GEO– ENERGY

SUSTAINABILITY

INSPIRED BY LIFE

MANIPAL
ACADEMY of HIGHER EDUCATION
BENGALURU CAMPUS
(Institution of Eminence Deemed to be University)

Presented
by
ALIVE
AFTER
DAWN

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PROBLEM STATEMENT

- Design an integrated AI system that leverages remote sensing data, climate modeling, and urban analytics to optimize both renewable energy generation and urban green space development, aiming to maximize biodiversity conservation an environmental sustainability. The challenge lies in harmonzing the dynamic interplay between energy grids, ecological habitats, and urban infrastructure, while providing actionable insights for resource management and urban planning in the face of climate variablity.

ENERGY GENERATION

PROBLEMS FACED BY BIG COMPANIES TODAY

The Challenges

HIGH INITIAL COSTS

Sustainable power plants (e.g., solar, wind, geothermal) require large upfront investments in infrastructure, materials, and technology.

LAND AND ENVIRONMENTAL IMPACT

Large-scale renewable plants (e.g., wind farms, hydro dams) require significant land use, which can disrupt ecosystems and communities.

GRID INTEGRATION

Ensuring new plants can integrate smoothly with existing grids requires significant planning and investment

REGULATORY HURDLES

Permitting and compliance with environmental laws can delay projects

Why is location critical for power plants?

- Determines energy efficiency
- Impacts environment & biodiversity
- Affects cost & return on investment

How can AI optimize this?

- Processes large datasets for best locations
- Considers climate, environment, and economy
- Ensures sustainability & efficiency

The Energies

Focusing on the big three energies : Solar, Wind ,Hydro and Geothermal power.

01.

SOLAR

Harnesses sunlight for clean energy, reducing carbon footprints.

02.

WIND

Uses wind turbines for renewable power with minimal emissions.

03.

HYDRO

Generates electricity from water flow while preserving ecosystems.

04.

GEOTHERMAL

Harnesses Earth's natural heat to generate electricity while minimizing disruption to local ecosystems.

How Does It Work? User Input

USER TYPE: CORPORATE COMPANIES LOOKING FOR LARGE SCALE INVESTMENT IN ENEGRY

- Kind of energy required
- Location preferred
- Investment


PARAMETERS

Geographical Factors

- Elevation, land type, water bodies, wind speed, solar radiation
- Filters out urban, forested, and water areas (only uses barren, shrubland, and grassland)
- Removes steep areas (slope > 10°) (solar panels need flat land)

- Solar power plants typically range from 10 MW to 1,000 MW (1 GW) for industrial-scale projects.
- An industry-scale solar power plant requires approximately 5–10 acres per MW, meaning a 100 MW plant needs 500–1,000 acres depending on panel efficiency and location.

- For wind power stations energy Output: ~2.5–4 GWh per MW annually
- Land Requirement: 50–100 acres per MW (including spacing)

Environmental Impact

- Endangered species and migration patterns
- deforestation risk
- carbon footprint

Climate Data

- Past & future temperature trends
- natural disaster risk
- Displays an Interactive Map (showing solar radiation, land cover, and flat terrain)

Economic Feasibility

- Urbanization, return on investment, energy transport efficiency
- Estimates Infrastructure Cost (based on distance to roads & power grids)
- For Wind power stations, Construction: ~8–12 workers per MW (~800–1,200 for 100 MW)
- For Solar power, Low Workforce Requirement due to automation, for 100 MW Plant: ~20–40 full-time employees

Technology & AI Model Used

Databases Integrated

- Google Earth Engine , Kaggle(Geospatial & climate data)
- World Bank & NASA Data (Environmental & economic factors)
- Real-time Weather API (Wind, solar radiation, temperature trends)
- Chatgpt

Technology & AI Model Used

FORMULAE USED:

- composite = wind_speed.subtract(vegetation).subtract(urban_distance).rename('score')
  best_value_band = 'wind_speed'
  combined = wind_speed.addBands(vegetation).addBands(urban_distance).addBands(composite)

