

Using PostgreSQL and PostGIS for Climate Resilient Agriculture

Asim Rama Praveen, Sameer Mannava

Outline

- Who are we?
- What is PoCRA?
- Climate impact on agriculture
- Water budget framework
- Water budget based planning for climate resilience
- A tool for field staff - representative sample of farm plots
- Conclusion

Who are we?

- A team of field staff, students, consultants, faculty @ IIT Bombay
- Employed by Prof. Milind Sohoni, principal investigator
- Currently deputed on PoCRA



What is PoCRA?

World Bank sponsored **Project on Climate Resilient Agriculture** \$600 million (Rs. 4500 Cr)

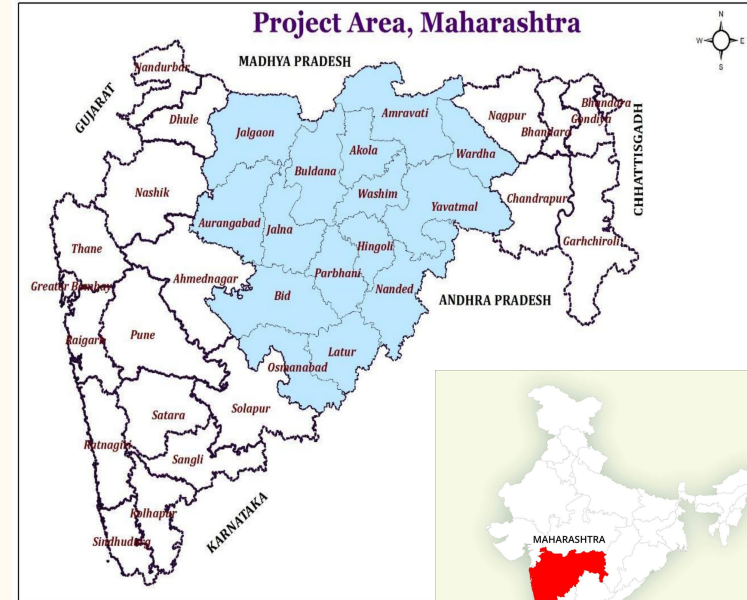
Series of 5 MoUs between IIT Bombay and Department of Agriculture, Maharashtra state

<https://www.cse.iitb.ac.in/~pocra/>

Time frame: 2018 to 2024

Project objective: improve climate resilience of smallholder farmers

Region: 5000+ villages in 15 districts



Impact of climate change

- Long dry spells during monsoon
 - 25+ days in Aug 2023
 - Crop water deficit
- Wet spells
 - 124mm in 1 hour (Yawatmal on 22 July 2023)
 - Water logging & erosion
- Hivargavhan farmer: (70% loss)
 - cotton yield down from 6 to 2 quintal/acre
- Tembha farmer: (40% loss)
 - cotton yield down from 8 to 5 quintal/acre
- The most impacted: small farmers (<2ha)
 - who depend solely on agriculture



Hivargavhan,
(Beed)
Oct 2023

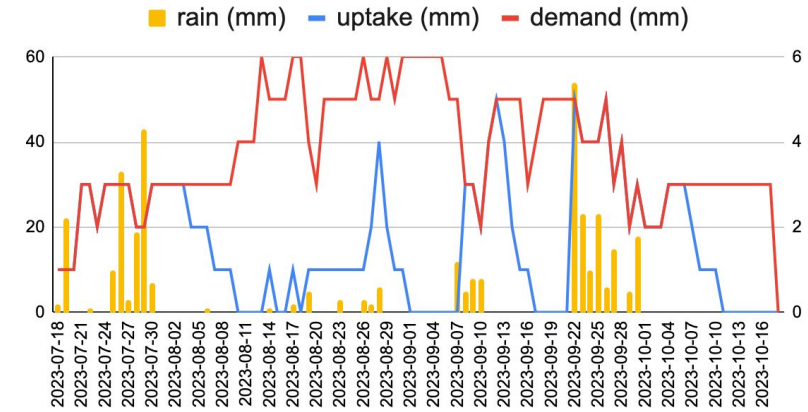


Tembha,
(Wardha)
Sept 2023

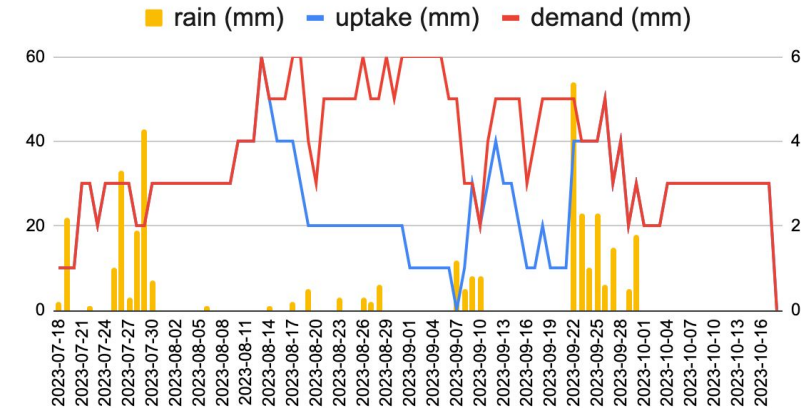
Impact of climate change

- Same village different farms - vastly different impact
- How to quantify vulnerability?
- How to measure climate resilience?
- How to improve it?

Soybean crop water deficit 2023, shallow soil (20cm), Limba (Beed)



Soybean crop water deficit 2023, deep soil (80cm), Limba (Beed)



Current solution

[indianexpress.com](https://www.indianexpress.com)

