Phase 1 Results of the Water Index for Sustainability, Equity, and Resilience (WISER) Framework

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About this Report

This report is the second in a two-part series capturing the findings from Phase 1 (July 2024–March 2025) of the Water Index for Sustainability, Equity, and Resilience (WISER) initiative. It summarises the literature review we conducted to develop a framework of indicators to assess water security. These indicators were tested through a pilot survey across five different aquifer typologies.

We also conducted stakeholder interviews, listening circles, feedback sessions, and a roundtable discussion to gather feedback on the framework. The key learnings from the stakeholder engagements are in Part 1 of this series.

About Water Index for Sustainability, Equity, and Resilience (WISER)

The Water Index for Sustainability, Equity, and Resilience (WISER) initiative bridges gaps in water security monitoring by providing a structured framework for tracking meaningful, outcome-based indicators.

By systematically tracking key water security indicators, WISER enables data-driven decision-making, improves resource allocation, and fosters more effective interventions to achieve water security in India.

About WELL Labs

Water, Environment, Land and Livelihoods (WELL) Labs is a research and innovation centre driving social impact in the field of water sustainability. Based in Bengaluru, it is part of the Institute for Financial Management and Research (IFMR) Society. WELL Labs co-creates science-backed solutions that improve people's lives and livelihoods and sustain nature. It works closely with multiple stakeholders such as governments, businesses, multilateral institutions and civil society groups.

About the Technical Consulting Programme at WELL Labs

The Technical Consulting programme enables better decision-making in the natural resources management sector through the use of data, models, and evidence-based approaches. It focuses on systematising monitoring, evaluation, and learning (MEL) for the water sector while developing simple, accurate indicators to assess water security. Additionally, the team is building tools and frameworks to improve problem diagnosis in the sector.

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List of Abbreviations

ASER	Annual Status of Education Report
CGWB	Central Ground Water Board
FAO	Food and Agriculture Organization
FVI	Flood Vulnerability Index
GEC	Ground Water Resource Estimation Committee
GW	Groundwater
IGB	Indo-Gangetic Basin
IMD	India Meteorological Department
IPCC	Intergovernmental Panel on Climate Change
IWRIS	India Water Resource Information System
LPA	Long Period Average
LULC	Land Use Land Cover
NDVI	Normalised Difference Vegetation Index
NRSC	National Remote Sensing Centre
PET	Potential Evapotranspiration
SDD	Secchi Disk Depth
SDG	Sustainable Development Goals
SPEI	Standardised Precipitation Evapotranspiration Index
SSWR	Seasonal Surface Water Reduction
TSS	Total Suspended Solids
VCI	Vegetation Condition Index
WISER	Water Index for Sustainability, Equity and Resilience
WRIS	Water Resources Informational System

Executive Summary

India's water crisis is worsening as over-extraction, pollution, and climate change deplete resources. Droughts, floods, and contamination affect both urban and rural areas. Despite substantial investments in water management programmes, there is little clarity on their long-term impact, highlighting the need for systematic outcome-based tracking.

The **Water Index for Sustainability, Equity, and Resilience (WISER)** initiative aims to address this gap by developing a comprehensive framework to measure water security across resilience, sustainability, equity, and productivity. WISER will provide actionable insights for policymakers and practitioners by leveraging remote sensing, stakeholder engagement, and large-scale data collection. The initiative will build a set of simple, scalable scientific indicators that are relevant to diverse aquifer types. A related goal is to build a multi-stakeholder consortium to ensure long-term adoption. Ultimately, WISER aims to drive evidence-based decision-making, improve resource allocation, and foster sustainable water security solutions in India.

We spoke to over 10 major stakeholders in the water sector to understand the current gaps in the assessment of water security in India. We found that:

a) Stakeholders recognise the need for landscape-level indicators, but say that such indicators are currently missing in impact assessments.
b) A lot of time and money is spent by the sector on collecting data that might not actually be helpful.
c) Despite differences in approach, most stakeholders agree that water is interlinked with the different aspects of society and environment, and cannot be worked on in isolation.

Drawing from education sector reforms like the Annual Status of Education Report (ASER), we propose a similar indicator-driven framework to evaluate water security in rural India. **The WISER framework considers water security through six dimensions: balance, access, productivity, resilience, governance, and ecosystem health.** It ensures context-specific, actionable, and measurable outcomes.

We conducted a pilot data collection exercise across five different aquifer typologies to test the indicator framework before presenting it to the sector for consensus building. Hindustan Unilever Foundation (HUF) partner organisations helped conduct primary surveys in two villages in each typology. A total of 30 households were surveyed in each of the 10 villages (total sample n=300). Village-level data was also collected around indicators such as groundwater levels and surface water extent to help validate the values obtained from remote sensing (n=10 villages). The indicator framework and pilot findings were presented to technical experts and sector stakeholders for their feedback. The discussions across various listening circles and expert consultations focused on refining the WISER framework, ensuring scientific rigor while simplifying communication and usability. A roundtable was convened in March 2025, where over 20 leading academics, grassroots organisations, and donors in the water sector participated in providing feedback on the WISER indicator framework and setting the vision for subsequent phases of the exercise.

BACKGROUND

Water Challenges in India

India is experiencing a severe and escalating water crisis, driven by multiple factors, including over-extraction of groundwater, pollution, and climate change. The country ranks as one of the most water-stressed globally, with demand outpacing sustainable supply across sectors. Water security in India is a multidimensional challenge, encompassing different aspects like sustainability, equity, resilience, and productivity.

These dimensions, while critical, do not always align. Sometimes, achieving one might be at the expense of another. For example, enforcing groundwater extraction bans may improve sustainability but could disproportionately impact marginalised users who lack access to alternative water sources.

India's water crisis manifests in several ways:

1. **Too little:** Seasonal and chronic water shortages are prevalent across urban and rural areas, exacerbating competition for limited resources.
2. **Too much:** Climate change is intensifying extreme weather events, like floods, and the seasonality of water, which disrupts lives.
3. **Too polluted:** Water quality has degraded due to untreated sewage, industrial discharge, and agricultural runoff, compromising public health and ecosystems.

There have been significant investments in water management by the government and philanthropic initiatives to address these exacerbating challenges. Despite this, there is limited clarity on whether these efforts are yielding measurable improvements in water security. The situation raises critical questions like 'Are worsening forces stronger than improving ones?', 'What indicators should guide interventions?', and 'How do we measure progress effectively?'.

The principle of 'what gets measured gets managed' underscores the need for a robust framework to track water security outcomes beyond traditional input-output metrics.

The water sector would benefit from agreeing on the most important outcomes to focus on, and getting data on them regularly.

Current water security assessments primarily focus on inputs (for example, funds allocated) and outputs (for example, the number of check dams constructed) rather than long-term outcomes. This results in some gaps. For instance, reporting on the volume of water infrastructure created does not necessarily indicate whether communities have achieved reliable access to water. A shift toward outcome-oriented tracking is essential to address this gap.

Lessons from other sectors highlight the transformative potential of systematic monitoring. The health sector, through the National Family Health Survey (NFHS), and the education sector, through the Annual Status of Education Report (ASER), have successfully shifted focus toward meaningful outcomes. ASER, launched in 2005, demonstrated that despite high school enrollment rates, learning outcomes were alarmingly poor, prompting a policy shift toward improving education quality rather than just increasing access. A similar approach in the water sector could provide data-driven insights into whether interventions are making a tangible difference.