Output

SOLAR POWER

Flow of Data

```python
# Climate Data (Temperature & Precipitation from ERA5)
temperature = ee.ImageCollection('ECMWF/ERA5_LAND/HOURLY') \
                .filterDate('2024-01-01', '2024-01-31') \
                .select('temperature_2m') \
                .mean().clip(aoi)

precipitation = ee.ImageCollection('ECMWF/ERA5_LAND/HOURLY') \
                  .filterDate('2024-01-01', '2024-01-31') \
                  .select('total_precipitation') \
                  .mean().clip(aoi)

# Stack all features into a single dataset
stack_solar = solar_rad \
        .addBands(albedo) \
        .addBands(landcover_masked) \
        .addBands(urban) \
        .addBands(slope) \
        .addBands(elevation) \
        .addBands(temperature) \
        .addBands(precipitation)

# Sample points for solar suitability
points_solar = stack_solar.sample(
    region=aoi,
    scale=500,
    numPixels=3000,  # Adjust based on memory limits
    geometries=True,
    seed=42
)

# Export to Google Drive as CSV
task_solar = ee.batch.Export.table.toDrive(
    collection=points_solar,
    description='Solar_Suitability_Data',
    folder='GEE',
    fileFormat='CSV'
)
task_solar.start()
```

Solar_Suitability_Data

system:index	Map	built	elevation	slope	surface_net_solar_radiation	temperature_2m	total_precipitation	.geo
0	0	2	1422	13.356675413779700	1.15843735340278E+07	297.76925644344800	6.445717444546E-04	{"type":"Point","coordinates":[75.22508043822747,13.143713922927908]}
1	0	2	560	1.8551539860318100	1.17618093222222E+07	297.48354952070400	2.66223044114591E-04	{"type":"Point","coordinates":[74.8771998793971,14.458422060963704]}
2	0	2	831	0.39730058880869900	1.09183525013889E+07	295.95852510664200	2.80899232699008E-04	{"type":"Point","coordinates":[76.46282663497627,13.183263855312795]}
3	0	2	748	0.6240905418811150	1.05707047055556E+07	296.9779180102880	2.63429648119325E-04	{"type":"Point","coordinates":[76.05381207971612,13.714548931418351]}
4	1	2	516	2.380575443394870	1.06708386902778E+07	297.8362404929270	6.56902754168027E-05	{"type":"Point","coordinates":[77.54462795693048,14.266302807362386]}
5	1	5	748	1.0669188836267500	1.069866485625E+07	296.4840242385860	5.02748400935893E-04	{"type":"Point","coordinates":[76.63623824759974,12.338554373777285]}
6	0	2	565	0.6750187329362130	1.11101400083333E+07	297.7504304885860	1.53541741148248E-04	{"type":"Point","coordinates":[75.32522528953561,14.744573750046731]}
7	0	2	271	7.335308800882030	1.20723006104167E+07	297.9185647116770	2.51706965402793E-04	{"type":"Point","coordinates":[74.66966435988476,14.432546634115]}
8	0	2	663	0.6668684059200750	1.09346144006944E+07	297.30883435143400	9.87330958977653E-05	{"type":"Point","coordinates":[76.33486985304333,14.62248402012704]}
9	0	2	607	1.5647518245999600	1.17618093222222E+07	297.48354952070400	2.66223044114591E-04	{"type":"Point","coordinates":[74.93322816382313,14.497752218919464]}
11	0	2	583	0.8329365714304030	1.14784487590278E+07	297.23606145646800	2.4356874925042E-04	{"type":"Point","coordinates":[75.00566969484694,14.296320329381919]}