November 30, 2023

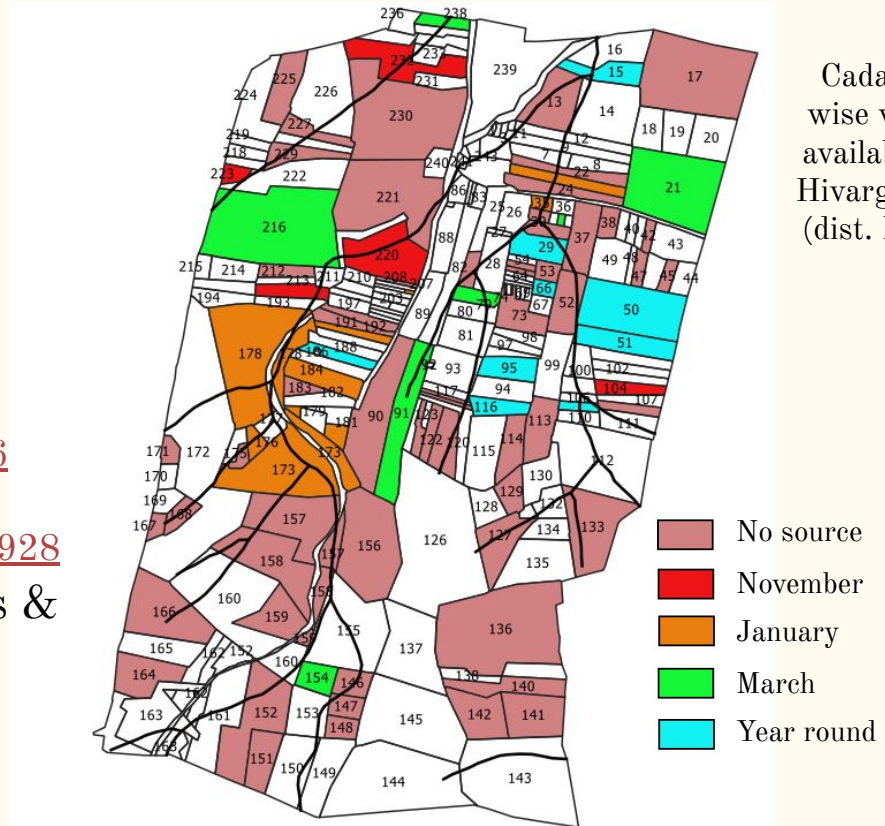
10k crore approved to compensate farmers in June 2022-Sept 2023, Maharashtra cabinet told

Alok Deshpande

- Why 10,000 crore? - aged methodology
- Lived reality remains grim

Climate resilience: village as a unit

- **Baseline: capture lived reality**
 - Median yield (quintal/acre)
 - Access to irrigation
 - Availability of water
- **Biophysical vulnerability**
 - Crop water deficit and their locations
 - Supply demand allocation framework
 - Water Policy
 - <https://doi.org/10.2166/wp.2023.036>
 - CACM
 - <https://dl.acm.org/doi/10.1145/3554928>
- **Enable DoA to target interventions & advisories**
- **Make it work for 20000 villages**
 - PostgreSQL, PostGIS, Geoserver



Climate resilience: village as a unit

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-
- Boots on the ground
- Water budget model, developed by IIT Bombay
- Water budget frontend

Climate resilience: village as a unit

- Baseline: capture lived reality
 - Median yield (quintal/acre)
 - Access
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Field work, DoA

All of this is backed by
PostgreSQL and PostGIS

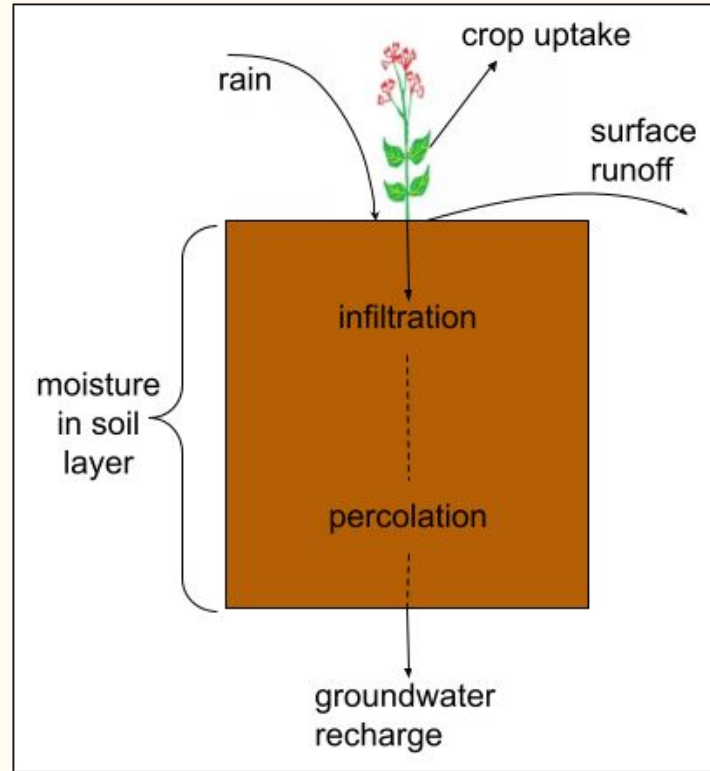
model, developed
by IIT Bombay

Water budget frontend

Water Budget Model

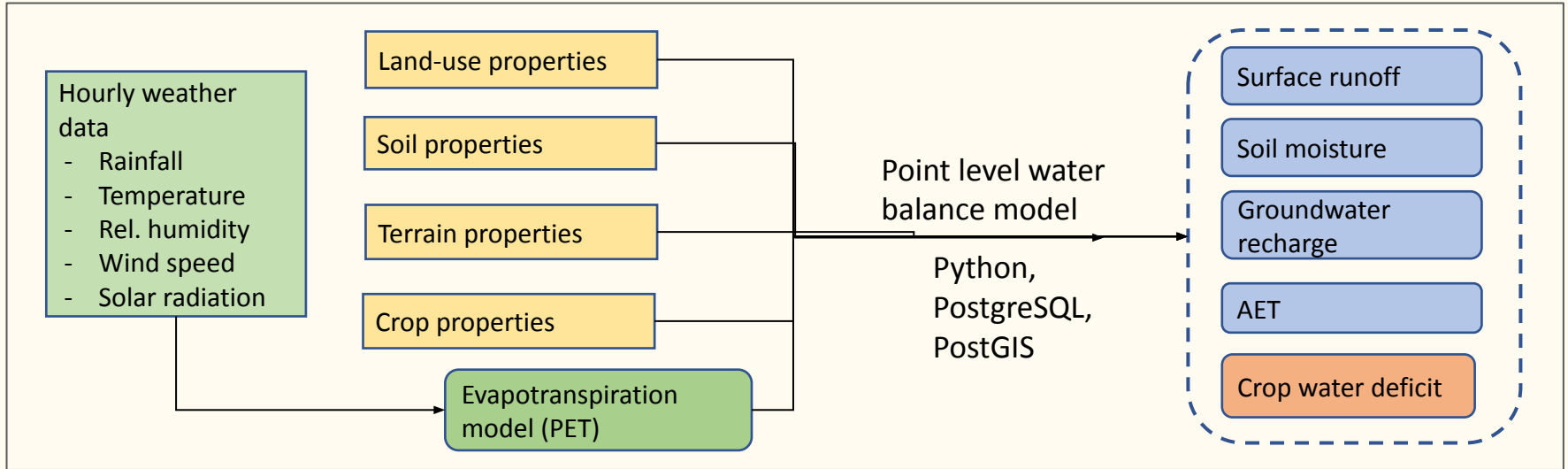
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Water budget model: computations at a point



