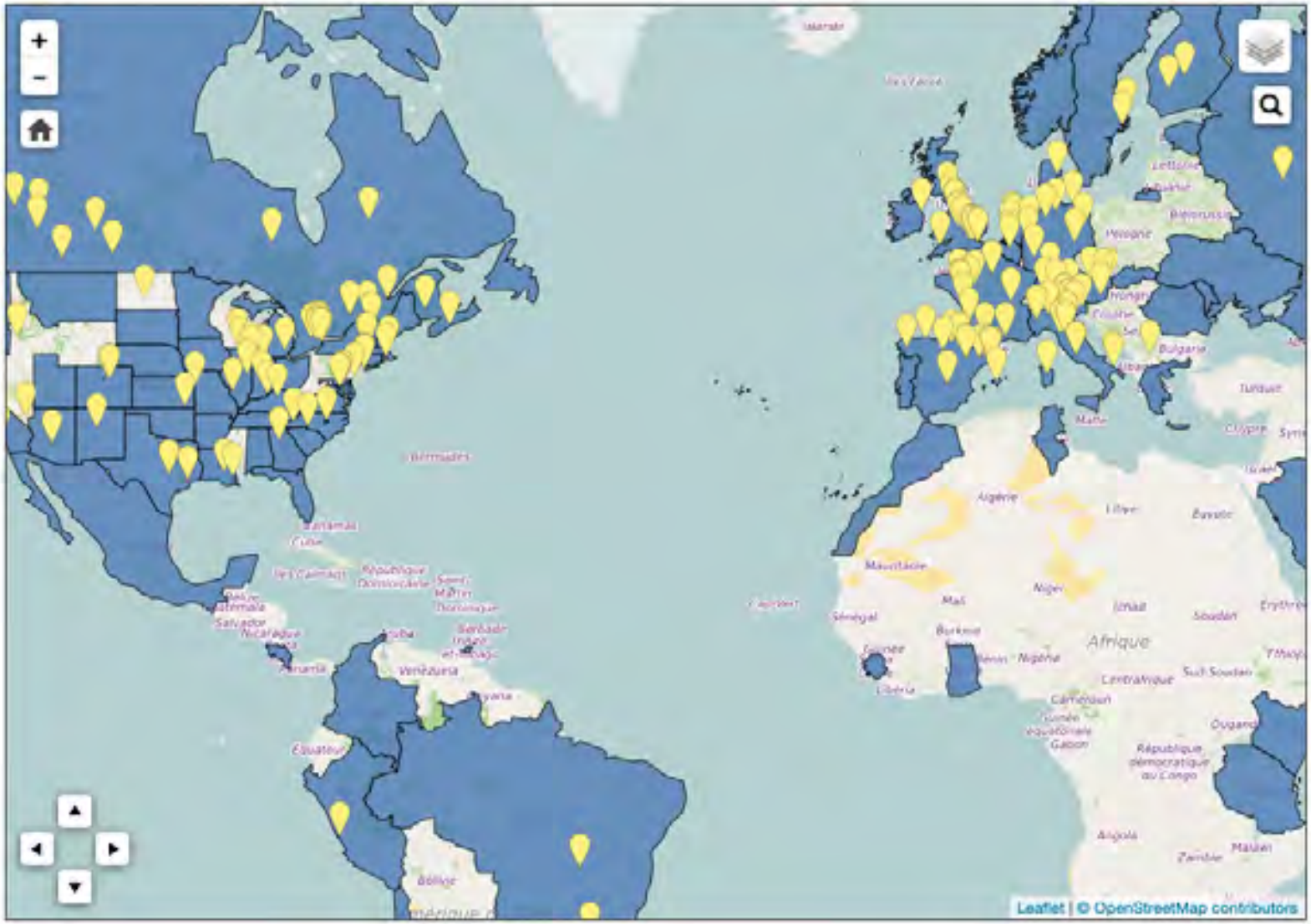
Portals and data brokers

- Collect and catalog many sources of geographic data
- example: World Food Programme (WFP) Geonode[12]
- example: Soil Geographic Databases[13]
- example: OpenGovernment[14]
- problem: **searching** for relevant (to the user) information
  - WFP Geonode: search by region, type of information, keyword, date, extent, file type

[12] https://geonode.wfp.org
[13] https://www.isric.org/explore/soil-geographic-databases
[14] https://www.data.gov/open-gov/

