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Satellite-Based Irrigation Stress Monitoring for Enhancing Water Use Efficiency in Agricultural Systems

A Case Study of the Upper Narmada Basin, Madhya Pradesh

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TF-15: Water Use Efficiency & Conservation: Best Practices & Success Stories

OUTLINE

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Irrigation Decisions in a Monsoon Basin Are Made Without Spatial Evidence

In a monsoon basin, the binding constraint is not how much water exists. It is knowing where, within the basin, crops are actually water stressed.

52 lakh ha

Soybean sown in Madhya Pradesh which is the country's largest producing state (SOPA, 2024-25)

3 weeks

Rainfall gap after sowing in the 2023 Kharif that left major crop belts critically short of soil moisture

38 %

India's overall water use efficiency, against 50-60% in developed economies (NITI Aayog, CWMI)

~75,000 ha

Sugarcane in Narsinghpur alone is about 65% of Madhya Pradesh's cane area, roughly 80% of its sprinkler-irrigated

What happens in the field

- In August 2023 the rain stopped for three weeks over Narmadapuram district. Soybean, paddy and maize began drying in the field. Farmers who owned a pump saved a few acres. The rest of the crop was lost.
- The basin does not have a monocropping system. Paddy, maize and millets in the east. Soybean and wheat in the central plains. Sugarcane all year in the west. Each needs water at a different time and in a different amount, so one basin-wide answer cannot work.

Why that information does not exist today

- Irrigation advisories and canal release schedules are set from seasonal rainfall statistics, which say nothing about where within a basin crops are short of water.
- Ground measurement cannot cover 45,013 km² at the frequency the decision requires.
- Optical sensor satellites, the obvious alternative, suffers from 60-90% cloud cover due to monsoon for the whole of the Kharif season.

The question this study asks: can freely available satellite data provides that missing spatial layer for an entire basin during the monsoon, at a finer resolution to address real world problems?

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- Existing frameworks are constrained by single-source dependence and by nationally derived stress thresholds.
- This study develops a multi-source, basin-validated alternative and evaluates its operational reliability.

IDENTIFIED RESEARCH GAPS

I Single-source reliance

Most studies rely on a single data source, neglecting the integration of SAR and optical sensor observations, which limits performance under monsoon cloud cover.

II Unvalidated drought classes

National drought classifications are applied without basin-specific validation, resulting in mischaracterisation of local stress conditions.

OBJECTIVES OF THE PRESENT WORK

1. Develop a cloud-robust, multi-source satellite framework integrating Sentinel-1 SAR and MODIS on Google Earth Engine.
2. Characterise irrigation stress and WUE patterns across three sub-zones under contrasting Kharif rainfall conditions.
3. Train and evaluate a Random Forest classifier as a validated, operational tool for sub-zone level WUE assessment.
4. Identify priority zones for WUE intervention and provide evidence-based recommendations aligned with national and global targets.

- The Upper Narmada Basin (79.5°- 82.2°E, 22.0° - 24.0°N) covers 45,013 km^2, extending from the river source at Amarkantak to Jabalpur, Madhya Pradesh.
- It was subdivided into three longitudinal subzones: upper (Amarkantak, 12,797 km^2), forested headwaters; middle (Mandla-Dindori, 14,514 km^2), forest-agriculture transition zone; and lower (Jabalpur-Narsinghpur, 17,703 km^2).