Distribution of rainfall into stocks

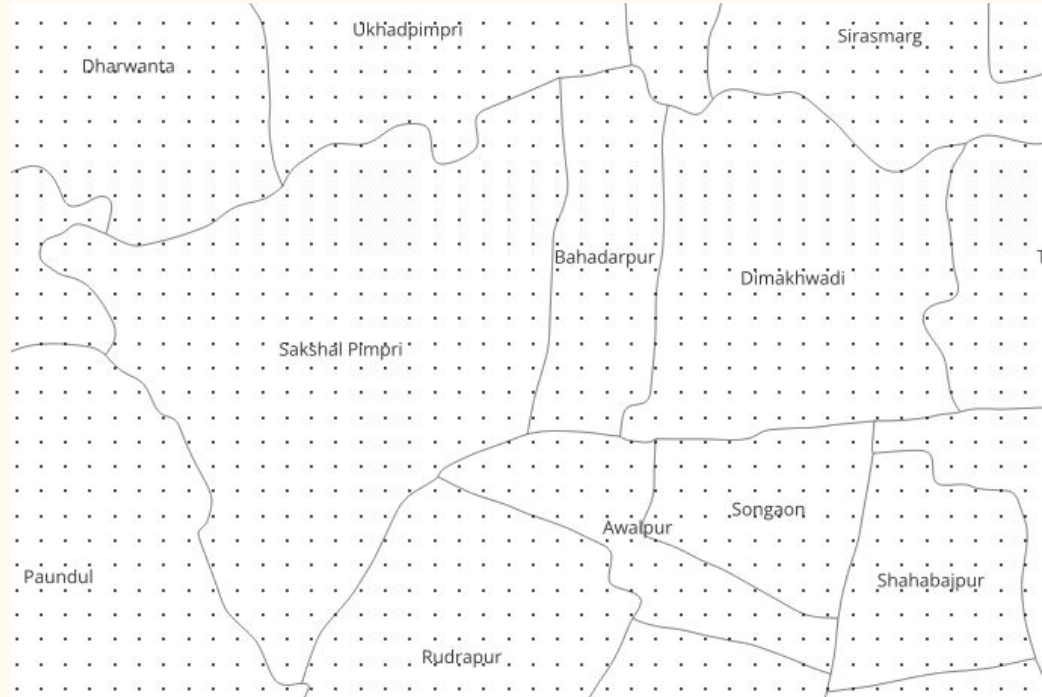
Water budget model: computations at a point



- Distribution of rainfall into stocks
- Vulnerability in terms of crop water deficit
- Dynamic: hourly/daily output during monsoon
- Validated in multiple villages

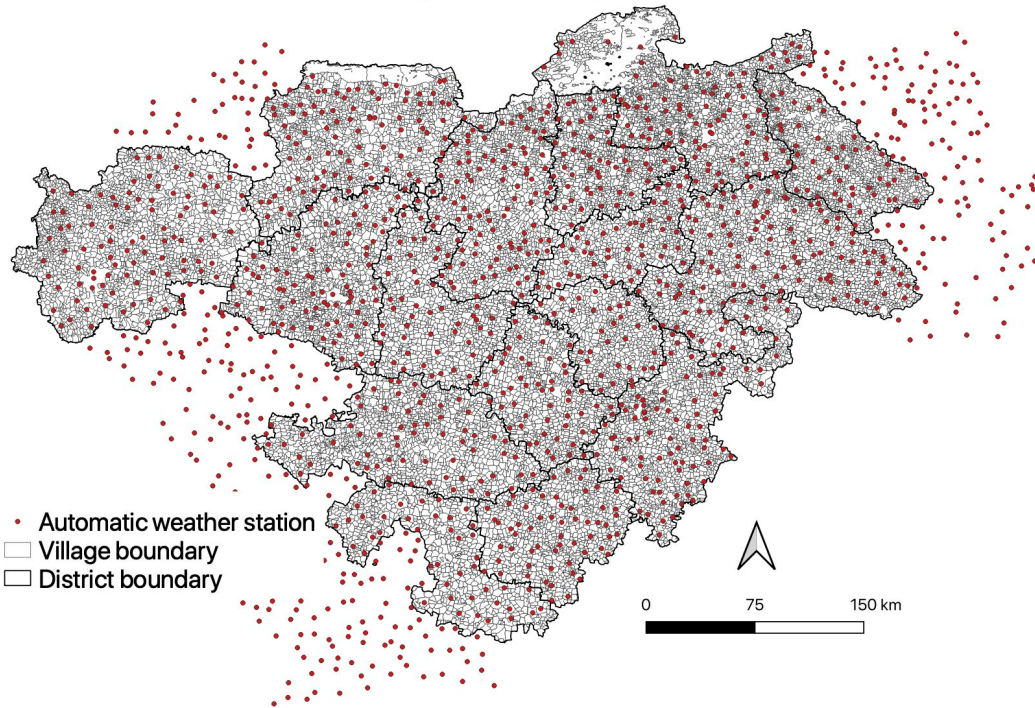
Water budget model: grid of points

- Points table: a district is divided into square grid of size **200m**.
- Input parameters are added as columns to the grid points table
- Output table: one new record per crop, per day, per point
- 15 districts → 129,000 sq. km.
- **3,225,000 points**
- 150 days * 32 crops = **15.48B** output records per monsoon