Portal: OpenGovernment

Map representation of Open Data Sites

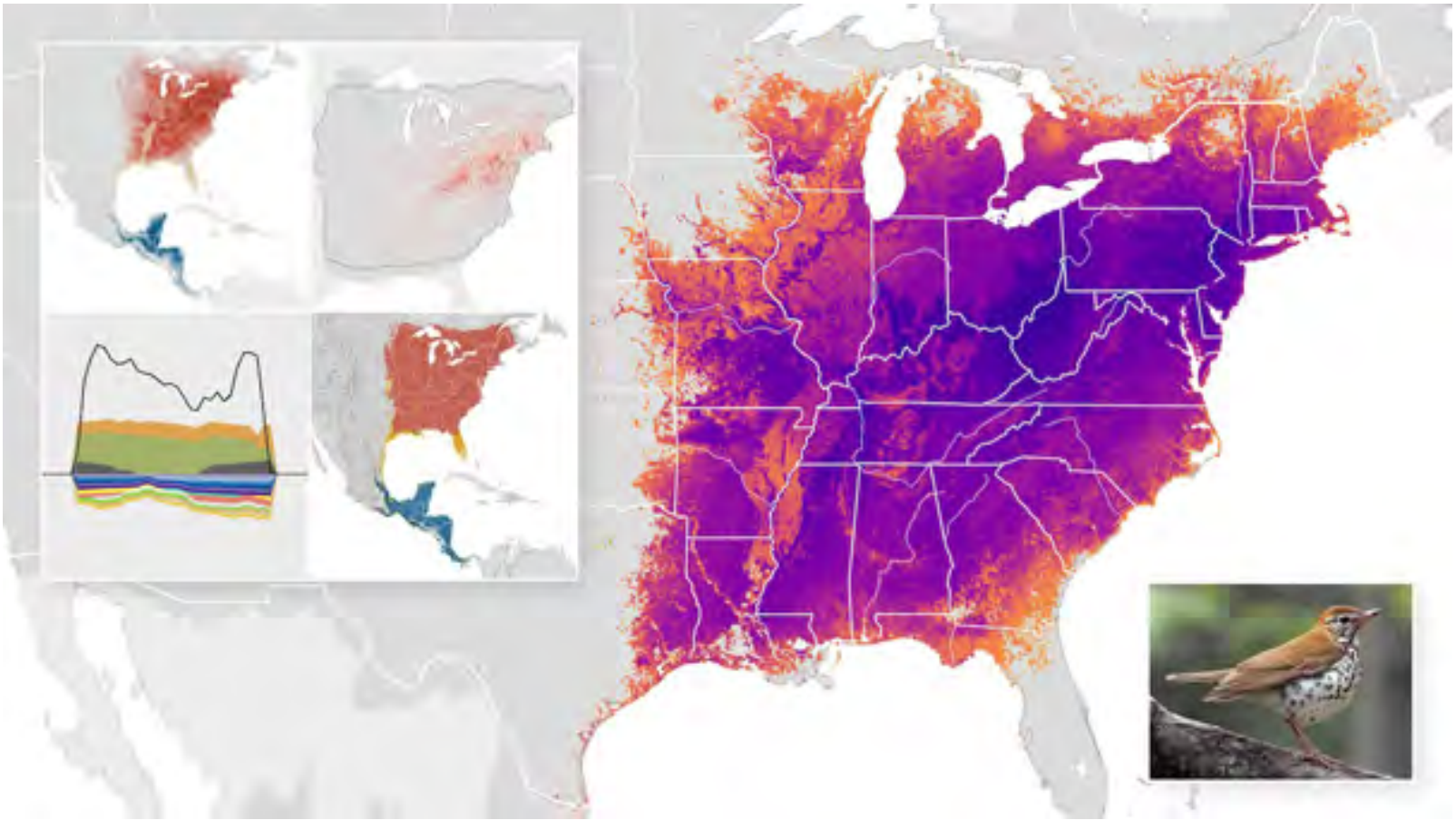


Uses of Big Data

- Scientific research into processes
  - e.g., eBird Science applications[15]:
  - "connect[s] birdwatchers around the world in a way that informs research and conservation . . . 2019 featured the first annual update of eBird Status and Trends, which now provides status and distribution information for 302 species ... "[16]
- Mapping
  - e.g. SoilGrids, POLARIS
- Prediction, decision support
  - e.g., Ag-Analytics, Gro Intelligence
- Visualization, hypothesis formation

[15] https://ebird.org/science
[16] https://ebird.org/news/ebird-2019-year-in-review