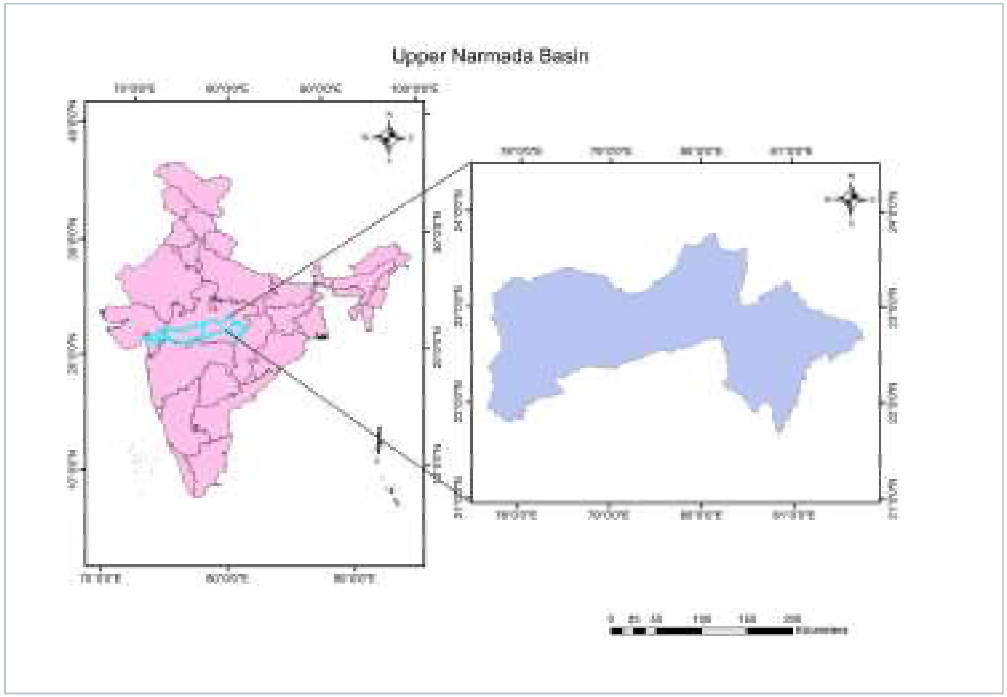


Figure 1. Location of the Upper Narmada Basin, extending from the river source at Amarkantak to Jabalpur, Madhya Pradesh.

Total basin area - 45,013 km^2

Longitudinal sub-zone	Area (km^2)	Character
Upper - Amarkantak	12,797	Forested headwaters
Middle - Mandla - Dindori	14,514	Forest-agriculture transition
Lower - Jabalpur - Narsinghpur	17,703	Intensive soybean-wheat cropping system

Three Kharif seasons selected on CHIRPS basin-mean rainfall

Rainfall class	Year	Basin-mean rainfall
Low	2021	1,137 mm
Medium	2018	1,187 mm
High	2019	1,345 mm

Yearly classification uses observed basin-specific rainfall rather than national drought categories, ensuring local hydro-climatic relevance.

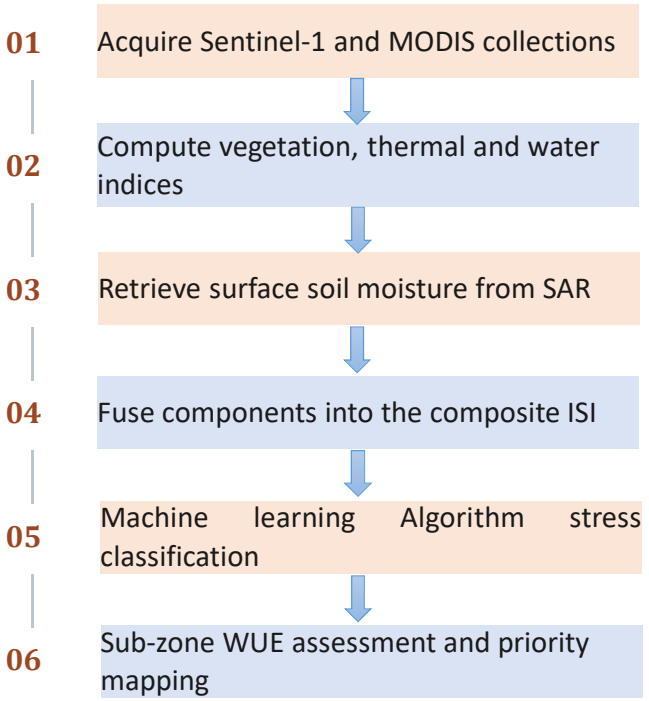
Datasets and Processing Framework

Table 1. Satellite and ancillary datasets, all accessed and processed on Google Earth Engine.

Dataset	Source	Spatial	Temporal	Variables computed
Sentinel-1 SAR (VV+VH)	ESA	10 m	6-12 days	SSM, DpRVI, NDPI
MODIS MOD13A2	NASA	1 km	16-day	NDVI, EVI, VCI
MODIS MOD11A2 LST	NASA	1 km	8-day	LST, TCI, TVDI
MODIS MOD09A1	NASA	500 m	8-day	NDWI
CHIRPS Daily	UCSB	5 km	Daily	Rainfall, year class
ERA5-Land Daily	ECMWF	9 km	Daily	VPD
ESA WorldCover 2020	ESA	10 m	Annual	Cropland mask

Why MODIS rather than Sentinel-2? Cloud cover reaches 60-90% over the basin during Jun-September. MODIS 8- and 16-day composites eliminate cloud-gap artefacts that leave Sentinel-2 spatially fragmented and unsuitable for basin-scale analysis.