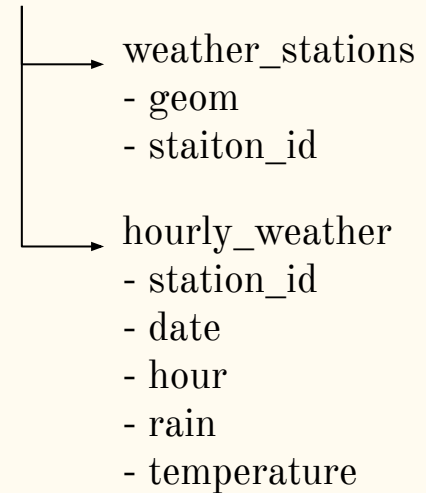


Water budget inputs: hourly weather

15 districts in Maharashtra, covering the PoCRA region



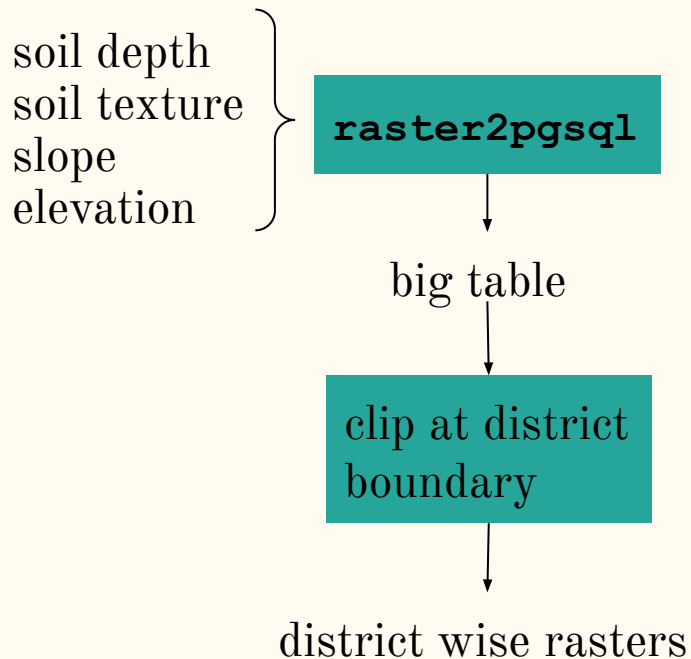
Skymet API
@5am daily



Water budget inputs: hourly weather

- Weather stations may go down
- Model doesn't tolerate missing data
- Identify missing data slots (station_id, date, hour)
- Replace null values with data from the nearest weather station

Water budget inputs: raster data



```
insert into district_wise_raster
select
  st_clip(
    big.rast,
    st_buffer(small.geom, 100),
    -32768
  ) as rast
from
  bigtable as big
inner join
  districts as small
on
  st_intersects(
    big.rast,
    st_buffer(small.geom, 100))
and
  small.district_name = '...';
```

Attaching raster data to grid points

- Points table → 200m squares
- Raster table pixel size → 30m
- Intersection of a point square with raster tile → multiple raster values
- Value at the point:
`(st_summarystats()) .mean`

```
select
  point.id,
  (st_summarystats(
    st_union(
      st_clip(
        soil.rast,
        st_expand(point.geom, 100))
      )
    ).mean as soil_depth
from
  {district}_soildepth as soil
inner join
  {district}_points as point
on
  st_expand(point.geom, 100)
  && s.rast
group by
  p.id
```

Water budget inputs: vector data

- Administrative boundaries
 - district, taluka, village
- Land use land cover (LULC)
 - agriculture (kharif, rabi), forest, habitation, ...
- `st_containsproperly()`: grid points within a land use class

```
select
  point.id
  Lulc.class_id as landuse_class
from
  {district}_points as point
join
  {district}_lulc as lulc
on
  st_containsproperly(
    lulc.geom,
    point.geom
  )
```

Assign nearest weather station to each village

- Villages: polygon geometry
- Weather stations: point geometry
- Lateral join, order by distance
(PostGIS <-> operator), limit 1

```
select
  v.vincode,
  nw.station_id as nearest_station,
  nw.distance
from
  villages v
cross join lateral
  (select
    station_id,
    st_distance(
      w1.geom,
      v.geom
    ) as distance
  from
    Weather_stations w1
  order by
    v.geom <-> w1.geom
  limit 1) as nw
```

Water budget output: results table

District wise results table

- point_id
- date
- crop
- uptake
- deficit
- soil_moisture
- runoff
- groundwater_recharge

New records inserted daily

Water budget daily cadence

Fetch hourly weather, smoothen missing data

Trigger parallel district runs

District run:

```
for each weather station in district
  read hourly weather
  for each point
    for each crop
      advance state: compute new stocks
      hourly to daily accumulation
      insert new record into output table
```

Water Budget: Demand Side



Planning for rabi (post monsoon season)

- Village wise cropping pattern (from DoA)
 - $\langle \text{crop}, \text{crop_area} \rangle$ pairs
- Exact crop uptake for the village
 - $\text{village_crop_uptake} = \text{avg}((\text{corp_area}/\text{village_area}) * \text{uptake})$
- Volumetric water budget
 - $(\text{point wise output in mm}) * (\text{village agricultural area})$

Planning for rabi (post monsoon season)

- Water available in Hivargavhan (536 ha) on 31 October 2023

Rainfall	Crop uptake	Runoff	Impounded runoff	Soil moisture	Groundwater
3769 TCM	911 TCM	1515 TCM	2 TCM	70 TCM	394 TCM

- Gram water requirement: 300 mm
- Feasible rabi area under gram: 156 ha (29% agricultural land)

Planning for rabi (post monsoon season)

- Water available in Hiranagar (526 ha) on 31 October 2023

Rainfall	Groundwater
3769 TCM	394 TCM

Sustainable cropping pattern for
the village
based on water budget

- Gram water re
- Feasible rabi area under gram: 154 ha (28% agricultural land)