12	1	2	780	2.285774797786590	1.12384409090278E+07	297.18226100073900	1.59825157250578E-04	{"type":"Point","coordinates":[76.52228477981198,13.728695156364692]}
13	0	2	594	4.136418134693200	1.09717137743056E+07	295.9038159052530	0.0013786680663010600	{"type":"Point","coordinates":[77.66706146955507,12.33116311551399]}
14	0	2	724	0.5077691239836670	1.06691246020833E+07	297.07672172122500	2.45820431122132E-04	{"type":"Point","coordinates":[76.31755010108466,13.574275024262846]}
15	1	2	512	2.377034549411460	1.06535662388889E+07	297.7656513002180	1.84455465091382E-04	{"type":"Point","coordinates":[77.85005488827294,14.333288555668002]}
16	0	2	43	1.2141706088683000	1.15255894451389E+07	299.62342311011400	8.39564420521456E-04	{"type":"Point","coordinates":[74.85725141717025,13.091252245708928]}
18	1	2	702	2.007997859735610	1.08721962090278E+07	297.3313522550800	3.47323537499851E-05	{"type":"Point","coordinates":[76.72268571415572,14.949820480569818]}
19	0	2	816	0.43228323808933200	1.07333578006944E+07	296.0094365649750	2.72971769671256E-04	{"type":"Point","coordinates":[76.68282807724343,13.001514815838224]}
20	0	2	719	2.699693623304460	1.08812800701389E+07	296.34714815351700	7.1709644233662E-04	{"type":"Point","coordinates":[77.30586901815364,12.554464064640941]}
21	0	2	394	0.2967856536916590	1.12033544083333E+07	298.9978290345930	1.10456438589226E-06	{"type":"Point","coordinates":[76.96827778721729,15.393370944815782]}
22	0	2	598	0.3906287318248830	1.05801558875E+07	296.73266790178100	8.12444644753087E-04	{"type":"Point","coordinates":[77.40335917796146,12.064787691979413]}
23	0	2	514	0.3645370555672150	1.06086184597222E+07	298.0710766474410	3.87952588297738E-05	{"type":"Point","coordinates":[76.81029173575384,14.896789368049054]}
24	0	2	890	4.2355788875408	1.19364172965278E+07	295.77573430803100	1.19815104827895E-04	{"type":"Point","coordinates":[74.31100519811565,15.839412146518406]}
25	0	2	577	0.7769485495502650	1.11142780152778E+07	298.0865334616770	2.12672316863088E-04	{"type":"Point","coordinates":[75.73464085108225,14.101725882940368]}
26	0	1	555	1.6945225620295000	1.24168139972222E+07	296.73069036271800	2.95346890245657E-04	{"type":"Point","coordinates":[74.92192984842495,13.952240407769157]}
27	0	2	704	0.73556229221654	1.114557251875E+07	297.0460657967460	9.42479459781925E-05	{"type":"Point","coordinates":[76.42755433571399,14.235129534920778]}
28	0	2	690	0.6613042839998810	1.09346144006944E+07	297.30883435143400	9.87330958977653E-05	{"type":"Point","coordinates":[76.33265452223164,14.553414641599552]}
29	1	2	486	0.40577050166459000	1.08753570715278E+07	298.3780780580310	1.63110234677275E-05	{"type":"Point","coordinates":[76.88969059760376,14.985894543701336]}
30	0	2	854	0.6234594384792990	1.06885130256944E+07	296.02142929501	1.64425167700679E-04	{"type":"Point","coordinates":[77.12868085111856,13.171146515839014]}
31	0	2	582	0.7905104998744650	1.13285280777778E+07	296.83534531063500	2.69525995147508E-04	{"type":"Point","coordinates":[75.05879065350517,13.94000739886216]}