PROCESSING CHAIN



SAR Preprocessing and Surface Soil Moisture Retrieval

Preprocessing

- Sentinel-1 GRD images from both ascending and descending orbits, 60-77 images per season.
- Lee-sigma speckle filtering applied in the linear power domain to suppress SAR noise.
- Median compositing to a single seasonal backscatter composite per study year.

Relative soil moisture from fixed dry and wet references

$$SSM = (\sigma°VV - \sigma°min) / (\sigma°max - \sigma°min) \quad (1)$$

Where, σ°min = −18 dB (dry bare soil) and σ°max = −5 dB (saturated soil), from published C-band VV ranges for agricultural soils.

Output is dimensionless relative soil moisture on a 0-1 scale (degree of saturation), not volumetric water content. The dry and wet references are held constant across all three years so that inter-annual differences are preserved.

Validation of the retrieval

- Retrieved SSM reproduces the observed CHIRPS rainfall ordering across all sub-zones, confirming that the fixed dB scale preserves the inter-annual signal.

Table 2. Retrieved relative soil moisture by rainfall year, upper sub-zone (Amarkantak)

Rainfall year	Mean SSM	Expected rank
High - 2019	**0.819**	1
Medium - 2018	**0.793**	2
Low - 2021	**0.730**	3

Values shown for the upper sub-zone (Amarkantak); the same ordering holds in the middle and lower sub-zones.

C-band penetration is limited under dense canopy, so SAR is treated here as a complementary and independently validated term rather than the dominant stress signal.

The Composite Irrigation Stress Index

The Irrigation Stress Index is a composite indicator of crop water stress; the qualifier 'irrigation' denotes the management decision it is designed to inform, not a process it measures. The index does not detect irrigation events or attribute stress to irrigation deficit.

Component indices from MODIS cloud composites

VCI	(NDVI − NDVI_min) / (NDVI_max − NDVI_min)
TCI	(LST_max − LST) / (LST_max − LST_min)
VHI	0.5 × VCI + 0.5 × TCI
TVDI	LST_norm / (NDVI + 0.1), scaled to [0,1]
NDWI	(NIR − SWIR) / (NIR + SWIR)

NDWI follows the NIR–SWIR formulation of Gao (1996), which responds to canopy liquid water content.

Terminology used in this study: Water use efficiency here refers to the spatial targeting of water application applying water where crops are genuinely stressed. We do not compute the SDG 6.4.1 economic ratio; this framework provides the diagnostic layer that efficiency interventions require.

Composite index

$$ISI = 0.30 \cdot TVDI + 0.30 \cdot (1 - VHI) + 0.20 \cdot (1 - NDWI_{norm}) + 0.20 \cdot (1 - SSM) \quad (2)$$

Following the multi-component approach established for composite drought indices, four scaled stress terms are combined linearly, spanning thermal dryness, vegetation health, canopy water status and soil moisture status.

Post-processing

- Spatially smoothed with a 1,500 m focal mean filter.
- Masked to ESA WorldCover 2020 cropland (Class 40, dilated 300 m).
- Classified into Low, Medium and High stress by quantile thresholds.

Rationale for the Index Weights

Weights were assigned a priori on physical grounds: the thermal–vegetation pathway is how crop water stress physically manifests, so it is weighted above the terms describing antecedent water availability.

Component	Weight	Physical process represented	Supporting evidence
TVDI	**0.30**	Thermal dryness from the LST-NDVI feature space; a proxy for suppressed actual evapotranspiration.	Sandholt et al. (2002); Jackson et al. (1981) show CWSI = 1 − E/Ep from canopy energy balance.
1 − VHI	**0.30**	Canopy vigour and thermal condition combined into a single vegetation-stress state.	Kogan (1995): itself a 0.5 / 0.5 weighted composite of VCI and TCI.
1 − NDWI	**0.20**	Canopy liquid water content from the NIR-SWIR contrast; an early, pre-visual stress signal.	Gao (1996): an index independent of, and complementary to, NDVI.
1 − SSM	**0.20**	Direct soil water status from C-band VV; the only all-weather, non-optical term.	Weight capped because C-band saturates under dense Kharif canopy (Bauer-Marschallinger et al., 2019).