One of the key challenges in defining water security indicators is the inherent complexity and dynamism of water systems. Unlike education or health, where indicators such as literacy rates or immunisation coverage provide clear outcome measures, water security is influenced by spatial, temporal, and socio-economic factors. For instance, the same intervention may yield different results in Punjab (where groundwater depletion is severe) compared to tribal areas (where the primary concern is access). Finding an affordable yet comprehensive way to measure biophysical complexities such as rainfall variability, runoff, surface water availability, and groundwater dynamics is critical.

Further, different stakeholders—water users, government agencies, donors, and civil society organisations—have varied perspectives on what constitutes water security. Farmers may prioritise irrigation reliability, while policymakers may focus on sustainable groundwater levels. A robust indicator framework must integrate these diverse perspectives while ensuring scientific rigour and practical applicability.

Objectives and Scope of the Project

The Water Index for Sustainability, Equity, and Resilience (WISER) initiative seeks to bridge the current gaps in water security monitoring by establishing a structured framework for tracking meaningful, outcome-based indicators. The overarching objectives of WISER are:

- **Developing a coherent indicator framework:** Creating a scientifically sound, stakeholder-informed set of indicators to measure water security across multiple dimensions.
- **Leveraging existing data and remote sensing:** Combining secondary data sources with advanced remote sensing techniques to enhance the accuracy, scalability, and real-time tracking of water security trends.
- **Conducting large-scale primary data collection:** Moving beyond anecdotal evidence by engaging a broad coalition of civil society organisations in systematic data collection efforts.

Project components

The initiative is structured around key components that will ensure that it is broad-based and robust:

1. **Stakeholder consultations:** Engaging practitioners, policymakers, donors, and technical experts to ensure the selected indicators reflect ground realities and diverse needs

2. **Literature review:** Drawing lessons from international and national water security measurement frameworks to ensure that we are benchmarking it to the best practices in the sector.

3. **Pilot testing:** Validating the indicators in diverse hydrogeological contexts to ensure their applicability and adaptability across different water-stressed regions in India.

4. **Building a multi-stakeholder consortium:** Establishing partnerships with civil society organisations, research institutions, and government agencies to drive long-term institutionalisation and policy adoption

By systematically tracking key water security indicators, WISER aims to enable data-driven decision-making, improve resource allocation, and foster more effective interventions for achieving sustainable water security in India. The project represents a crucial step toward transitioning from fragmented, anecdotal assessments to a comprehensive, evidence-based approach that can drive policy and investment decisions for the long-term resilience of India's water resources.

LITERATURE REVIEW

The Need for an Index for Water Security in the Indian Context

India, home to 18% of the global population, possesses just 4% of the world's freshwater resources. The stress on water resources has been exacerbating significantly since the 1900s (Kummu et al., 2016). Rural areas, in particular, face increasing vulnerability due to rapidly rising water demands, dependence of livelihoods on water, fragile governance institutions, and increasing climate change induced vulnerability (Basu et al., 2021; Dinesh Kumar et al., 2022). Governmental initiatives like the Mahatma Gandhi National Rural Employment Guarantee Scheme (MGNREGS) and Atal Bhujal Yojana (Payal & Singh, 2024), and non-governmental efforts (Jaysawal & Saha, 2015) have aimed to improve water security. However, evaluating their effectiveness remains challenging without robust, universally accepted indicators tailored to India's diverse hydrological and socioeconomic contexts.

India's education sector faced a comparable challenge in shifting from input-centric interventions toward measurable outcomes. This was effectively addressed through the Annual Status of Education Report (ASER) led by Pratham, a prominent civil society organisation. ASER established clear outcome-based indicators to measure child learning levels, facilitating rapid, reliable, and comprehensive assessments of educational quality across India's diverse linguistic and cultural landscapes (Banerji et al., 2013; Ministry of Finance, 2022). ASER's success underscores the potential benefits of adopting a similar indicator-driven approach in water governance (Bassi & Kumar, 2010).

India's intricate regional hydrology (Blöschl & Sivapalan, 1995), hydrogeological (Mukherjee et al., 2015), and diverse ecohydrological (Bejagam et al., 2022) and socio-hydrological conditions (Pande & Savenije, 2016; V. Srinivasan, 2015) pose significant challenges to understanding and ensuring water security.

Given that the observed climate represents one realisation of a chaotic system (S. Jain et al., 2023), substantial uncertainties persist regarding how climate change will influence India's water availability and demand annually (Krishnan et al., 2020). Developing a comprehensive, robust, and scientifically credible set of water security indicators is thus essential for systematically assessing climate-induced impacts on water resources. Drawing lessons from ASER's widespread acceptance, these indicators should be relevant and actionable for stakeholders, supporting informed policy-making and effective governance.

What does 'water security' actually mean?

It is critical to define 'water security' before establishing such indicators. The term entered academic discourse prominently in the 1990s within the context of international conflicts (Starr, 1991, 1992). Schultz and Uhlenbrook (2008) identified key elements, including sustainable management and protection of water resources, mitigation of water-related hazards, and the fulfilment of long-term human and environmental needs. Expanding on this, Van Hofwegen (2008) highlighted the role of actors, their capacities, and infrastructure, suggesting a hierarchy of water security—from basic human needs to economic growth.

A widely accepted definition by Grey and Sadoff (2007) describes water security as **'the adequate availability of water quantity and quality for health, livelihoods, ecosystems, and production, coupled with manageable water-related risks to communities, environments, and economies'.** For the purpose of this project, we broadly endorse this definition from Grey and Sadoff (2007), while focusing on its adaptation for the Indian context.

Cook and Bakker's (2012) systematic review revealed significant variability in definitions based on discipline and scale, underscoring the need for context-specific integration of multiple dimensions—quantity, quality, human, and environmental. Further, Gerlak et al. (2018, 2022) found that water security definitions consistently prioritise elements such as water quality, quantity, ecosystem sustainability, health, and economic growth. Their analysis also emphasised the ongoing challenge of scale, indicating substantial differences in indicators for household versus transnational water security concerns, and advocated participatory, place-based governance approaches.

Lastly, Octavianti and Staddon (2021) examined various tools used to quantify water security, highlighting methodological disparities between experiential (household-level) and resource-centric (larger-scale) approaches, frequently employing frameworks such as Driver-Pressure-State-Impact-Response (DPSIR). Collectively, these scholarly insights stress the necessity of contextually adapting water security definitions and indicators, reinforcing the idea that a universally applicable framework remains elusive.

Navigating the Indian Landscape

Given the critical role of region and scale in measuring water security, focusing specifically on rural India is warranted. Rural regions host nearly twice India's urban population, experiencing substantial anthropogenic impacts from changes in land and water use. Agriculture remains the primary employment and the largest water-consuming sector in rural India, making it the focal point for socio-ecological water security analyses.

Regarding the scale of studies, consultations suggest that while hydrological boundaries simplify analytical calculations like water balances, political boundaries (especially village-level units) offer actionable frameworks aligned with existing governance structures. Although the cross-scale approach explored by Doeffinger & Hall (2021) in the United States presents an innovative method, its limited development and unclear applicability discourage immediate adoption in the Indian context. For the pilot stage, we focus on the village as a unit of analysis while exploring cross-scale analysis at a later stage.

Furthermore, India's climate and hydrological context significantly shape rural water security dynamics. Rainfall distribution is highly uneven, both spatially and temporally, and is driven predominantly by the Indian summer monsoon (Singh et al., 2019; Sahoo & Kumar Yadav, 2022). The limited rainfall outside monsoon months necessitates extensive irrigation, intensifying water stress.

