Geospatial Analytics at Global Scale

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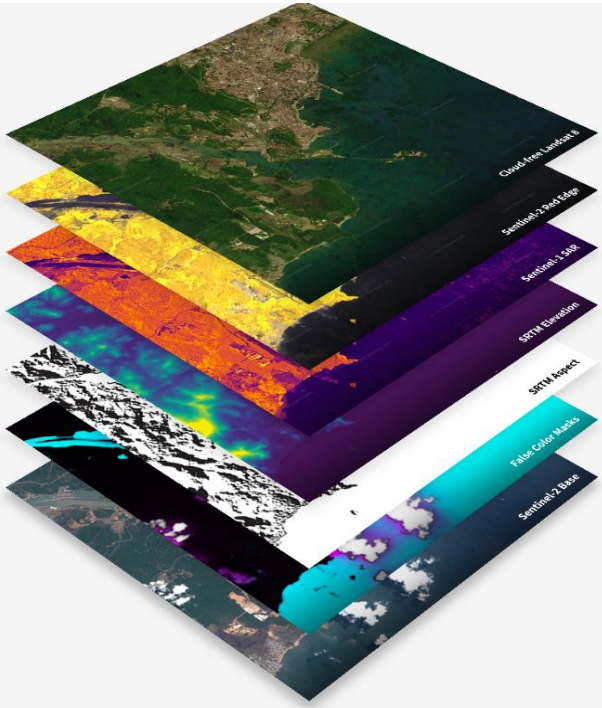
The Descartes Labs team

- 70+ people, 16 PhDs, $38m in Venture Capital investment
- Decades of experience in machine learning, remote sensing, large-scale computing
- Acquire, process, and store imagery (NASA, USGS, NOAA, ESA, commercial) in the cloud
- Headquartered in Santa Fe, offices in Los Alamos, Denver, San Francisco and New York City

We closed $30M Series B financing in August 2017

A data refinery, built to understand our planet



DARPA Geospatial Cloud Analytics (GCA) project kickoff today in Arlington

Our geospatial analysis platform

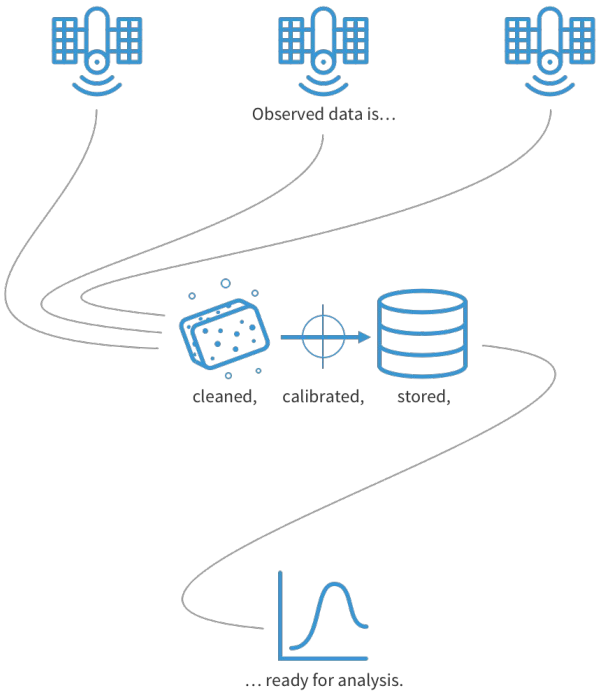
A growing archive of analysis-ready images, with historical records for back-testing models.

Robust pipeline for continuous updating as new images become available.

Multiple satellite image datasets integrated into a single system.

Cloud-based data and services, ready-to-use for data science teams anywhere.

Elastic computing model—scaling compute resources quickly and only when needed.