Established precedent

Unequal weights are normal in this family of indices. SDCI uses 0.25 / 0.25 / 0.50 for scaled NDVI, LST and rainfall (Rhee et al., 2010). MIDI weights its microwave terms the same way (Zhang & Jia, 2013). IDSI uses AHP weights in an Indian Kharif setting (Guria et al., 2025).

Random Forest Classification Design

Model configuration

Trees	300
Maximum depth	12
Class weights	Balanced
Training samples	1,812 stratified - 300 per stress class per year
Evaluation	80:20 stratified train-test split with 5-fold cross-validation
Classes	Low (1), Medium (2), High (3) - quantile thresholds on a composite stress score

➢ Quantile-based thresholds ensure equal class representation and remove the dependence on national drought categories identified as a gap in the literature.

Ten input features

Vegetation	NDVI · EVI · VCI
Thermal	LST · TCI · TVDI
Composite	VHI
Water	NDWI
SAR	SSM · DpRVI

➢ The ISI itself was deliberately excluded from the feature set, so the classifier provides an assessment of index behaviour that is independent of the weighting scheme.

Multi-Index Zonal Statistics Across Sub-Zones and Years

Table 2. Mean index values by sub-zone and rainfall year.

Sub-zone	SSM	NDVI	VHI	TVDI	ISI	Rain (mm)
Low rainfall - 2021						
Upper (Amarkantak)	0.730	0.510	0.641	0.118	0.268	1,137
Middle (Mandla-Dindori)	0.715	0.462	0.548	0.133	0.277	1,050
Lower (Jabalpur-Nars.)	0.702	0.411	0.501	0.152	0.283	990
Medium rainfall - 2018						
Upper (Amarkantak)	0.793	0.381	0.558	0.207	0.328	1,187
Middle (Mandla-Dindori)	0.791	0.364	0.502	0.223	0.347	1,230
Lower (Jabalpur-Nars.)	0.773	0.343	0.481	0.234	**0.358**	1,200
High rainfall - 2019						
Upper (Amarkantak)	0.819	0.438	0.579	0.173	0.308	1,345
Middle (Mandla-Dindori)	0.800	0.428	0.553	0.163	0.329	1,520
Lower (Jabalpur-Nars.)	0.782	0.389	0.474	0.183	0.338	1,600

Observations

1. SSM ordering validated

- SSM correctly ranks High > Medium > Low in every sub-zone, confirming the fixed SAR scale.

2. Non-linear NDVI response

- Low-rainfall 2021 records the highest NDVI (upper: 0.510) despite the least rain, explained by better intra-seasonal distribution during vegetative growth.

3. Consistent ISI gradient

- Lower > Middle > Upper holds in all three years, identifying the agricultural plains as a zone of structural stress.

4. Totals mislead

- Medium-rainfall 2018 produced the highest ISI of all (Lower: 0.358) despite more rain than 2021.