Consequently, any chosen indicators must balance environmental sustainability with socio-economic development needs, reflecting India's unique developmental realities.

The climate impacts on India are still fairly uncertain. There are indications of decreasing overall rainfall in eastern India, with some indications of increasing rainfall in northwestern India. However, with increasing temperatures, the frequency and intensity of droughts and floods are expected to increase and warrant better water resource management (Krishnan et al., 2020).

Framework and Measurement of Water Security

Based on comprehensive reviews of global literature and the Indian context, we propose a structured framework adapted from the DPSIR approach (Babel et al., 2020; Rafaai & Lee, 2024). Unlike Babel et al. (2020), who maintained fixed indicators across regions, our approach is context-sensitive, inspired by the socio-ecological systems framework (SESF) (Ostrom, 2007), ensuring relevance to specific regional conditions.

We selected six dimensions for rural India's water security based on the review of and context provided in the previous sections:

- **Balance**
- **Access**
- **Productivity**
- **Resilience**
- **Governance**
- **Water and ecosystem health.**

These dimensions provide a holistic and integrated perspective, capturing the diverse and interconnected aspects of water security. The aim was to have these dimensions be mutually exclusive and collectively exhaustive.

Each dimension comprises specific indicators, carefully selected based on specific criteria to ensure their effectiveness and applicability. Each indicator was evaluated based on their orientation (outcome, output, or input-oriented); sensitivity to ground-level interventions; relevance to diverse stakeholders and geographic contexts; and ease of data capture. Preference was given to choosing indicators that can be outcome-oriented, highly sensitive to interventions, widely relevant across regions, and easy to measure using available or easily accessible data sources. This structured approach ensures the chosen indicators effectively capture meaningful changes, remain relevant and actionable for stakeholders, and can be reliably monitored over time.

Balance: Sufficient water availability is fundamental for achieving water security, making water scarcity—a ratio of water demand to supply—a central consideration in water security assessments (Gerlak et al., 2018; Octavianti & Staddon, 2021). Recent research highlights the importance of incorporating green water, environmental flow requirements, and water quality into scarcity evaluations for a more comprehensive understanding (Liu et al., 2017; Singh & Kumar, 2021). Traditional annual assessments often fail to reflect experienced scarcity accurately (Mekonnen &

Hoekstra, 2016; Wolkeba et al., 2024). Practical scarcity assessments commonly involve estimating water supply through remote sensing-based water balances, considering precipitation, evaporation, and discharge flows, compared against agricultural water demands (Golian et al., 2019; Mialyk et al., 2024). Groundwater assessments typically utilise GRACE satellite data or Central Ground Water Board estimates, although these have resolution and methodological limitations at smaller scales (Bhanja et al., 2016; Vaishnavi & Kumar, 2023). Given these limitations, direct measurements of groundwater level changes are recommended.

Additionally, measuring the seasonal and inter-annual changes in surface water extent provides critical insights into water availability variations influenced by climatic conditions, anthropogenic activities, and groundwater extraction. Regular monitoring of surface water through remote sensing approaches—such as using Landsat and Sentinel data with indices like the Normalised Difference Water Index (NDWI)—allows for effective identification of water stress trends and potential sites suitable for water recharge interventions.

Water scarcity may be assessed through a hydrological balance approach, integrating groundwater level changes and surface water dynamics. Water stress may be calculated following Central Ground Water Board guidelines (GEC, 2015), incorporating rainfall infiltration factors. Surface water extent may be evaluated using Landsat and Sentinel-2 satellite imagery, applying Normalised Difference Water Index thresholding techniques (Ashok et al., 2021).

Access: Access encompasses access to water for domestic use as well as for irrigation. Although irrigation dominates water use in rural areas (Dangar et al., 2021; Siebert et al., 2010), ensuring sufficient quantity and quality of drinking water remains critical, with at least 50 liters per person per day needed for basic activities (Gleick, 1996).

Drinking water quality may be assessed by checking for contaminants such as fluoride and arsenic (Saha et al., 2020), biological pollutants like total coliform (Tambi et al., 2023), and organic or chemical pollutants measured by biological and chemical oxygen demand (Jouanneau et al., 2014; Li et al., 2018), according to Indian drinking water standards (BIS, 2012).

Access to irrigation water for crops depends on climatic factors influencing evaporation and transpiration (Buckley & Sack, 2019; Brutsaert, 2013). Given the complexity of detailed crop water models (Belsare et al., 2022; Surendran et al., 2015), remote sensing-based vegetation indices, especially during the rabi season, offer practical proxies for irrigation water access across rural India (Ambika et al., 2016; Bhagia et al., 2017). Based on the reviewed literature and established selection criteria, we identified indicators that effectively capture the adequacy and quality of drinking water, as well as reliable access to irrigation, reflected by crop production across agricultural seasons.

Productivity: Crop water productivity, a key dimension of continued water security, varies significantly across crops and regions, as each crop differs in water requirements and economic returns. Physical water productivity refers to the crop yield per unit of water consumed, while economic water productivity denotes the revenue generated per unit of water (Molden et al., 2010). Studies in India highlight substantial spatial variation in water productivity (B. Sharma et al., 2018), and literature suggests it can be enhanced through agricultural system reforms (Kukal et al., 2014; B.

R. Sharma et al., 2010), albeit with certain limitations (Molden et al., 2010). Improving water productivity is particularly crucial under changing climate conditions (Kang et al., 2009).

This review emphasises economic water productivity, where yield estimates from remote sensing must be complemented by market price data to accurately capture the value of water use. Expressing this as income (in Indian rupees) per unit of water used offers a robust indicator, potentially requiring primary data collection but yielding valuable insights into the economic efficiency of water use in agriculture.

Resilience: Climate change poses multifaceted risks to rural agrarian India by intensifying floods and droughts, raising temperatures, and altering precipitation patterns. The diversity of flood and drought types, shaped by India's climatic and geomorphological conditions, has substantial impacts on agricultural productivity (K. Ray et al., 2019; A. K. Mishra & Singh, 2010; Bhardwaj et al., 2020; X. Zhang et al., 2017). Their frequency, duration, and severity are expected to increase (Mujumdar et al., 2020). Rising temperatures elevate atmospheric water demand, increasing crop transpiration (Allen et al., 1998; Sadok et al., 2021), while increasingly erratic rainfall patterns (Kulkarni et al., 2020) further stress water availability.

These climatic shifts have been linked to changing crop water requirements (Lobell & Burke, 2008; A. Kumar & Sharma, 2022), and drive adaptive changes in agrarian communities and economic systems (Jha et al., 2018; Gupta et al., 2014), rendering water security a highly dynamic concern.

Drought risks can be assessed using indices from IndiaSat data, the Drought Atlas (Chuphal et al., 2024), and real-time SMAP-based methodologies (A. Mishra et al., 2017). For our meteorological drought indicator, we used the Standardised Precipitation Evapotranspiration Index (SPEI), which is a widely utilised drought metric that integrates both precipitation and potential evapotranspiration (PET) to quantify drought severity (Vicente-Serrano et al., 2010). SPEI addresses a notable limitation of the precipitation-only Standardised Precipitation Index (SPI) (McKee et al., 1993) by explicitly incorporating temperature-driven evaporative demand, a critical factor influencing drought severity under climate change. Although the Palmer Drought Severity Index (PDSI) (Palmer, 1965) also includes temperature and soil moisture, its complexity and dependency on extensive soil parameters introduce uncertainty.