Catalog

About

Products

Descartes Labs products

Search

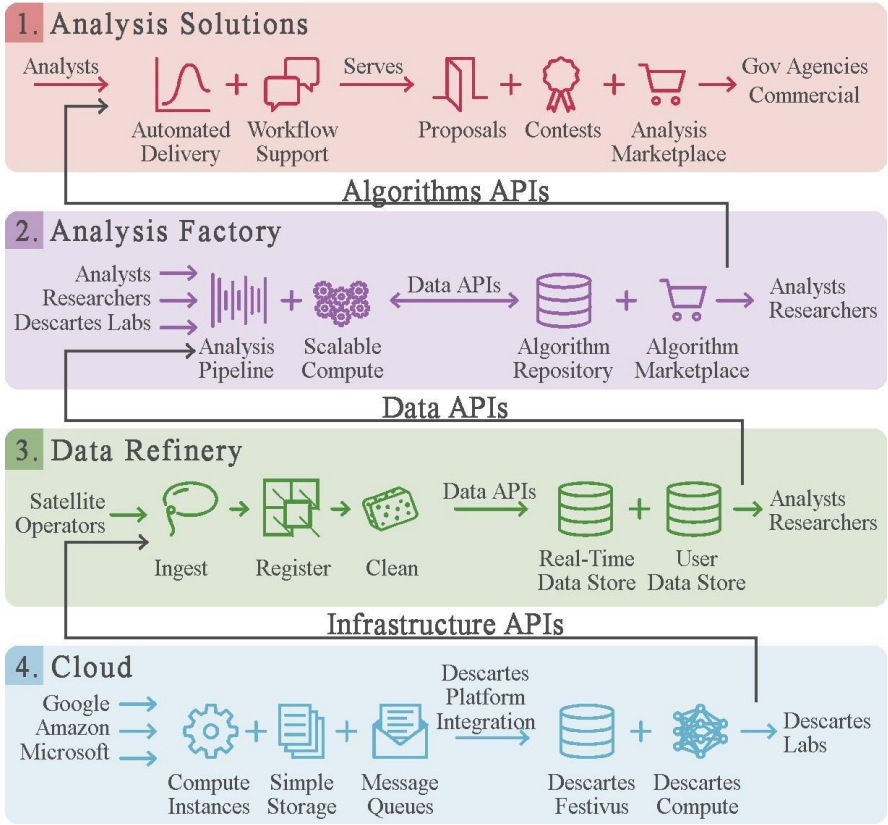
+ Add New Product

Title	Start	End	Resolution	Revisit Rate
Airbus OneAtlas Pléiades High Resolution	2012-02-21		0.5 m	
Airbus OneAtlas Pléiades High Resolution v2	2012-02-21		0.5 m	
Airbus OneAtlas SPOT			1.5 m	
Airbus OneAtlas SPOT v2			1.5 m	
Cropland Data Layer	2008-01-01	2016-01-01	30 m	1/year
Cropland Data Layer v1	2008-01-01	2018-01-01	30	1/year
DLFields	2017-07-16	2017-07-16	15m	
Daily weather interpolated from GSOD data	1980-01-01	2017-12-31	0.08333333333333 …	1 day
Interferogram of Sentinel 1 VV band		present	20	
LC08 LaSRC composite				
Landsat 4	3/1/1984	11/1/2011	30	16
Landsat 5	3/1/1984	11/1/2011	30	16
Landsat 7	4/1/1999	present	15	16
Landsat 7 Real Time Collection 1	1999-01-01		15m	16 days
Landsat 7 Tier 1 Collection	4/1/1999	present	15	16
Landsat 7 Tier 2 Collection	4/1/1999	present	15	16
Landsat 8	2/1/2013	present	15	16
Landsat 8 Pre-collection LaSRC Surface Reflectance	2/1/2013	present	15	16
Landsat 8 Real Time Collection 1	2013-01-01		15m	16 days

A Vision of a Geospatial Cloud Analytics Platform

A Platform that provides a marketplace for global-scale, automated, deep learning and remote sensing Analytics-as-a-Service products via an Open API our multi-modal Analysis Factory and Data Refinery, all built on scalable, secure and massively-parallel commercial cloud infrastructure.