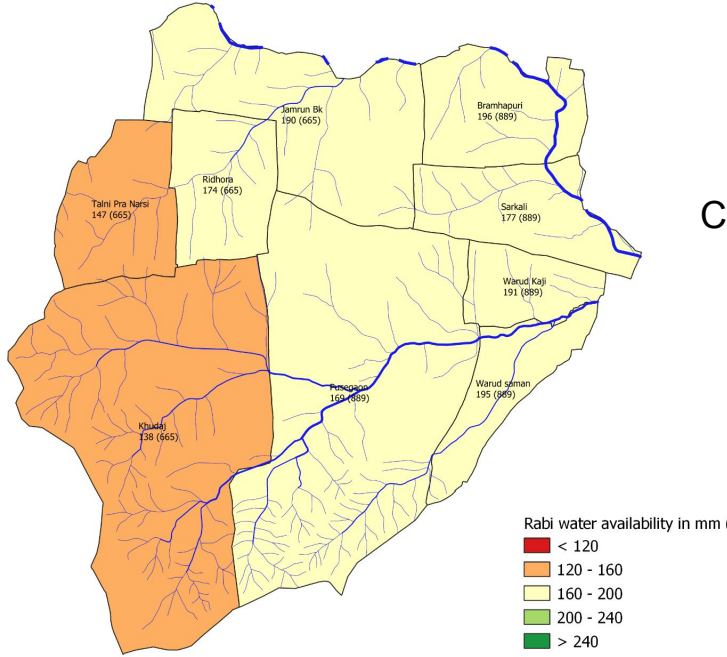
We tried this exercise in 12 villages



Takeaways for village community

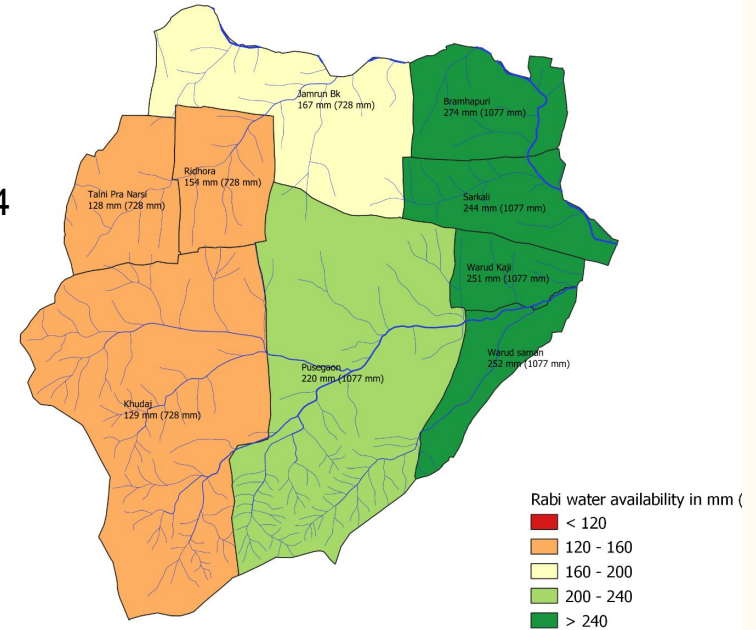
- Knobs for sustainable rabi cropping pattern:
 - Area under crop
 - Choice of crop
- Long term (before next monsoon)
 - Structures to impound surface runoff

Yearly variation in rabi water availability



Year 2018

Cluster: 512_ppg-1_04
Taluka: Hingoli
District: Hingoli

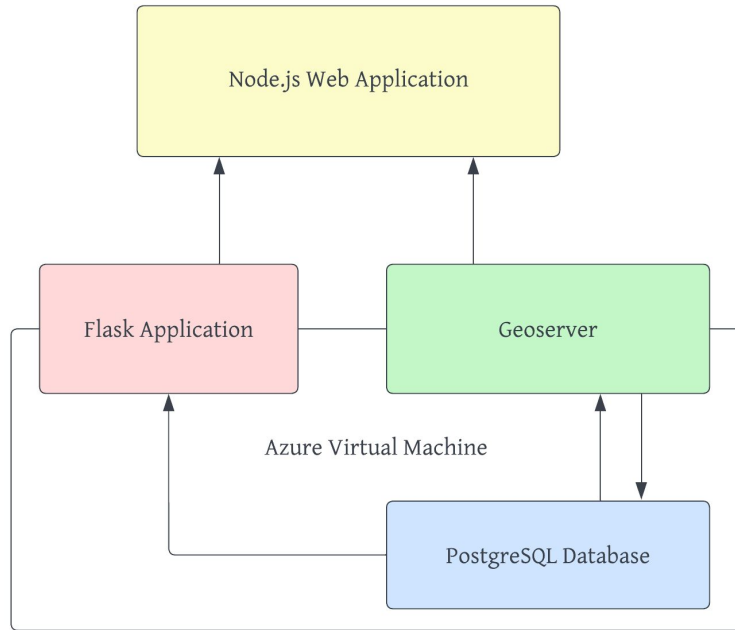


Year 2022

Water Budget Reporting



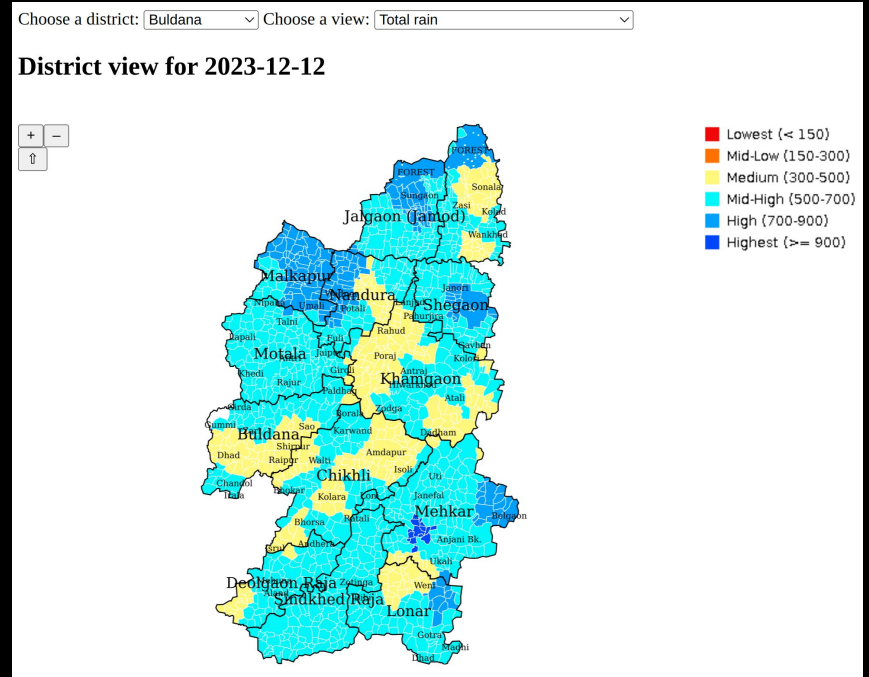
Water Budget Reporting Stack



- Spatial and temporal aggregation of daily water budget results
- End users:
 - DoA planners at district and taluka
 - Village community, village level DoA staff
- Geoserver to host maps
- Flask to run PostGIS queries (e.g. village wise soybean deficit on 07 Oct)
- UDFs to query water budget that accept district code, taluka code, crop, date, etc.