Thus, SPEI offers a robust yet computationally efficient measure sensitive to both precipitation deficits and warming-induced evapotranspiration increases, making it particularly suitable for drought assessments across diverse temporal scales (Chuphal et al., 2024). To measure the agricultural drought, we used the Vegetation Condition Index (VCI) as it is superior to the Vegetation Health Index (VHI) for agricultural drought monitoring due to its direct sensitivity to vegetation moisture stress (Eyoh et al., 2019). By normalising NDVI data against historical extremes, VCI effectively isolates drought-related vegetation stress, accurately detecting drought onset and severity without confounding temperature influences (Kogan, 1995). This specificity makes VCI particularly valuable in rainfed agricultural systems, where water availability is the primary constraint on crop productivity.

For flood propensity, while past flood records offer insights into frequency and severity (Engeland et al., 2018; Macdonald et al., 2017), such data are often incomplete or unavailable at the village level. Similarly, CWC's Flood Watch provides reservoir-level information, limiting its applicability for local-scale assessments. To address these gaps, we use the Flood Vulnerability Index (FVI) developed by NRSC, which combines time-series rainfall, LULC, topography, and proximity to water bodies to offer a comprehensive measure of flood propensity (Borowska et al., 2024; Rasool et al., 2024). This index captures both the exposure and vulnerability of villages to flooding, with implications observable through fluctuations in agricultural output—an indicator of both risk and resilience.

Governance: Governance is a critical yet complex dimension of water security at the village level, influencing how resources are managed, allocated, and sustained. While there is no universal metric for governance, social network analysis offers a quantitative lens to assess polycentric, multi-level, and adaptive structures (Nabiafjadi et al., 2021; Stein et al., 2011). However, its intensive data and resource demands limit scalability. Governance indicators must evaluate the presence and effectiveness of local water management through governance structures and participatory decision-making processes. As a pragmatic alternative, a carefully designed and context-specific survey can offer a scalable, reliable proxy for capturing key aspects of local water governance (Boateng et al., 2018).

Water and Ecosystem Health: Water governance is intrinsically linked to the protection and health of ecosystems (Parkes et al., 2010), with aquatic systems providing vital ecosystem services, including the growing freshwater fisheries sector in rural India (Daily & Matson, 2008; Jayasankar, 2018). Maintaining ecological flows—minimum river flows to sustain aquatic life—is a key strategy for preserving ecosystem functions (Bunn & Arthington, 2002). Despite promising developments (Jumani et al., 2020; Krishnaswamy et al., 2017; Samad et al., 2022), ecological flow implementation remains limited in scale across India (Jain & Kumar, 2014).

Beyond aquatic systems, India's diverse terrestrial ecosystems also rely on stable water supplies, which are increasingly threatened by climate-induced disruptions (Singh & Chaturvedi, 2017; Kaur & Dutta, 2022). In light of these challenges, three proxy indicators can help assess ecosystem water sufficiency: (1) the presence of perennial water bodies, identifiable via inundation metrics; (2) water quality, measurable through indicators like chlorophyll-a and total suspended solids; (3) vegetation health, detectable through remote sensing of dieback (Fitzgerald et al., 2023). Complementary biological signals, such as healthy fish populations and the absence of eutrophication, further strengthen assessments of ecosystem integrity. Given considerations of logistics and scalability, one may employ a primary survey to assess ecosystem health.

The literature is further replete with information on different indicators. However, instead of focusing on a comprehensive literature survey, the exercise here focused on how we can find the most appropriate indicators for each of the six dimensions, integrating scientific rigour with practical applicability, forming a comprehensive yet contextually adaptable approach to measure and enhance water security in rural India.

WISER INDICATORS AND RESULTS

We have prioritised **12 indicators** across **6 dimensions**

The WISER Indicator Framework

LEGEND

- Primary Data
- Ground Truthed Secondary or Remote Sensing Data
- Purely Remote Sensing or Secondary Data

Alongside the literature review, we spoke to over 10 major stakeholders in the water sector to understand the current gaps in the assessment of water security in India[1]. We then selected these indicators based on four criteria: outcome-orientedness, sensitivity to work on the ground, relevance to stakeholders and geographies, and ease of capturing. The table below provides a snapshot of how each selected indicator ranks on these criteria. Annexure A explains what each selection criteria category means.

Dimension	Indicator	Type of data	Outcome-oriented / Output- oriented / Input-oriented[2]	Sensitivity to work on the ground[3]	Relevance to stakeholders & geographies	Ease of capturing
BALANCE	Groundwater levels	Ground-truthed secondary data	Outcome-oriented	Moderately sensitive	Partially relevant	Easy
	Surface water extent	Ground-truthed remote sensing data	Outcome-oriented	Moderately sensitive	Highly relevant	Moderate
	Water stress	Purely remote secondary data	Outcome-oriented	Moderately sensitive	Highly relevant	Difficult
ACCESS	Cropping intensity	Ground-truthed secondary / remote sensing data	Outcome-oriented	Highly sensitive	Highly relevant	Easy
	Domestic water access	Primary data	Outcome-oriented	Highly sensitive	Highly relevant	Moderate
	Domestic water quality	Primary data	Outcome-oriented	Moderately sensitive	Highly relevant	Moderate
PRODUCTIVITY	Crop water productivity	Primary data	Outcome-oriented	Highly sensitive	Highly relevant	Moderate
RESILIENCE	Variation in cropping intensity	Ground-truthed secondary / remote sensing data	Outcome-oriented	Moderately sensitive	Partially relevant	Easy
	Propensity to droughts	Purely remote sensing / secondary data	Input-oriented	Least sensitive	Highly relevant	Easy
	Propensity to floods	Purely remote sensing / secondary data	Input-oriented	Least sensitive	Highly relevant	Easy
GOVERNANCE	Local water governance	Primary data	Output-oriented	Moderately sensitive	Partially relevant	Difficult
WATER & ECOSYSTEM HEALTH	Ambient water quality	Primary data	Outcome-oriented	Moderately sensitive	Highly relevant	Moderate

[1] For more details regarding stakeholder engagement in Phase 1, see Part 1 of the report.
[2] This criteria reflects if the indicator is oriented to capture *a.* input(s) or contextual factors that may affect an intervention, *b.* the immediate output(s) of an intervention, or *c.* outcome(s) that are ends in themselves, for either socio-economic or biophysical conditions in the landscape.
[3] This criteria reflects whether there will be any change in the indicator value based on interventions being implemented to address this parameter. If 'highly sensitive' on this criteria, it means the indicator will be very good at reflecting the change that occurs in the parameter that the intervention is trying to address.

Pilot Study to Test WISER Indicators

We conducted a pilot data collection exercise to test the indicator framework properly, before presenting it to the wider sector for consensus building. Between November 2024 and January 2025, we worked with four HUF partner organisations and one WELL Labs partner across five different aquifer typologies to conduct primary surveys in two villages in each typology. A total of 30 households were surveyed in each of the 10 villages (Total sample n=300).

We also used this opportunity to collect village-level data around indicators such as groundwater levels and surface water extent to help validate the values obtained from remote sensing (n=10 villages). The villages part of the pilot are described in the table below.