Spatial Patterns of the Irrigation Stress Index

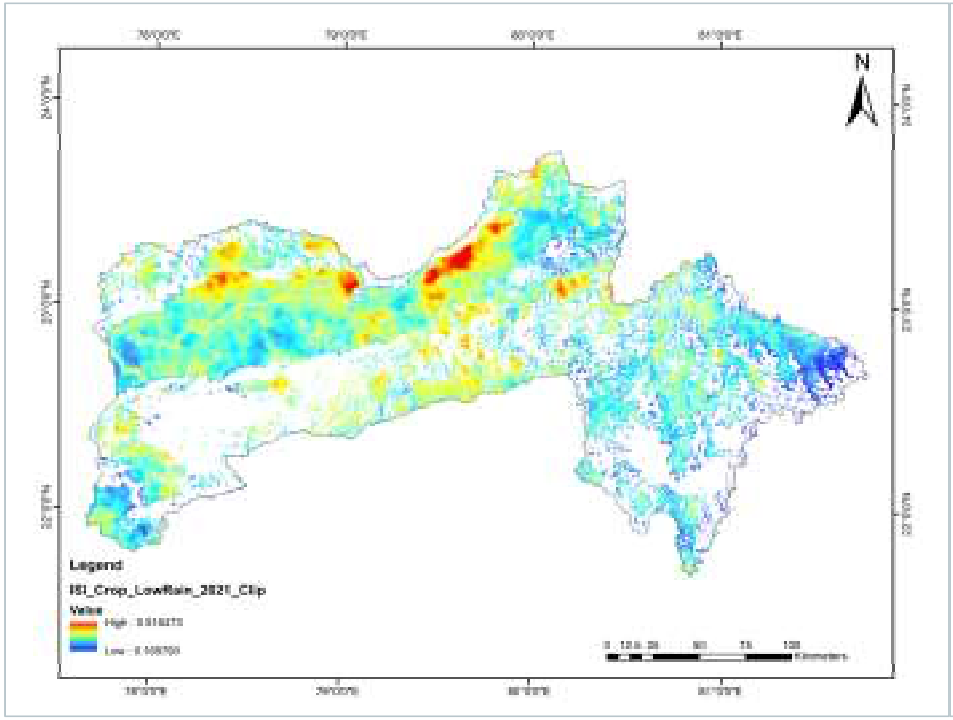


Figure 2. ISI Composite Map of Low Rainfall in 2021

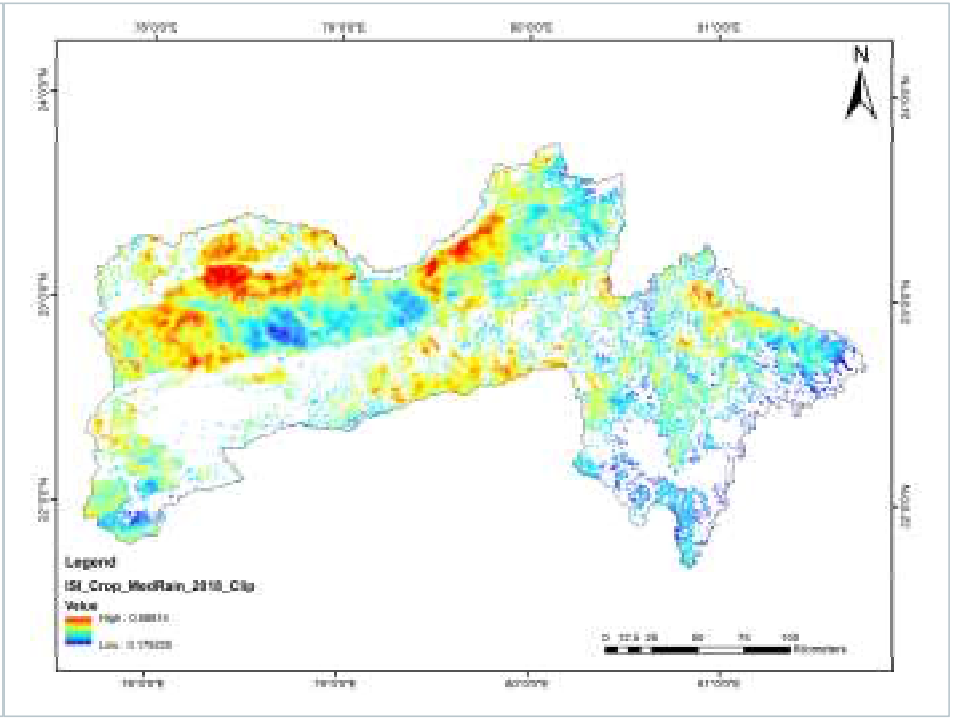


Figure 3. ISI Composite Map of Medium Rainfall in 2018

Spatial Patterns of the Irrigation Stress Index

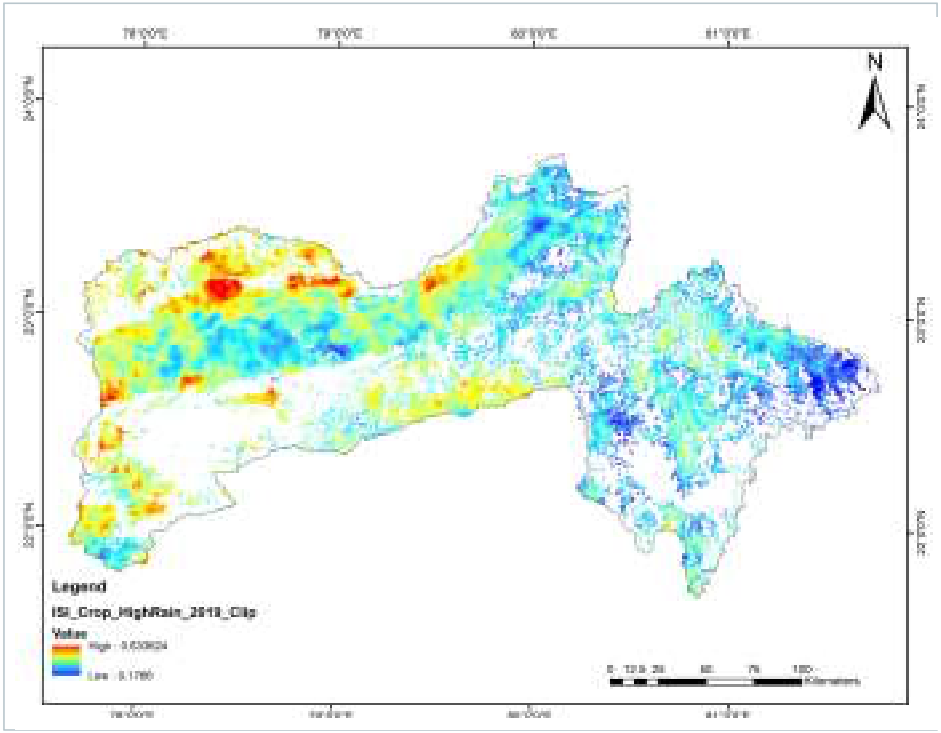


Figure 4. ISI Composite Map of High Rainfall in 2019

Observations

- **Persistent, not seasonal** - the Lower sub-zone shows the highest stress in all three years, wet or dry.
- **Lowest stress in the forested Upper sub-zone** - every year, suggesting water applied there may exceed crop requirement.