Analysis: eBird analytics



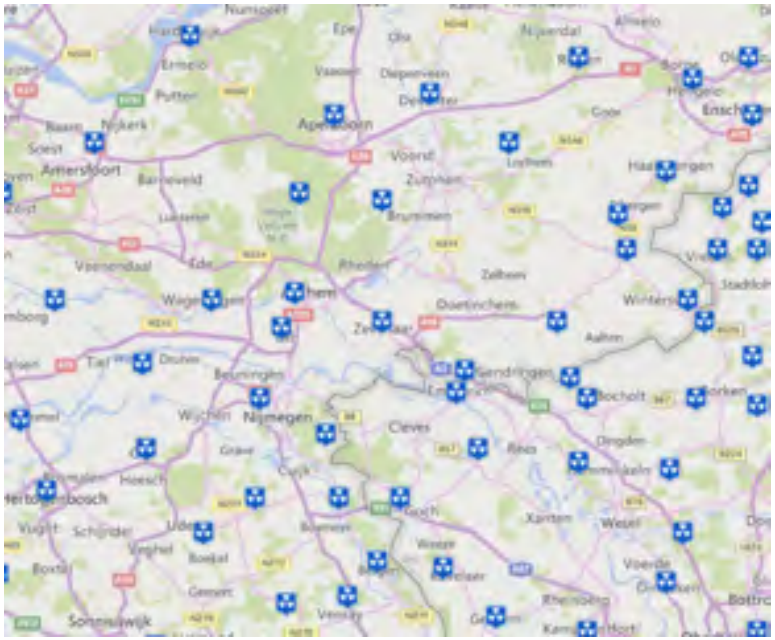
Status & trends for wood thrush (*Hylocichla mustelina*)

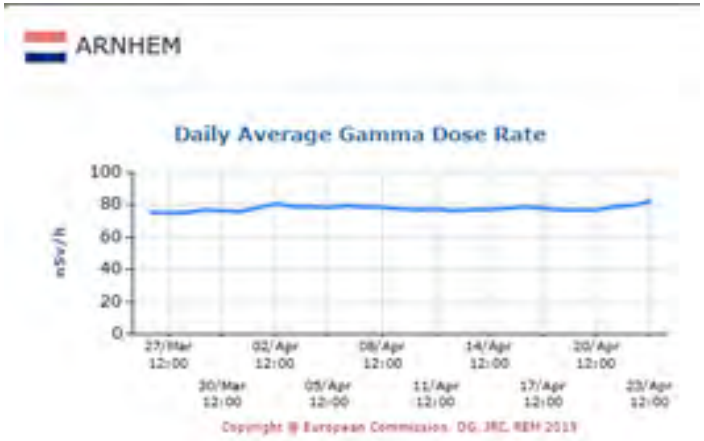
Prediction, (near) real-time

- European Radioactivity Environmental Monitoring[17]
  - "Gamma dose rate averages and maxima for the last 24 hours in almost real time"
  - European Radiological Data Exchange Platform (EURDEP): a **network** for the **exchange** of radiological monitoring data between most European countries
  - Large network of sensors, automatic reporting and summarizing
- Methods: see [5] "**Real-time automatic interpolation** of ambient gamma dose rates from the Dutch radioactivity monitoring **network**"

[17] https://remap.jrc.ec.europa.eu

Radiation monitoring





Some applications

- General discussions: [2, 4]
- Ecology: [6]
- Geographic sociology: [7]
- Epidemiology: [9, 12]
- Agroecosystems: [8]
- Agricultural entomology: [11]
- Radiation monitoring: [5]

How to deal with big (spatio-temporal) data?

- **automated** methods for data capture, data screening (quality control)
- **robust** statistical methods, not sensitive to outliers, not dependent on manual selection of model form
- **massive** computing resources
- **collaborative** science – combine different disciplinary knowledge; also requires experts in inter-, multi-disciplinary collaboration

Computing platforms for big data

Massive datasets can not be handled on many personal/departmental computers.
So **cloud computing** must be used.

- Example: Google Earth Engine[18]
  - "A **planetary-scale** platform for Earth science data & **analysis** – Powered by Google's **cloud infrastructure**"
  - "hosts satellite imagery and stores it in a **public data archive** that includes **historical earth images** going back more than **forty years** . . . made available for global-scale **data mining**.
  - Aimed at consistent Earth-wide analyses, but can be used regionally or locally
  - Must register an account[19] (free for research, education, and nonprofit use), and log in to use.

[18] https://earthengine.google.com/
[19] https://signup.earthengine.google.com/

Use of GE Engine

- Computation is all done **remotely** (parallel processing)
  - local computer only for coding/viewing
- Accessible via an Application Programming Interface (**API**)
  - Javascript (built into GEE)[20], Python, **R** with rgee package[21]
- Built-in code editor
- Direct access to the datasets
- **Image processing**, **Geometry** algorithms
- **Machine-learning** algorithms: un/supervised classification

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[20] https://developers.google.com/earth-engine/guides/getstarted

[21] https://r-spatial.github.io/rgee/

GE Engine datasets

Many datasets are also too large for local storage, so they are also in the cloud and used as needed; Google Earth Engine includes many datasets[22], including:

- Imagery (Landsat, Sentinel, MODIS . . .)
- Atmospheric conditions (can help correct other products)
- Weather
- Geophysical: terrain (e.g., SRTM), elevation
- Nighlights
- Administrative
- Interpreted: land cover, land use, cropland (e.g., USDA NASS; Global Food Security)

[22] https://developers.google.com/earth-engine/datasets/catalog

Conclusion

Ever-increasing amounts of data, ever-increasing computer power, allow integrating many “big” data sources to deal with “big”, complex, inter-disciplinary problems.

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