Aquifer typology	Grassroots partner	State	Villages
Indo-Gangetic basin (west)	Centre for International Projects Trust (CIPT)	Punjab (PB)	1. Chauke (Bathinda district) 2. Nagra (Sangrur district)
Indo-gangetic basin (east)	PANI Sansthan	Uttar Pradesh (UP)	1. Bangai (Ruphideeh block) 2. Rupaideeh (Jhanjhari block)
Hard rock areas (east)	Transform Rural India Foundation (TRIF)	Chhattisgarh (CG)	1. Bagrai (Bakawand block) 2. Kokanpur (Kanker block)
Basalt	Swayam Shikshan Prayog (SSP)	Maharashtra (MH)	1. Hipparga Rawa (Lohara block) 2. Malegaon (Lohara block)
Hard rock areas (south)	Prarambha (Community hydrologist programme)	Karnataka (KA)	1. Bhogiramanagunda or BR Gunda (Raichur district) 2. Suladgudda (Raichur district)

In the following pages, we summarise information about each indicator: what it tells us, how it was calculated, use cases, and limitations. The indicator information templates can help understand the proposed indicators in greater detail. The report also presents the highlights of village-wise findings from our pilot. These findings serve as an example of the indicators in action and can help understand how these indicators can be interpreted for a specific village or region. At the end of the following section, two matrices are provided. The first is a summary of the values for all 12 indicators, as calculated for the 10 pilot villages sampled in this study. The second matrix summarises the values on eight out of the 12 indicators[4] for another 40 villages situated in the HUF partner geographies listed above.

[4] Purely primary data based indicators are excluded from this matrix, as the pilot was not conducted in these 40 villages.

Dimension: Balance

Indicator: Groundwater Levels

Selection criteria scorecard

Outcome-oriented

Moderately sensitive to work on the ground

Partially relevant to stakeholders & geographies

Ease of capturing

Easy (Ground-truthed secondary data)

What does the indicator tell us?

This indicator tracks **annual groundwater level trends** that tell us whether the local water use is sustainable.

Additionally, it provides **information on seasonal fluctuations** in groundwater, which aids in estimating the monsoonal recharge volume for water budgeting.

How was it calculated?

Groundwater levels from the Central Ground Water Board (CGWB) were used for pre-monsoon and post-monsoon periods from 2005 to 2021. In the future, higher-density Jaldoot data may be used.

Spatial sorting: The two closest CGWB well stations per village were selected.

Temporal sorting: Stations with minimal missing data were prioritised.

Ground-truth validation: Data was cross-validated with primary survey data from three wells in each village.

Long-term change calculation: The difference between the earliest and the latest available groundwater levels was used to determine inter-annual variation.

What data sources were used?

CGWB data for groundwater level data for May (pre-monsoon) and November (post-monsoon).

Jaldoot data from the Ministry of Rural Development

Data was accessed via India-Water Resources Informational System (WRIS).

How can you use the indicator?

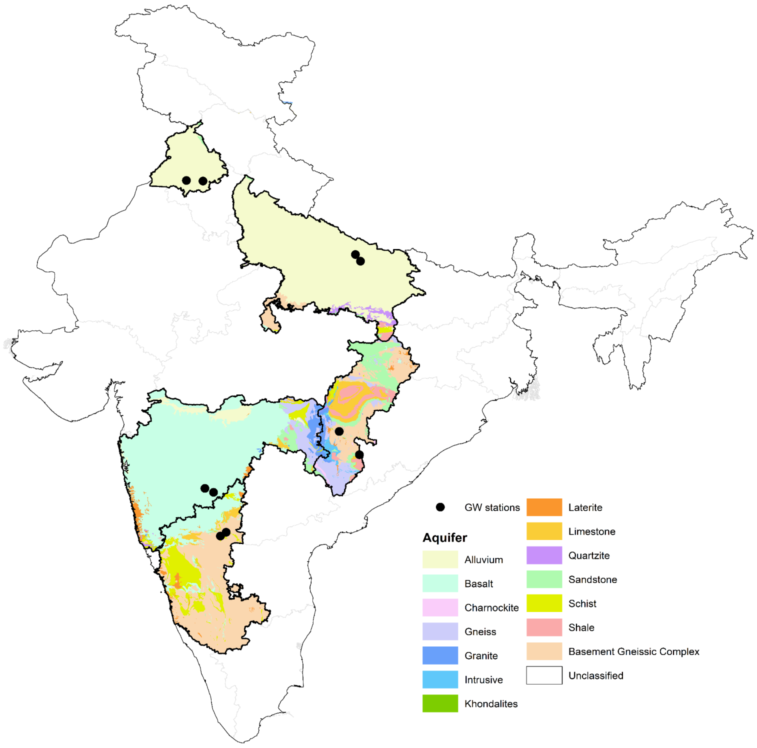
- The groundwater level indicator can help **diagnose problem areas,** which can then be prioritised by NGOs and governments for intervention and collective action. It can assist the industry with **risk management.**
- Understanding season fluctuation of groundwater can help **better planning.** Seasonal fluctuation indicates the amount of recharge, which may be used for water budgeting. It can also help in demarcating areas with high and low seasonal variability into recharge and discharge zones respectively.
- The indicator can be used for **impact assessment.** Maintaining groundwater levels is a crucial sustainability indicator, and future interventions can be evaluated based on favourable groundwater data.

Limitations:

This indicator is currently dependent on low-density CGWB data. In the long term, WISER may help in the validation of Jaldoot data, which has higher density but lower fidelity compared to CGWB data. This can be a game changer for the sector.

Findings from the Pilot

Principal Aquifers Map of Pilot Villages



Key takeaways

- Both villages in **Punjab** exhibit a **gradual yet distinct decline in groundwater levels.**
- Other villages have relatively sustainable GW levels.

State	Village	Change in GW level (in m)**		Seasonal trend (Station 1)
		Station 1	Station 2	
PB	Chauke	-12.93	-7.39	
	Nagra	-15.63	-17.05	
UP	Bangai	0.1	-0.25	
	Rupaideeh	-1.24	0.72	
CG	Bagrai	-1.55	-2.32	
	Kokanpur	2.79	0.25	
MH	Hipparga Rawa	-1.44	-2.4	
	Malegaon	0.9	0.22	
KA	BR Gunda	-0.48	3.16	
	Suladgudda	2	3.65	

Dimension: Balance

Indicator: Surface Water Extent

Selection criteria scorecard

Outcome-oriented

Moderately sensitive to work on the ground

Highly relevant to stakeholders & geographies

Ease of capturing

Moderate (Ground-truthed remote sensing data)

What does the indicator tell us?

This indicator tells us how the **water availability** in water bodies has been **changing** across seasons and years.

It helps in assessing the impact of anthropogenic activities, groundwater depletion, and climate variability.

How was it calculated?

Seasonal Surface Water Reduction (SSWR), i.e is the percentage decrease in surface water extent from post-monsoon (November) to the following summer (May) was noted.

Normalised Difference Water Index (NDWI) was used with thresholding to classify water pixels.

The surface water body maps were validated by ground-truthing during the primary survey. Water extraction was also checked.

What data sources were used?

Cloud-free satellite images from **Landsat 8** and **Sentinel-2** for November and May.

Time period: 2013 to 2024

Implementing the workflow using **Google Earth Engine** (GEE) for efficient and open-source processing.

How can you use the indicator?

- The indicator helps check reduction in water inundation over the years, which can directly indicate **worsening water stress** in the area. This can be due to
  - a) Decreasing rainfall
  - b) Higher runoff capture upstream
  - c) Decreasing groundwater levels
  - d) More extraction.
- It is useful to analyse **site suitability of water recharge structures.** Areas with high seasonal variability could be groundwater recharge areas, while low seasonal variability could indicate the need for groundwater support. With regular collection of similar and complementary data, these hypotheses may be checked further.

Limitations:

Since the method uses satellite data, cloud cover can affect remote sensing accuracy.