- **2018 was wetter than 2021, but more stressed** - rainfall timing outweighs the seasonal total.
- **Mixed cropping in the Lower zone** - paddy, soybean, wheat and sugarcane all year, so one stress value cannot suit every field.

Classifier Performance and Feature Sensitivity

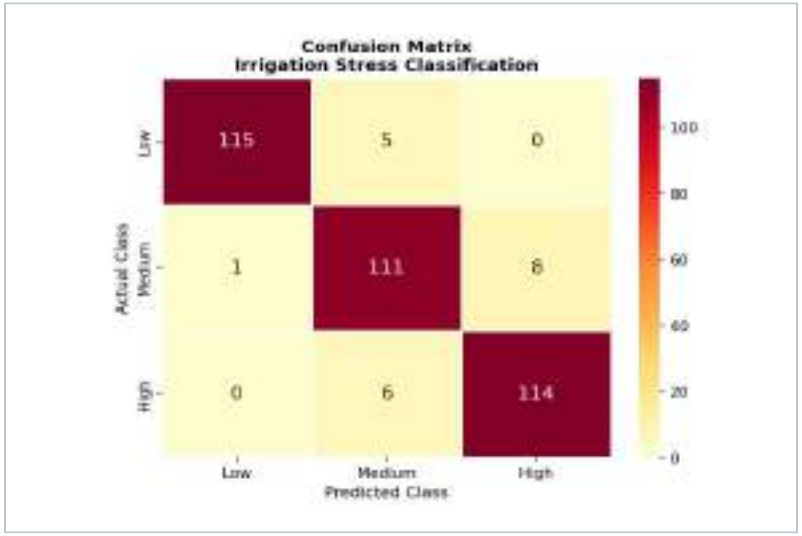


Figure 3. Confusion matrix. All 20 errors fall on adjacent class boundaries; there are no Low-High misclassifications.

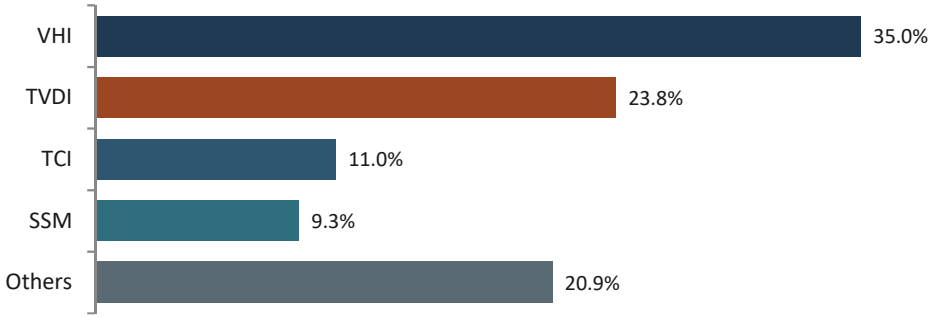
Stress class	Precision	Recall	F1	Support
Low (Class 1)	0.99	0.96	**0.97**	121
Medium (Class 2)	0.91	0.93	**0.92**	121
High (Class 3)	0.93	0.95	**0.94**	121