	Faster, Better, Stronger		New Paradigm
	Visualize 1 Scene	**Analyze 1 Scene**	**Analyze 10^6 Scenes**
Desktop Based Workflow	Find 1 Scene: ~ 1 Min Download: ~ 1 Min Load in ArcGIS: ~ 1 Min **Total: ~ 3 Minutes**	Atmosphere Correction: ~ 10 Min Apply Random Forest: ~ 1 Min Zonal Statistics: ~ 1 Min **Total: 12 Minutes**	Atmosphere Correction: x10^6 Min or 19 years Apply Random Forest: x10^6 Min or 19 years Zonal Statistics: x10^6 Min or 19 years **Total: x10^7 Min or 19 years**
Cloud Based Platform	Explore Web GUI - Modify Layer Config: ~ 1 Min - Pan-Zoom: Real-Time **Total: 1 Minutes**	Atmosphere Correction: 0 Sec Random Forest: 1 Min Zonal Statistics: 1 Min **Total: 2 Minutes**	Atmosphere Correction: 0 Sec Random Forest: x10^6 /10^4 CPU or 2 Hrs Zonal Statistics: x10^6 /10^4 CPU or 2 Hrs **Total: 4 Hours**
Speedup	3X	6X	10,000X

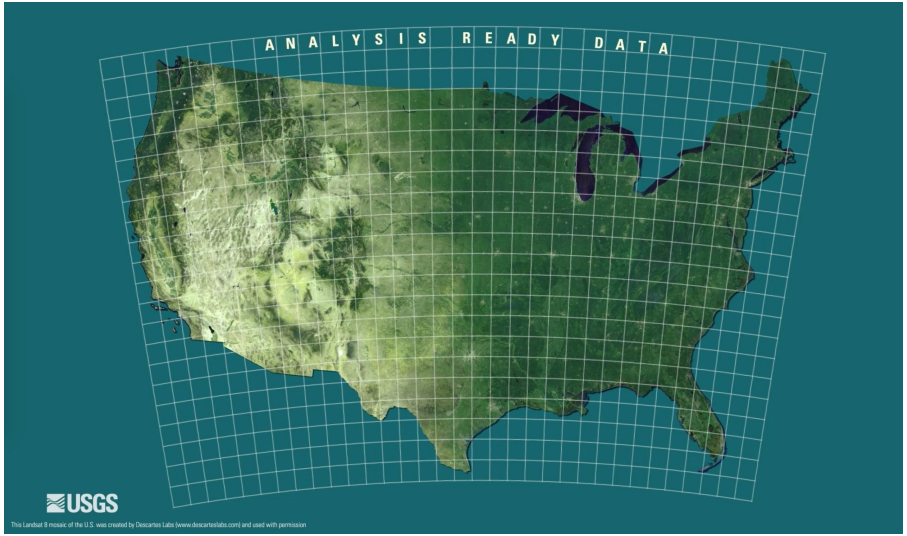


Analysis Ready Data (ARD) functionality is an API!

```
import descarteslabs as dl

scenes = dl.metadata.search(dltile=ardtile, products=["landsat:LC08:01:T2"], start_time=start_time, end_time=end_time)

img, meta = dl.raster.ndarray(scenes, bands=['nir', 'red', 'green', 'alpha'], data_type='Int16', resolution=15,
                                cutline=ardtile['geometry'], srs='EPSG:5070', processing_level='SR')
```



API documentation and examples to get started quickly

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- Installation
- Authentication
- Quickstart
- Guides
- Tutorials
- Examples
- API Reference
- Support

External Links

- Platform Account
- Platform Status
- Shapely Docs
- NumPy Docs

Documentation

Installation

Quick installation instructions of the latest client library via pip.

Authentication

Set up credentials prior to using the services provided by the platform.

Guides

Detailed information about individual Platform components.

Tutorials

End-to-end examples of attaining output, like a water mask, or plotting imagery.

API Reference

Complete definitions of all Platform API endpoints and modules.

Python Examples

Code examples to get you going on a new Platform project.

The Scenes API allows you to query our catalog of imagery. Here, we specify the geometry, product, and cloud fraction parameters to reflect our study's requirements. The `search` method returns a tuple containing the Scene Collection, and the GeospatialContext, where the first lists the image IDs and other metadata. The latter defines the spatial resolution, coordinate system, and other spatial parameters to appl to the Scenes.