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23	0	2	514	0.3645370555672150	1.06086184597222E+07	298.0710766474410	3.87952588297738E-05	{"type":"Point","coordinates":[76.81029173575384,14.896789368049054]}
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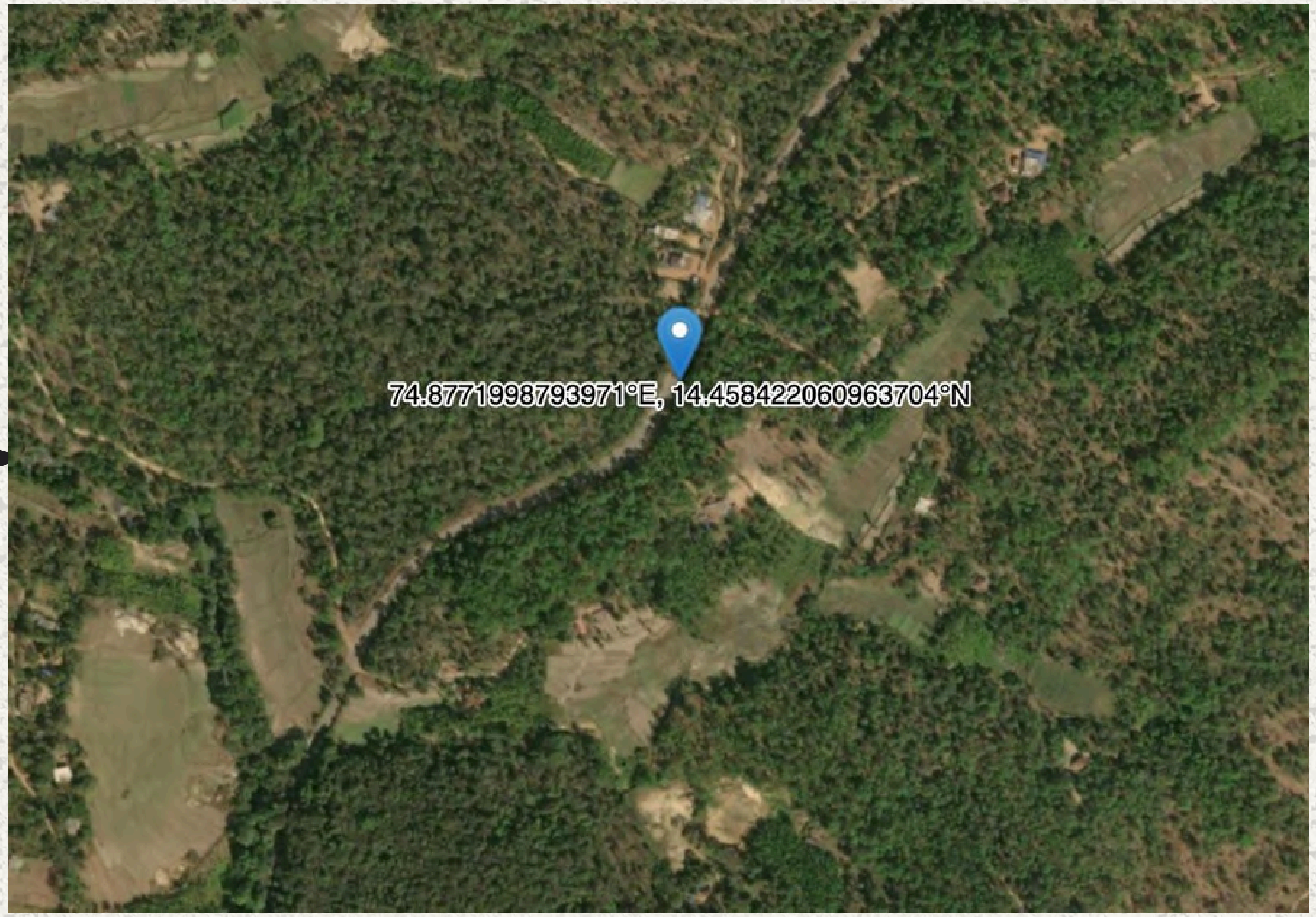
30	0	2	854	0.6234594384792990	1.06885130256944E+07	296.02142929501	1.64425167700679E-04	{"type":"Point","coordinates":[77.12868085111856,13.171146515839014]}
31	0	2	582	0.7905104998744650	1.13285280777778E+07	296.83534531063500	2.69525995147508E-04	{"type":"Point","coordinates":[75.05879065350517,13.94000739886216]}