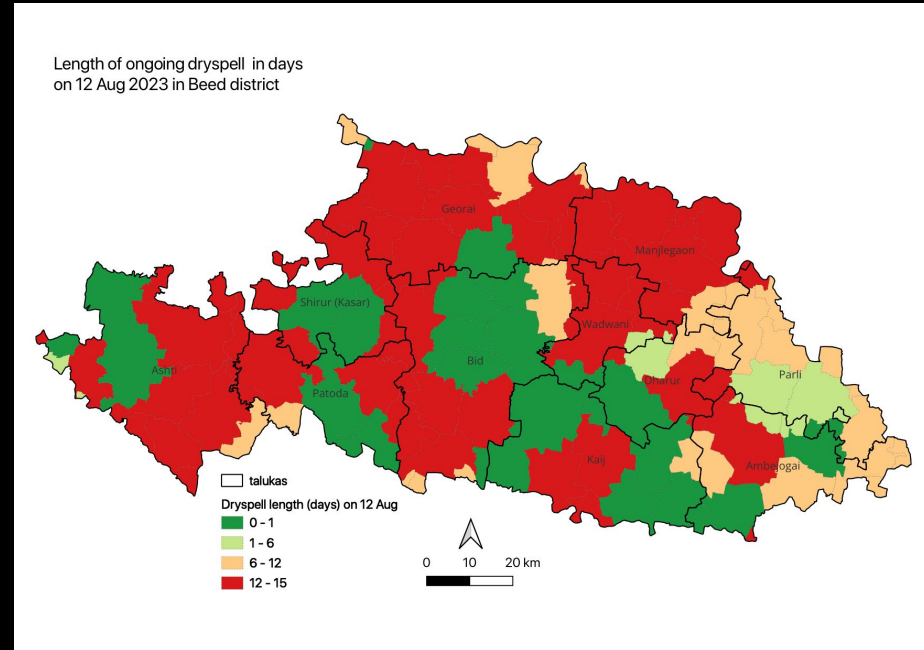
The District View

- 1) Total rainfall
- 2) Rainfall in the last 7 days
- 3) Length of the ongoing dry spell
- 4) Forecasted rainfall in the next 5 days



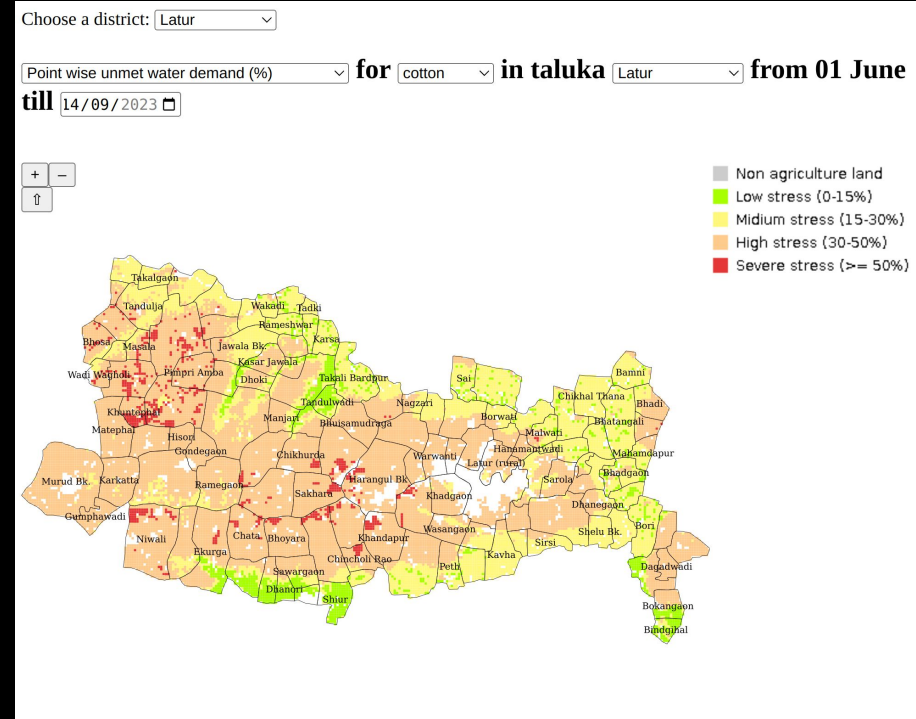
The District View

Length of the ongoing dry spell
for Beed district on 12 Aug 2023



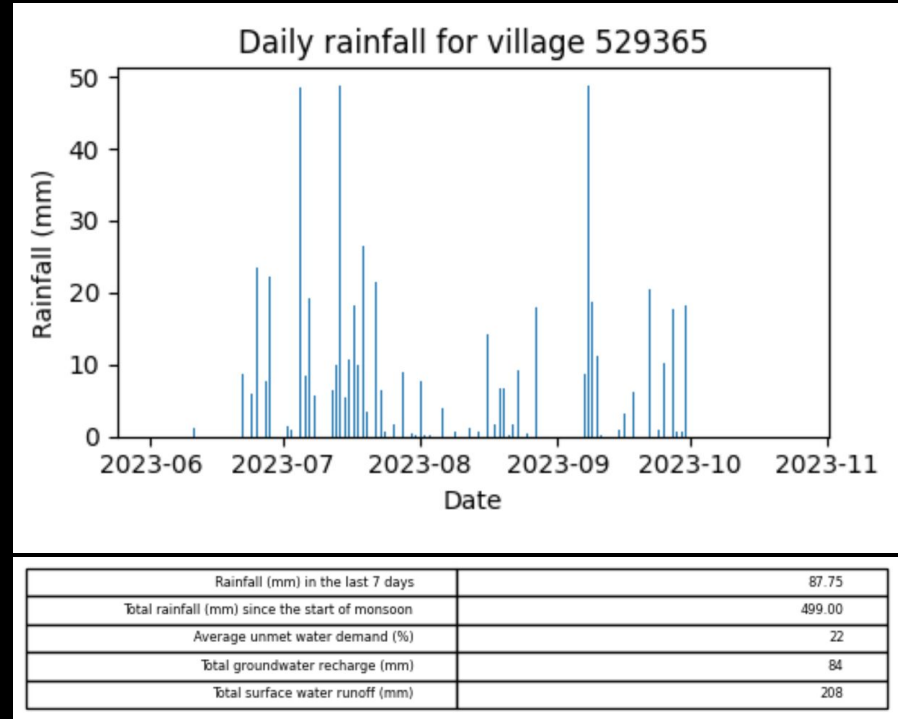
The Taluka View

- 1) Deficit percent
- 2) Available soil moisture
- 3) Need for protective irrigation