Copy

```
scenes, ctx = dl.scenes.search(lake_taupo['geometry'],
                    products=["landsat:LC08:01:RT:TOAR"],
                    start_datetime="2017-12-11",
                    end_datetime="2017-12-12",
                    cloud_fraction=0.7
                   )
ctx
```

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```
AOI(geometry=<shapely.geom... 0x1a17bc8828>,
    resolution=15,
    crs='EPSG:32660',
    align_pixels=True,
    bounds=(175.55877685546875, -39.27691581029594, 176.319580078125, -38.6383273080618
    shape=None)
```

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```
# You can modify the GeospatialContext as needed.
lowres_context = ctx.assign(resolution=60,crs='EPSG:32760')
```

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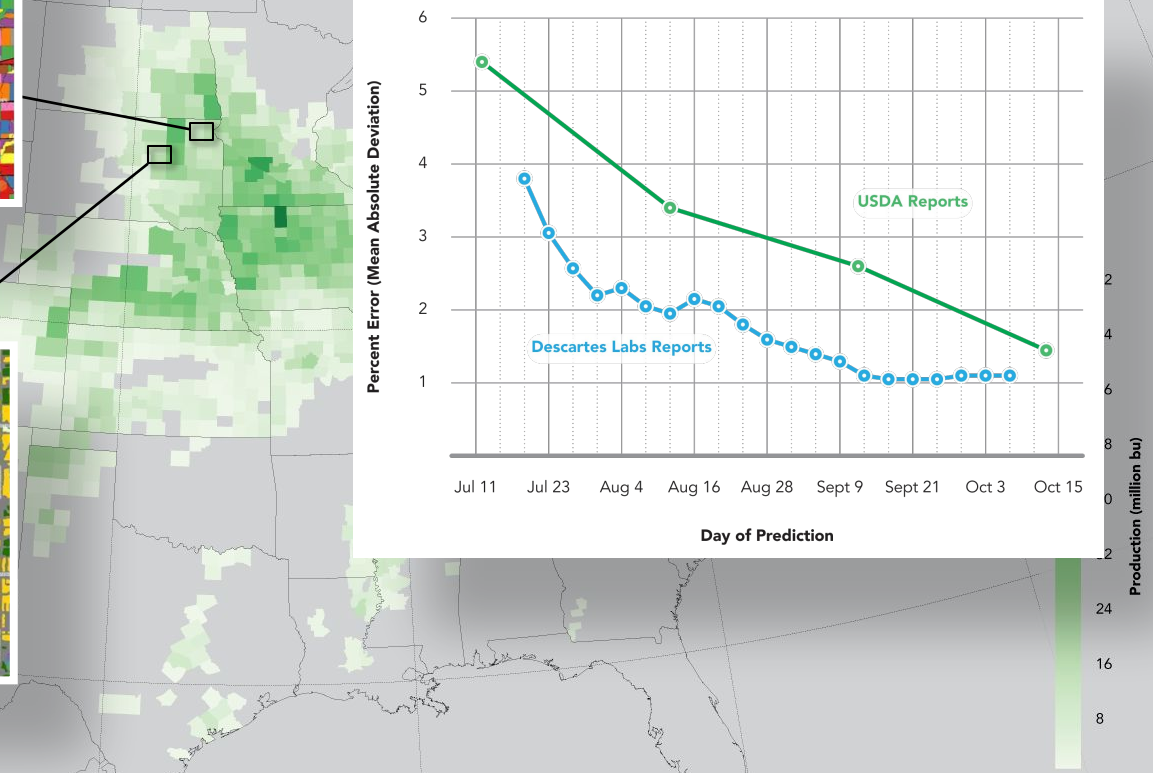
```
arr = scenes[0].ndarray("red green blue",lowres_context)
```