SOLAR LOCATION OPTIMIZATION MODEL

```
src — Python ‹ Python app2.py — 80×24
 * Debug mode: on
WARNING: This is a development server. Do not use it in a production deployment.
 Use a production WSGI server instead.
 * Running on http://127.0.0.1:5000
Press CTRL+C to quit
 * Restarting with stat
 * Debugger is active!
 * Debugger PIN: 328-015-029
/Users/jhagruth/optimal-energy-api/venv/lib/python3.13/site-packages/osmnx/_over
pass.py:267: UserWarning: This area is 11,588 times your configured Overpass max
 query area size. It will automatically be divided up into multiple sub-queries
accordingly. This may take a long time.
  multi_poly_proj = utils_geo._consolidate_subdivide_geometry(poly_proj)
/Users/jhagruth/optimal-energy-api/venv/lib/python3.13/site-packages/osmnx/_over
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 query area size. It will automatically be divided up into multiple sub-queries
accordingly. This may take a long time.
  multi_poly_proj = utils_geo._consolidate_subdivide_geometry(poly_proj)
```
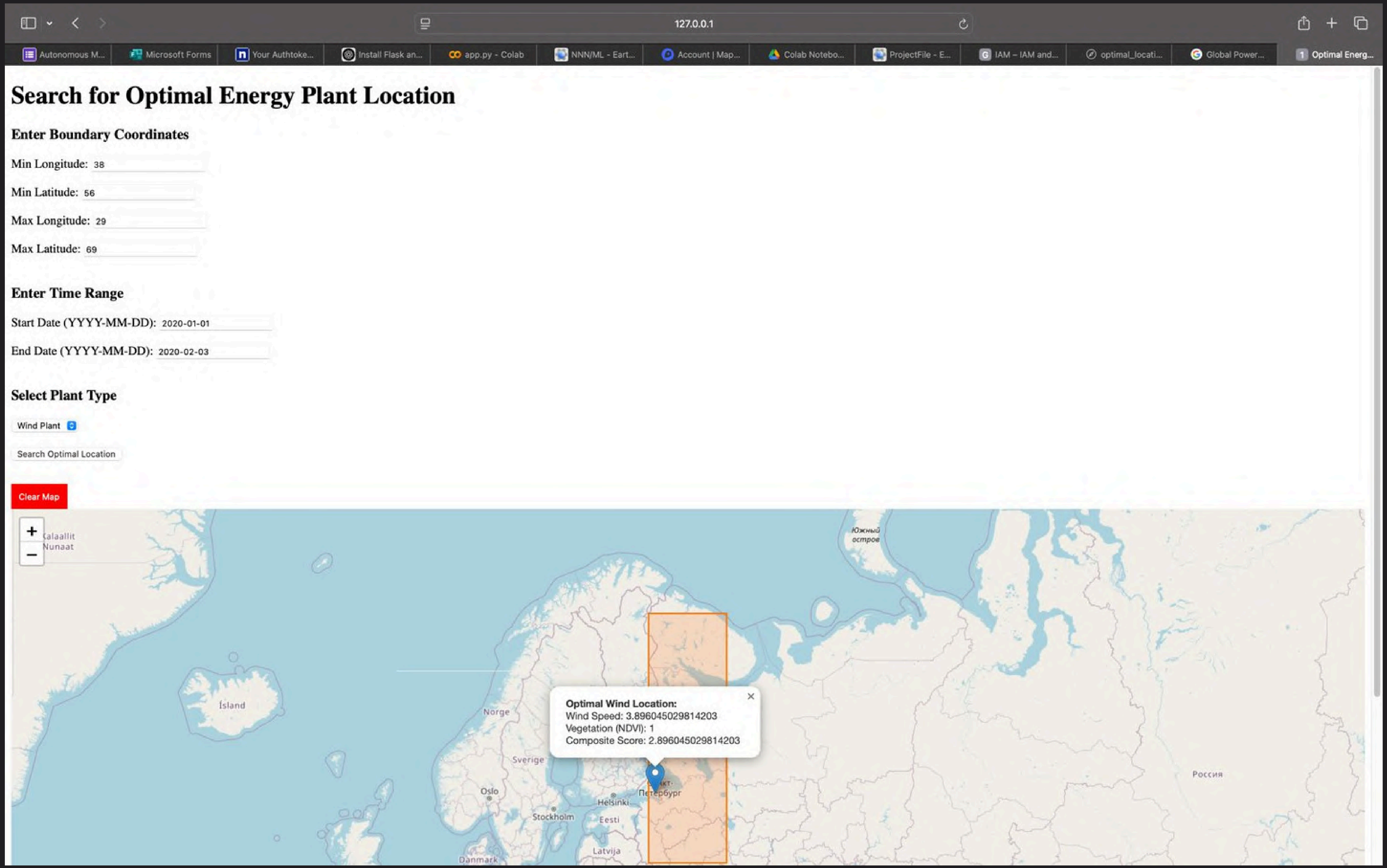