94.49 %
Overall accuracy

0.9174
Kappa coefficient

93.16 %
5-fold CV (± 1.23%)

Feature importance



The classifier reproduces the ISI classification from the ten raw indices at 94.49% accuracy, confirming that the composite signal is internally consistent and learnable from its constituent observations. Thermal-vegetation indices contribute 69.8% of importance; Sentinel-1 SSM ranks fourth at 9.3%, a direct soil moisture signal not redundant with the optical terms.

What Three Contrasting Monsoon Years Showed

1 **Intra-seasonal distribution governs WUE, not seasonal totals**

Low-rainfall 2021 produced a lower ISI and higher VHI than medium-rainfall 2018 despite 50 mm less rain. Irrigation advisories based solely on seasonal rainfall statistics will systematically misallocate water.

2 **MODIS compositing is essential through the monsoon**

Sentinel-2 suffers 60-90% cloud contamination during June-September, producing fragmented outputs unsuitable for basin-scale analysis. MODIS temporal compositing removes this limitation.

3 **The Lower sub-zone is a priority WUE intervention zone**

A consistent Lower > Middle > Upper gradient across all indices and all three years identifies Jabalpur-Narsinghpur as a zone of persistent structural stress requiring precision scheduling, micro-drip adoption and demand-side groundwater management.

4 **The classifier is reliable enough for operational deployment**

94.49% overall accuracy, $\kappa = 0.9174$ and zero Low-High misclassification confirm that the most water-critical cropland is identified dependably, the prerequisite for a trustworthy irrigation advisory.

5 **The framework supports dual-sided water allocation**

High-stress zones warrant additional allocation to prevent yield loss; low-stress zones offer savings through demand-side management. The approach is replicable to any Indian river basin using freely available data on Google Earth Engine.

From Stress Maps to Water Allocation Decisions

Each output layer has an existing institutional entry point and a named implementing authority.

Instrument	What it is	Where this work plugs in
Bureau of Water Use Efficiency	Established under the National Water Mission in October 2022; mandated to raise water use efficiency by 20% across irrigation, industry and domestic sectors.	Spatial benchmarking of where that 20% is achievable. Sub-zone stress gradients provide the diagnostic layer.
Atal Bhujal Yojana	Community-led, demand-side groundwater scheme covering Madhya Pradesh; gram panchayats prepare their own Water Security Plans.	Water Security Plans are written at village scale and need evidence of where demand reduction matters most. A 500 m ISI layer is directly usable.
PMKSY - Per Drop More Crop	Micro-irrigation promotion operating on area targets rather than spatial priority.	ISI classes can rank blocks for micro-irrigation investment, making subsidy allocation spatially targeted.

- The Lower sub-zone identified here corresponds to the Bargi (Rani Avanti Bai Sagar) canal command, a culturable command area of 2.198 lakh ha across Jabalpur and Narsinghpur districts, currently irrigating about 1.57 lakh ha. Priority intervention is therefore actionable through the Narmada Valley Development Authority and the Madhya Pradesh Water Resources Department, not only as a general recommendation.

Wider Context

- SDG Target 6.4 - substantially increase water-use efficiency across all sectors and ensure sustainable freshwater withdrawals by 2030.
- Belém Adaptation Indicators adopted at COP30 under the Global Goal on Adaptation, which include nine water and five agriculture indicators on a voluntary basis.

Suggested Future Works

Way forward

Ground validation

Evaluate retrieved SSM against IMD agromet soil moisture observations and, where coverage allows, the Indian COSMOS Network.

Yield-based external check

Correlate sub-zone mean ISI against district soybean yield anomalies for the three study years, giving validation independent of the index itself.

Weight sensitivity

Monte Carlo perturbation of each weight by ± 25% to confirm the sub-zone gradient is robust to the weighting scheme.

Extension to Rabi

Rabi wheat in this basin is fully irrigation-dependent, so the index has direct scheduling value there; a two-season framework is the next step.

Thank You

Questions and discussion welcome.

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