The Village View

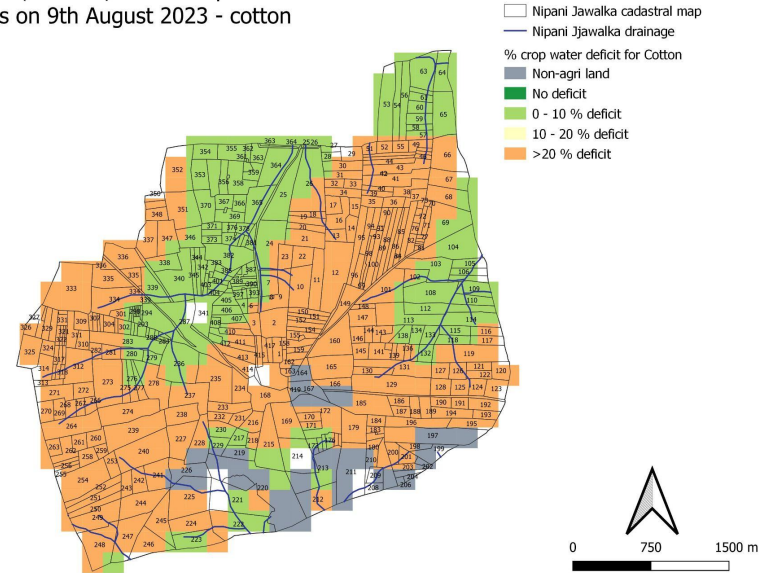
- A plot of daily rainfall
- Cumulative water budget results



The Village View

Point wise deficit for cotton,
village Nipani Jawalka,
on 9 Aug 2023

Nipani Jawalka, Georai, Beed crop water
deficit map as on 9th August 2023 - cotton



Sampling Tool

—

Conducting surveys and validating our models

- Project spread across 20000 villages, 44000 villages in Maharashtra
- How many farmers do we survey in any given village?
- How to pick out of the numerous (~ 500) farm plots?
- How to achieve a good sample space? Four criteria to consider:
 - Need varying types of soil
 - Need varying levels of elevation
 - Need to survey stream-side and land-locked farms
 - Need a good geographical spread

Soil depth partition

- {district}_soildepth - district wide raster with soil depth data
- st_clip() clips the raster at the village boundaries
- st_reclass() classifies into predefined ranges
- st_dumpaspolygons() converts the raster into vector geometry

```
select
    vrcode,
    (st_dumpaspolygons(
        st_reclass(
            st_clip(rast, geom),
            1, '[0-25]:1, (25-60]:2,
            (60-9999]:3', '4BUI', 0
        )
    )).*
from
    {district}_soildepth
join
    village
on
    st_intersects(rast, geom)
```

Elevation partition

- Elevation varies widely from village to village
- Predefined classes not feasible
- `st_pixelaspoints()`: Divide the village into pixels
- `row_number()`: Order the pixels by elevation
- `st_summarystats()`: Get the total number of pixels

```
elevation_pixels as (  
    select  
        vrcode, (st_pixelaspoints(rast)).*  
    from  
        elevation_raster  
),  
elevation_ranked as (  
    select  
        vrcode, val,  
        row_number() over (order by val, x, y) as  
rownum  
    from  
        elevation_pixels  
),  
elevation_summary as (  
    select  
        vrcode, (st_summarystats(rast)).*  
    from  
        elevation_raster  
),
```

Elevation partition

- Finally, divide into 33% and 67% percentile classes using a case statement

```
elevation_classified as (  
  select  
    r.vincode, r.val, r.rownum,  
    case  
      when  
        r.rownum <= s.count/3  
      then  
        1  
      when  
        rownum > s.count/3 and rownum <= 2*s.count/3  
      then  
        2  
      else  
        3  
    end as elevation_class  
  from  
    elevation_ranked r  
  join  
    elevation_summary s  
  using  
    (vincode)  
)
```

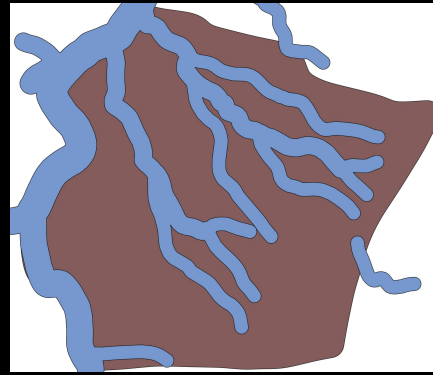
Stream proximity partition

- staticdata.“River” - Line geometries with magnitude indicating size of the stream
- st_buffer(): create a polygon geometry indicating ‘stream-fed’ farms
- Next, we take its complement using st_difference() to represent the ‘land-locked’ farms

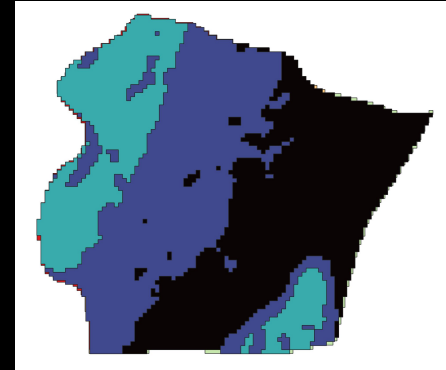
```
buffered_streams as (  
    select  
        st_union(st_buffer(geom::geography,  
magnitude)::geometry) as streamfed  
    from  
        staticdata.“River”  
),  
select  
    streamfed,  
    st_difference(v.geom, streamfed) as  
landlocked  
from  
    buffered_streams  
join  
    village  
on  
    true
```