WIND POWER

Framework of the integration of parameters



Google Earth Engine

Search places and datasets...

hacknite-25

Scripts | Docs | Assets

Filter scripts...

NEW

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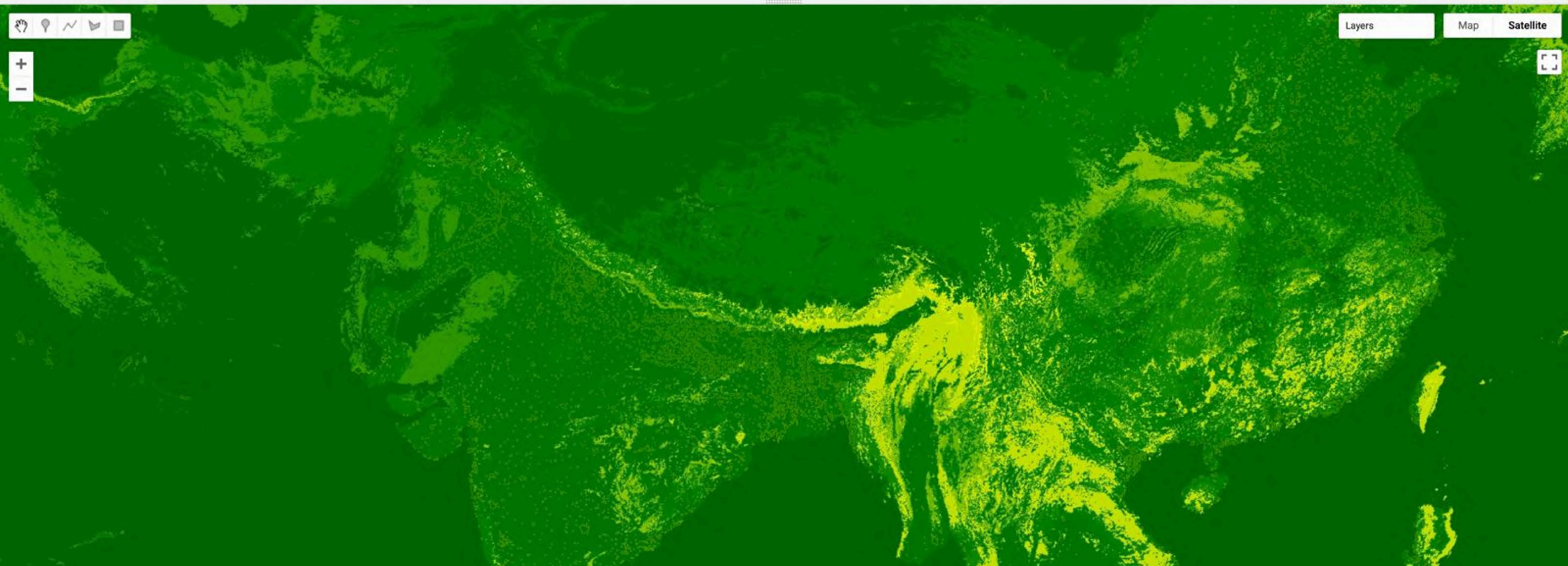
  - users/Jhagruth/hacknite-25
    - Project
    - ProjectFile
- Writer
  - No accessible repositories. Click Refresh to check again.
- Reader
  - No accessible repositories. Click Refresh to check again.
- Archive
  - No accessible repositories. Click Refresh to check again.
- Examples