Predicting Corn Yields

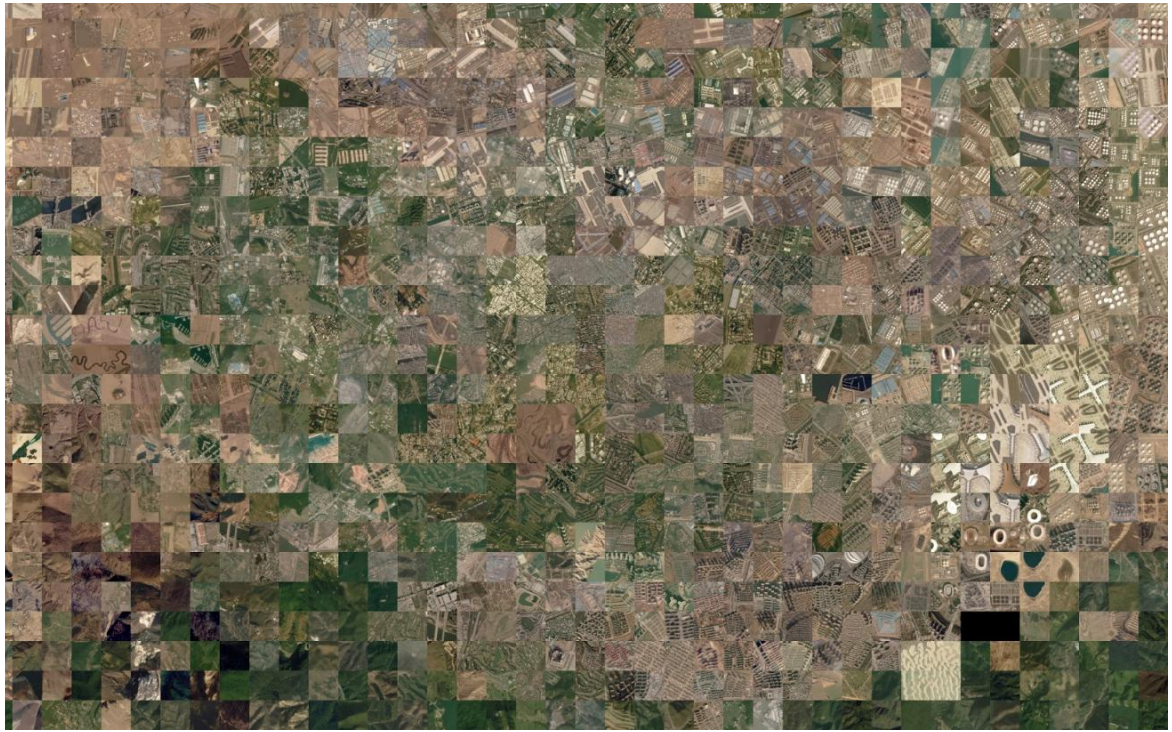


GeoVisual search

Divide the earth's surface into (billions of) small, overlapping images

Extract a "visual feature vector" from each image using a convolutional neural network

Search for neighbors in this feature space using either direct search or locality-sensitive hashing

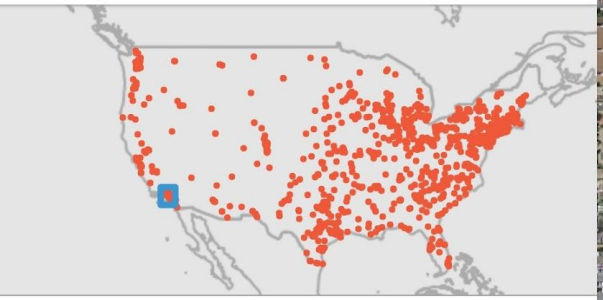


t-SNE visualization of image chips

Secure https://search.descarteslabs.com/?layer=naip_v2_rgb_2014-2015#dlkey=64_32_1.0_11_-1858_58833&lat=34.0221267&lng=-118.2847968&skipTut=true&zoom=16.5533

Search

Aerial Imagery (NAIP)



Top 978 Closest Matches:

Clear Results


Click box
to search
WEST JEFFERSON BLVD.
VERMONT AVENUE
BINNEY DR.
MCCLINTOCK AVE.
WEST 36TH PLACE
WEST 36TH ST.
WEST 37TH PLACE
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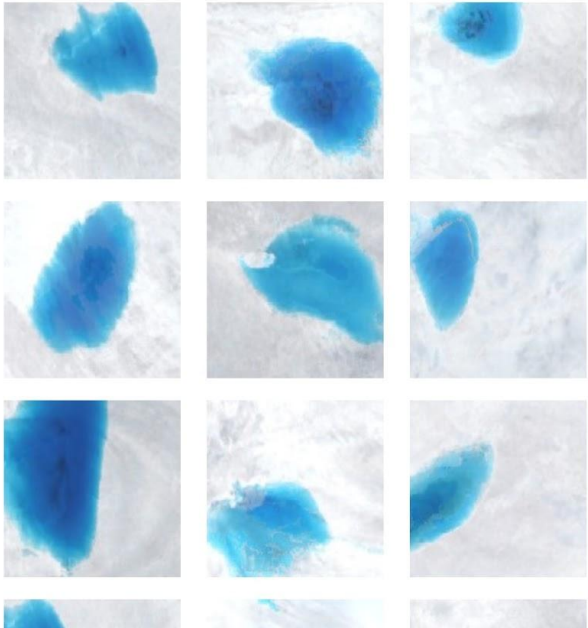
Search

Landsat 8

Top 1000 Closest Matches:

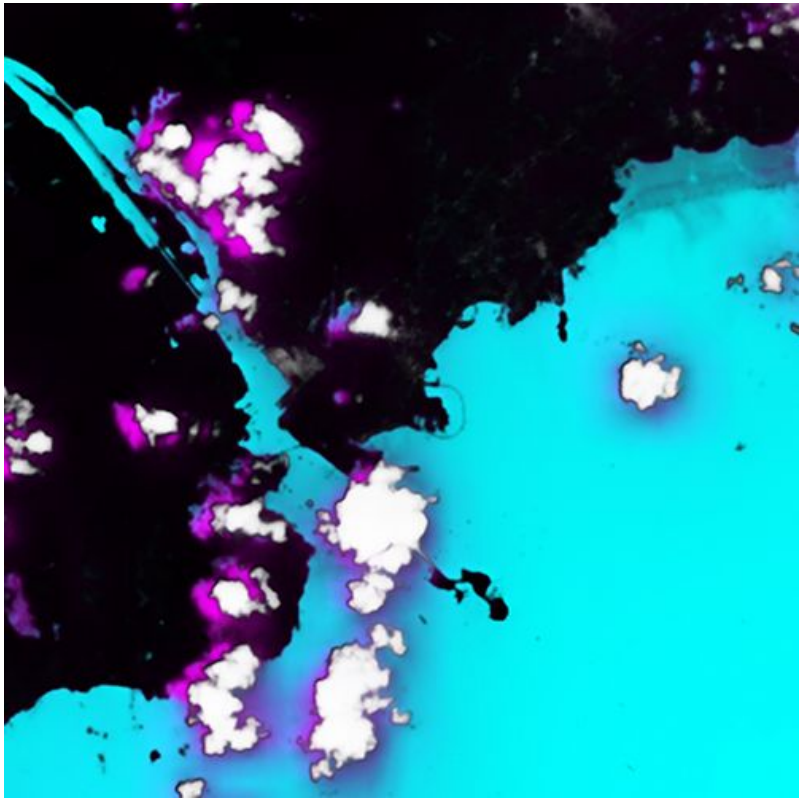
Clear Results



Cloud masks

- Preliminary work has leveraged our computer vision and deep learning technology to classify pixels as cloud, shadow, water & snow across multiple satellite sensors.

- With historical context via per-pixel models, we can extend our platform with more accurate and valuable derived data products.