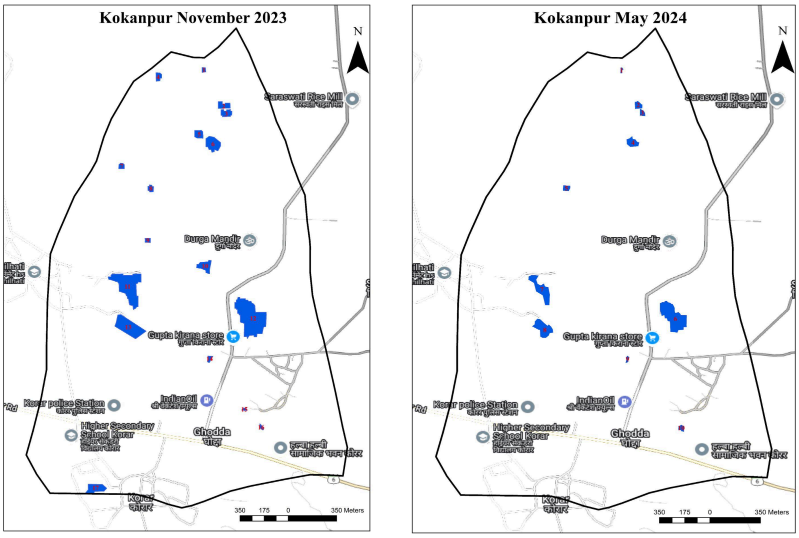
If water is extracted actively from the water body, it needs to be accounted for separately.

Findings from the Pilot

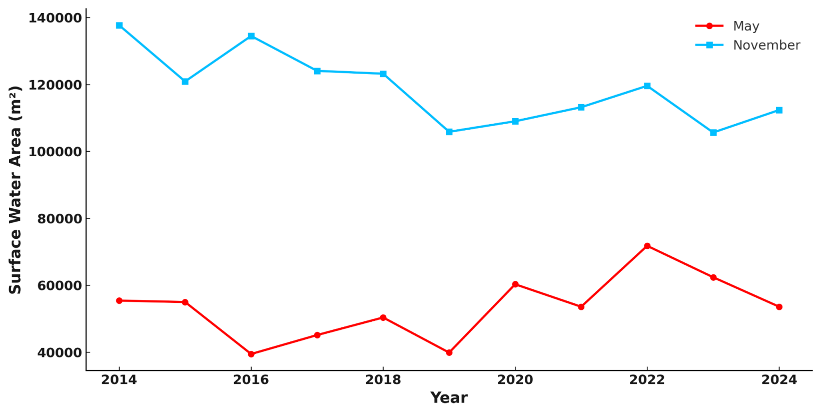
Key takeaways

- **Nagra (97%), Bangai (95%), Malegaon (93%), and Suladgudda (98%) show very high seasonal surface water reduction,** highlighting sharp post-monsoon to summer variation. This suggests that these areas need focused water conservation efforts.
- Moderate to high reductions were seen in Kokanpur (80%) and Hipparga Rawa (69%).
- A consistent decline in surface water over years signals **worsening water stress,** which may be driven by reduced rainfall, groundwater overuse, or upstream capture.

State	Village	SSWR	Seasonal change
PB	Chauke	80 %	High reduction
	Nagra	97 %	Very high reduction
UP	Bangai	95 %	Very high reduction
	Rupaideeh	49%*	Moderate reduction
CG	Bagrai	55 %	Moderate reduction
	Kokanpur	80 %	High reduction
MH	Hipparga Rawa	69 %	High reduction
	Malegaon	93 %	Very high reduction
KA	BR Gunda	No water bodies	
	Suladgudda	98 %	Very high reduction



Surface water bodies in Kokanpur (CG)



Inter-annual variation of surface water area in Kokanpur

Dimension: Balance

Indicator: Water Stress

Selection criteria scorecard

Outcome-oriented

Moderately sensitive
to work on the ground

Highly relevant
to stakeholders & geographies

Ease-of-capturing

Difficult
(Purely secondary data)

What does the indicator tell us?

This indicator illustrates the balance between groundwater availability and extraction.

This serves as a leading indicator for groundwater levels, signalling the stage of groundwater extraction. In alluvial aquifers, while the groundwater levels indicator does not respond until over-extraction is reached, this indicator identifies 'regions at risk' of water depletion before it is reached.

How was it calculated?

The indicator uses CGWB's guidelines[5] with a rainfall infiltration factor. **Recharge sources** are taken as rainfall, irrigation, canals, tanks, and conservation structures, while **Extraction** includes water usage for irrigation, domestic, and industrial purposes.

$$\textbf{Water Stress (\%)} = \frac{\text{Annual Groundwater Extraction} * 100}{\text{Annual Groundwater Recharge}}$$

This is categorised into:
Safe (<70%): Sustainable use;
Semi-Critical (70–90%): Monitoring needed;
Critical (90–100%): Conservation required and
Over-Exploited (>100%): Action needed.

What data sources were used?

The **CGWB** dashboard's block-level stage of development data was used.

A village-level primary data exercise was done with **GEC methodology** using extraction data from primary crop data.

Recharge from non-rainfall sources could not be completed due to lack of data. This may be part of WISER in the future with better primary data.

How can you use the indicator?

- NGOs and governments can use it to **prioritise high-risk areas,** enabling proactive conservation, policy planning, and groundwater recharge efforts.
- It is useful in **impact assessment** as interventions on both the supply and demand sides can be contextualised using the indicator to assess the impact.
- As these estimates improve, panchayats and local stakeholders can use them for **local water budgeting** and demand reduction.

Limitations:
The method relies heavily on assumptions. For recharge estimation, assumptions are made on the rainfall infiltration factor, return flows and water body recharge. For extraction estimation, the crop choice and cropping intensity numbers are based on a sample of the population, while crop water requirements are based on agronomic numbers rather than actual use.

[5] CGWB. (2023, September). *National Compilation on Dynamic Ground Water Resources in India, 2023.* https://cgwb.gov.in/cgwbpnm/public/uploads/documents/17056512151889452705file.pdf.

Findings from the Pilot

Key takeaways

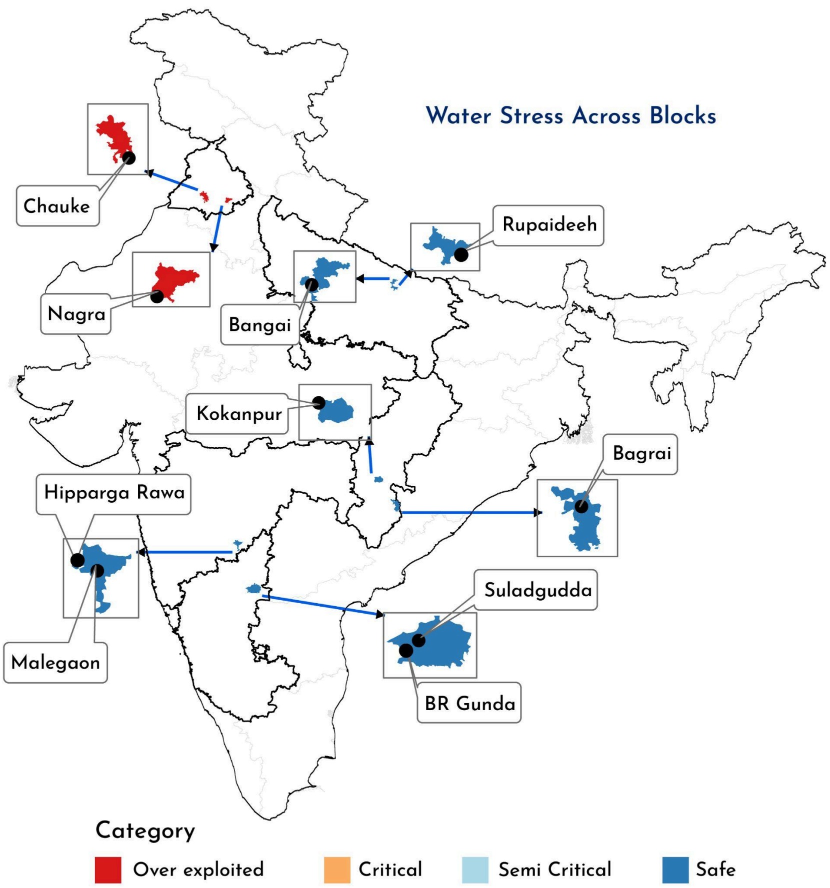
The regions in **Punjab showed critical groundwater depletion.**