ProjectFile | Get Link | Save | Run | Reset | Apps

```
// Import necessary datasets

// ERA5 - Wind speed data
var era5 = ee.ImageCollection('ECMWF/ERA5/DAILY') // ERA5 data
    .filterDate('2020-01-01', '2020-12-31')  // Example date range
    .select('u_component_of_wind_10m', 'v_component_of_wind_10m');  // Wind speed components (u = east-we

// MODIS Biomass - Vegetation structure and biomass density data (MODIS MCD12Q1 version 006)
var modisBiomass = ee.ImageCollection('MODIS/006/MCD12Q1') // MODIS vegetation dataset (version 006)
    .filterDate('2020-01-01', '2020-12-31')
    .select('LC_Type1');  // Use Land Cover type (LC_Type1 for primary land cover type)

// RealTide - Tidal currents data (for hydro power assessment)
var realTide = ee.ImageCollection('NOAA/CO-OPS/TidalCurrents') // RealTide data
    .filterDate('2020-01-01', '2020-12-31');
```

Inspector | Console | Tasks

Use print(...) to write to this console.



Solar Suitability AI Model

Overview

This project implements a machine learning-based solar suitability model using environmental and spatial data. The model leverages XGBoost for advanced predictions, incorporating polynomial features, hyperparameter tuning, and feature importance analysis.

Data Sources

The following datasets were used in this project:

1. **MODIS/006/MCD12Q1** - Vegetation data
2. **ECMWF/ERA5/DAILY** - Wind speed data
3. **ESA/WorldCover/v100** - Urbanization data
4. **NASA/GEOS-5/MERRA2** - Solar radiation data

These datasets were accessed via Google Earth Engine (GEE) and preprocessed for training the model.

Features and Methodology

- **Data Processing**: Extracted spatial data and normalized values using `MinMaxScaler`.
- **Feature Engineering**: Applied polynomial feature expansion.
- **Machine Learning Model**: Utilized XGBoost with hyperparameter tuning via GridSearchCV.
- **Evaluation**: Used R^2 scores and feature importance analysis.

Benefits of Our AI System

1.	EFFICIENCY – FINDS THE BEST LOCATION WITH MAXIMUM ENERGY OUTPUT
2.	SUSTAINABILITY – MINIMIZES ENVIRONMENTAL DAMAGE
3.	COST-EFFECTIVE – OPTIMIZES ROI BY SELECTING THE BEST ECONOMIC FACTORS
4.	REAL-TIME DATA – USES AI & LIVE DATABASES FOR UP-TO-DATE ANALYSIS
5.	INDUSTRY READY – SUITABLE FOR COMPANIES, GOVERNMENTS, AND ENERGY STARTUPS

AI and Machine Learning Models Used

XGBOOST
(EXTREME GRADIENT BOOSTING)

Type: Supervised Machine Learning (Regression)

Purpose: Predicts the *solar suitability score* based on environmental and spatial factors.

POLYNOMIAL FEATURE ENGINEERING

Type: Feature Engineering

Purpose: Enhances the dataset by creating interaction terms between variables.

HYPERPARAMETER TUNING WITH GRIDSEARCHCV

Type: Model Optimization

Purpose: Finds the best combination of parameters

MINMAXSCALER
(DATA NORMALIZATION)

Type: Preprocessing

Purpose: Scales all input features between 0 and 1 to ensure balanced model training.