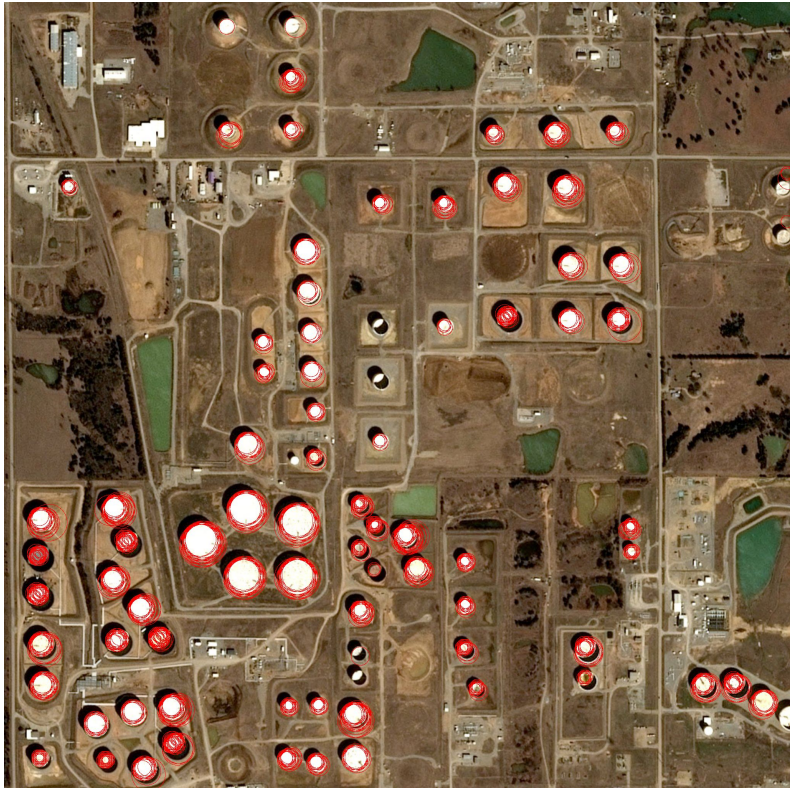


Atmospheric Correction

- Our Remote Sensing Scientists have developed an efficient way to atmospherically correct the visual bands of all of our imagery, using measurements provided from MODIS and the 6S model.

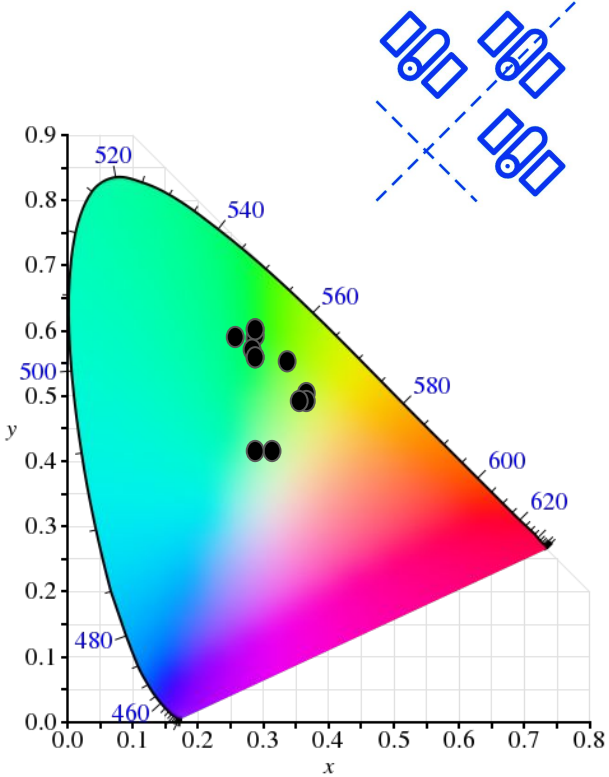
- Preliminary results show similar quality to satellite specific algorithms for Landsat and Sentinel-2 (developed by USGS and ESA) while being much faster.

Differential Template Object Finder



Learn a model for every pixel on the planet

- There are about 1 trillion pixels on the Earth's land surface at a scale of 10 meters.
- We have the resources to compute a 10-100 parameter model for each pixel, based on the time-series of historical observations, pixels nearby, and more frequent lower-resolution observations.
- This enables us to predict what each pixel should look like on any day, with applications to change detection, cloud masks, land use classification and many, many more.



If you'd like to learn more,

"Data-Intensive Supercomputing in the Cloud: Global Analytics for Satellite Imagery"
arXiv:1702.03935 [cs.DC]

https://medium.com/descartestech

https://www.descarteslabs.com

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