The blocks Rampura Phul (136%) and Bhawanigarh (348%), were in the **over-exploited** category, indicating excessive groundwater extraction beyond recharge capacity

Seasonal drying of wells was seen in hard rock areas:

- CG: 40% dry-up, mostly in Jan-Mar
- KA: 60% dry-up, mostly in Jan-Mar
- MH: 90% dry- up, mostly in Apr-Jun.

State	Block[6]	Village	Stage of GW extraction	Water stress
PB	Rampura Phul	Chauke	136 %	Over exploited
	Bhawanigarh	Nagra	348 %	Over exploited
UP	Rupa deeh	Bangai	60 %	Safe
	Jhanjhari	Rupaideeh	65 %	Safe
CG	Bakawand	Bagrai	52 %	Safe
	Kanker	Kokanpur	55 %	Safe
MH	Lohara	Hipparga Rawa Malegaon	57 %	Safe
KA	Devadurga	BR Gunda Suladgudda	42 %	Safe



[6] The methodology was first attempted at the village level. The results were not found to be satisfactory, so CGWB values were directly used, which are at the block level.

Dimension: Access

Indicator: Cropping Intensity

Selection criteria scorecard

Outcome-oriented

Highly sensitive to work on the ground

Highly relevant to stakeholders & geographies

Ease of capturing

Easy (Ground-truthed remote sensing data)

What does the indicator tell us?

This indicator is a measure of the **number of crop cycles** in a given area in a year. It is a useful way to get information about **irrigation cropping** that takes place after the monsoon season in India.

Low cropping intensity indicates reliance on rainfall, which may also indicate **climate vulnerability.**

How was it calculated?

Cropping intensity data from 2010-11 to 2022-23 was analysed to assess the relationship of cropping intensity with irrigation access.
Irrigation access was assessed based on the average cropping intensity value, which was derived from the most prevalent cropping intensity category over 12 years.

Cropping intensity data was used as a proxy for irrigation access and classified as:
Very Low: <90%
Low: 90%-120%
Moderate: 120%-150%
High: 150%-180%
Very High: >180%

What data sources were used?

Natural Resources Census: National Remote Sensing Centre (NRSC) Land Use Land Cover(LULC) at 1 : 250,000 (Bhuvan)

Other land use datasets were assessed, but NRSC data was found to be most suitable

How can you use it?

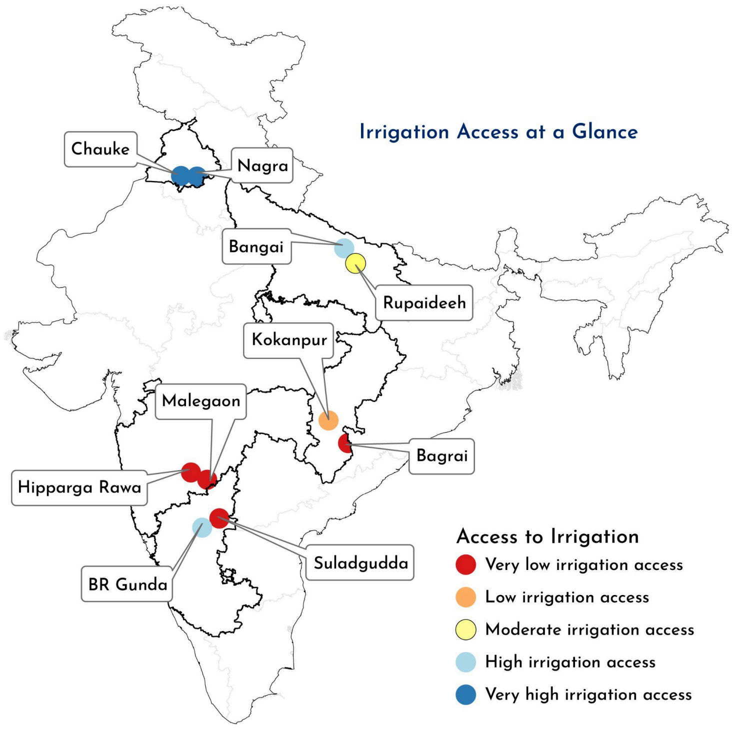
- If the water stress in the area is low and the cropping intensity is also low, NGOs and governments can prioritise **increasing access to irrigation** to support livelihoods.
- **Crop water budgeting** is an important step in the participatory governance of water resources. This data from this indicator (number of annual crop cycles) can be used in the local crop water budgeting processes.
- In water-stressed areas with high cropping intensity, the stakeholders may come together to find solutions to reduce overall water use to sustainable levels.

Limitations:
Cropping intensity may also depend on factors such as market access and the owner's proclivity. Some villages may achieve high cropping intensity even with limited irrigation by cultivating short-duration or drought-resistant crops.
This analysis is based on NRSC LULC data, but it could benefit from primary data, or ground-truthing in places where the numbers are not accurate.

Findings from the Pilot

Key Takeaways

- Both villages in **Punjab** exhibited **very high cropping intensity (>190%),** driven by extensive water availability from irrigation sources.
- In UP, **Bangai had better access (176%) compared to Rupaideeh (152%).** The latter had higher water stress, slightly declining groundwater levels, and lower resilience.
- In Karnataka, the data demonstrated a marked difference between **Suladgudda (72%), which is rainfed, and BR Gunda (168%), which is canal-fed.**
- Other villages had relatively low access.



State	Village	Average cropping intensity (%)	Most common irrigation source (% of farmers)	Second most common irrigation source (% of farmers)
PB	Chauke	192%	Well (97%)	Canal (53%)
	Nagra	198%	Well (100%)	Canal (42%)
UP	Bangai	176%	Well (100%)	Canal (33%)
	Rupaideeh	152%	Well (83%)	Buy Water (20%)
CG	Bagrai	84%	Well (43%)	Rainfed (30%)
	Kokanpur	97%	Well (53%)	Rainfed (40%)
MH	Hipparga Rawa	49%	Well (93%)	Buy Water (7%)
	Malegaon	54%	Well (100%)	None
KA	BR Gunda	168%	Canal (46%)	Rainfed (46%)
	Suladgudda	72%	Well (50%)	Canal (33%)

Dimension: Access

Indicator: Domestic Water Access

Selection Criteria Scorecard

Outcome-oriented

Highly sensitive
to work on the ground

Highly relevant
to stakeholders & geographies

Ease of capturing

Moderate
(Primary Data)

What does the indicator tell us?