Division of the village into distinct biophysical zones

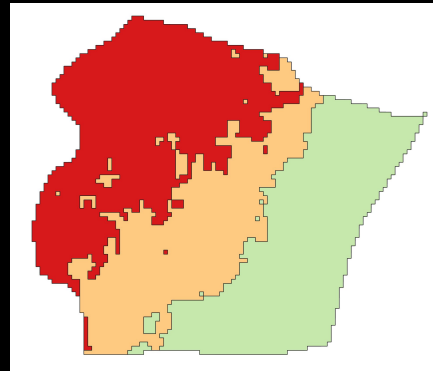
- Intersect the partitions created to form biophysical zones ($3*3*2 = 18$ types of zones possible)
- A new table is created with 5 columns:
 - farmplot id
 - geometry
 - soil depth class
 - elevation class
 - stream proximity



Stream proximity partition



Soil depth partition



Elevation partition

Division of the village into distinct biophysical zones

- `random()` is employed here so that the tool can be rerun if we desire a slightly different collection of farmplots

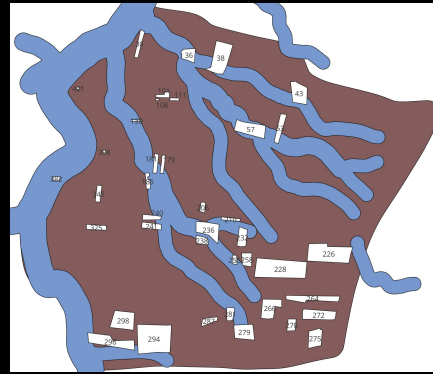
```
select
    pin,
    geom,
    eleclass,
    depthval,
    stream_region,
    row_number() over (
        partition by eleclass,
        depthval, stream_region
        order by random()
    ) as index
from
    biophysical_zones
```

How to achieve a good geographical spread?

- `drop_all_touching_farms` drops touching farms using `st_touches()` to evaluate adjacency
- The following algorithm is run:

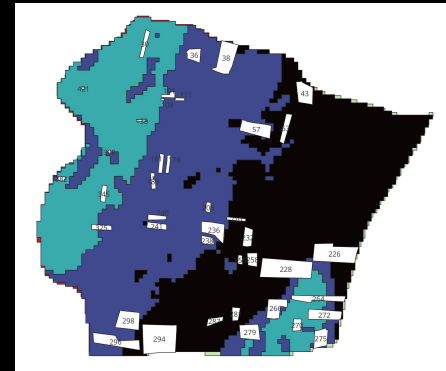
```
for zone in biophysical zones:  
  for farmplot in zone if not dropped:  
    drop_all_touching_farms(farmplot)
```

- The results overlaid on all the partitions ->

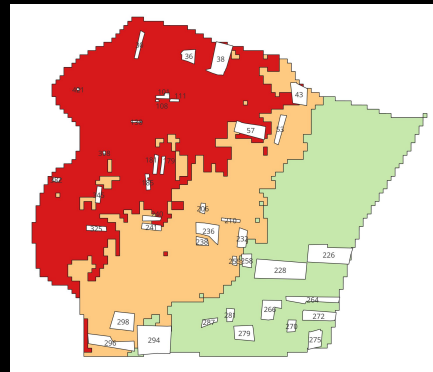


Stream proximity partition

Soil depth partition



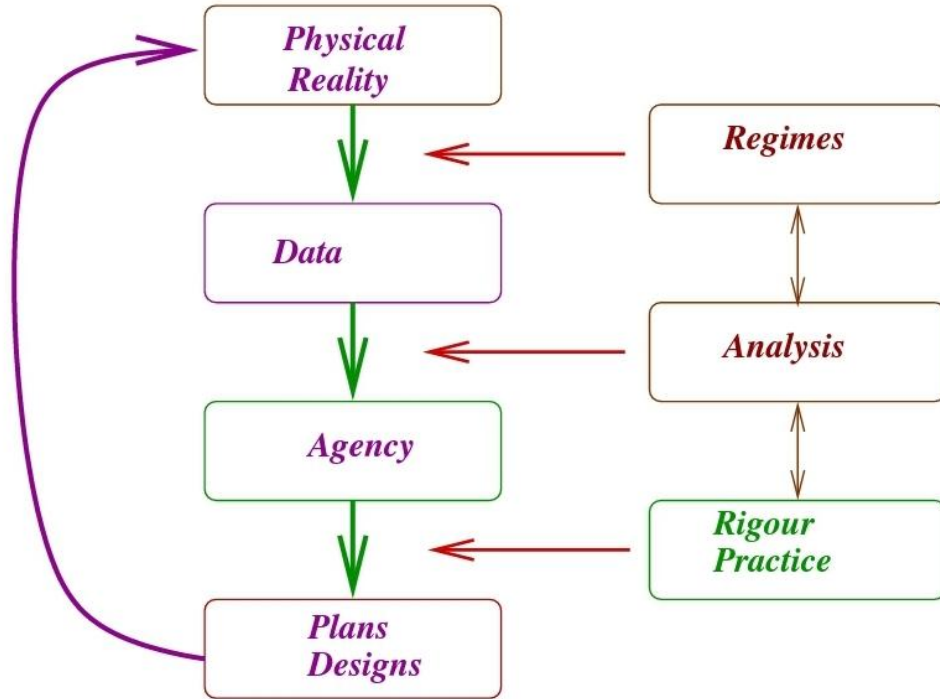
Elevation partition



In Summary



The infinite loop



- Generate data by capturing reality: baseline. Modernise the state methodology.
- The analysis of cause and effect, the parameters - create the authority and the will to act.
- The rigour and practice translates this will into concrete plans or designs.
- Thereby create space for AI, analytics
- And generate value. We are paid professionals!

Summary

PostgreSQL, PostGIS and geospatial community is

- enabling data driven decisions at village level
- helping DoA exercise its mandate in a sound scientific framework

We are also working on

- Generating accurate land parcel maps with Directorate of Land Records
- Flow based supply demand framework with Forest Dept. Himachal
- Drinking water and road network with CEO of Zilla Parishad, Ratnagiri district

Summary

PostgreSQL, PostGIS and geospatial community is

- enabling data driven decisions at village level
- helping DoA exercise its mandate in a sound scientific framework

IIT Bombay team is forever in gratitude, thank you!

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