This indicator measures how many households in the village have **adequate access to water** for domestic use, especially in the summer. Adequate access is defined as households being able to access sufficient quantities of water when needed.

It maps directly to the UN's SDG 6(Clean water and sanitation, under indicator 6.1.1 used to measure universal and equitable access to safe and affordable drinking water for all.

How was it calculated?

The WISER scorecard shows the percentage of households in the village that report adequate **access to water** all-year-round for **domestic use,** from their primary source.

Other variables of interest captured through household surveys are the percentage of households depending on a secondary source for domestic use, top sources for water for irrigation and livestock, and the percentage of households with adequate water access for irrigation and livestock.

What data sources did we use?

Primary data from household-level surveys across 10 villages in five states (n=300).

How can you use it?

- The indicator can be used to **track progress** toward the UN's SDG Target 6.1, that aims at universal and equitable access to safe and affordable drinking water for all.
- It could contribute a significant addition to our understanding of areas without **accessible drinking water** if done at scale through WISER. This could inform the **priority areas** for NGOs and government programmes working towards this common goal.
- When read along with other variables captured for this indicator, it can help understand drinking water sources, accessibility on premises, and the presence of more than one source the household depends upon. This gives us a more nuanced picture of the state of **water access in a village.**

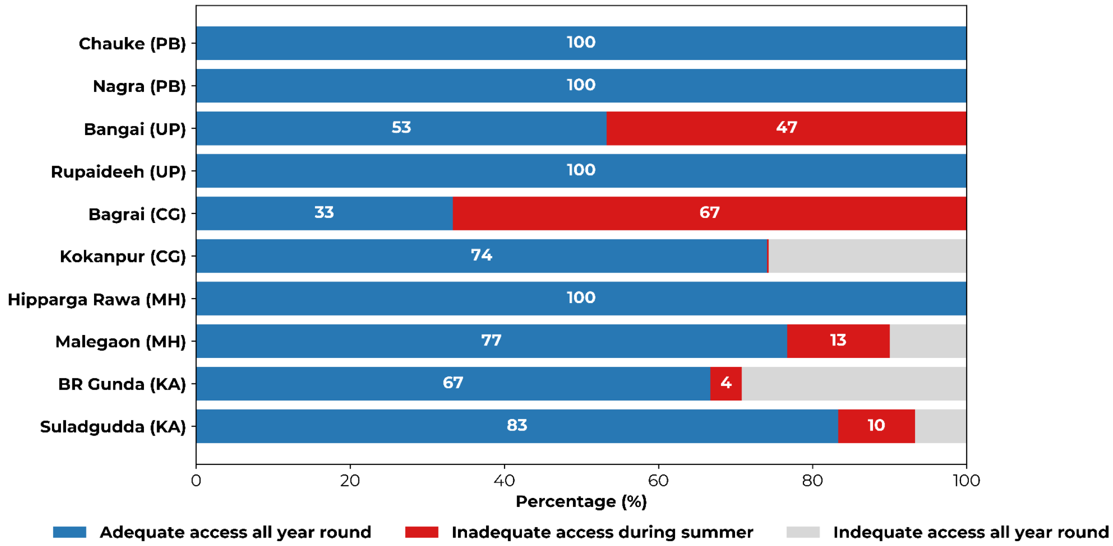
Limitations:

This data is self-reported and has not been triangulated with observation-based data from the field.

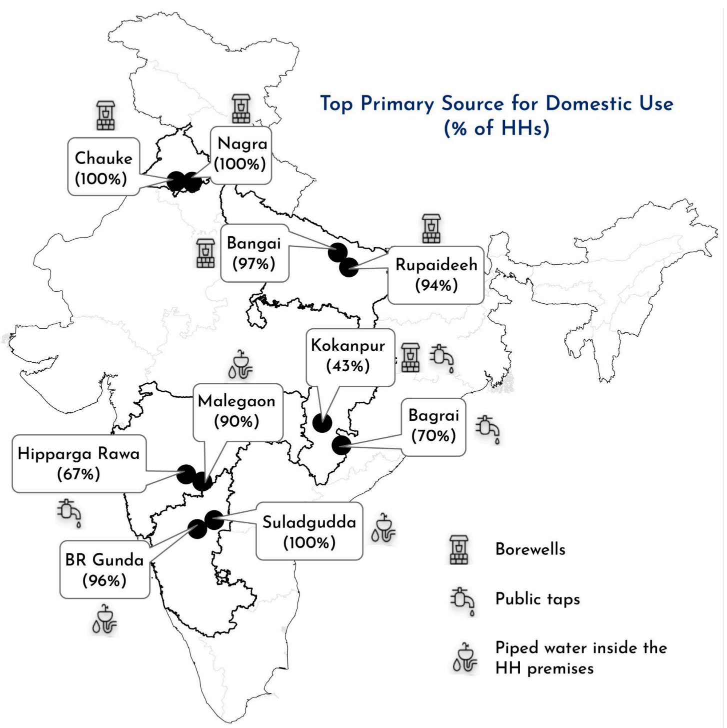
Findings from the Pilot

Key takeaways

- **Access to water for domestic use from primary source (% of HHs):** For most villages in the sample, **over 75% of households reported adequate access** from primary sources for domestic use all year round. In Bagrai (Chattisgarh) and Bangai (UP), however, seasonal water stress was reported by over 45% of households. Additionally, 7 of 10 villages had over 75% households depending on a secondary water source.



- **Top primary sources for domestic use:** Both villages in Punjab and UP were completely dependent on borewells for domestic use. The two in Karnataka had very high availability of piped water inside their premises.



Dimension: Access

Indicator: Domestic Water Quality

Selection criteria scorecard

Outcome-oriented

Moderately sensitive to work on the ground

Highly relevant to stakeholders & geographies

Ease of capturing

Moderate (Primary Data)

What does the indicator tell us?

The indicator measures how many households in the village have **access to self-reported clean water** for drinking and domestic use. 'Clean water' is defined as water that is free from faecal and chemical contamination.

This indicator maps partially to the UN's SDG 6 (clean water and sanitation), under indicator 6.1.1, used to measure universal and equitable access to safe and affordable drinking water for all.

How was it calculated?

The WISER scorecard shows the percentage of households in the village that **self-report** access to clean water for domestic use from their primary source. The confidence of the respondent about the quality of water they use is important in water quality assessment.

Other self-reported variables captured were the percentage who report access to secondary water sources, water quality of irrigation sources, and percentage of households that faced water-borne diseases in the past year.

What data sources were used?

Primary data from household-level surveys across 10 villages in 5 states (n=300)

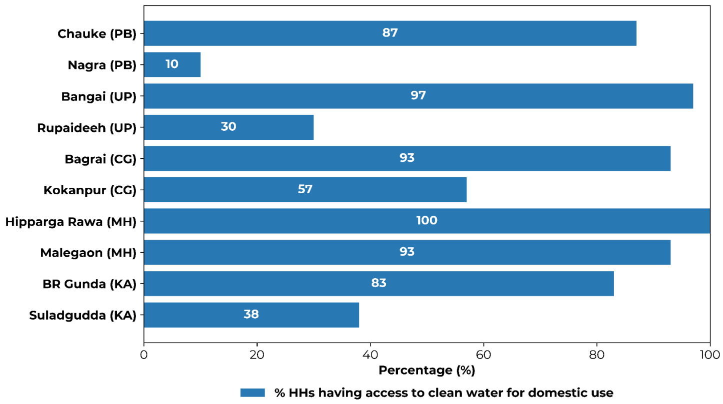
The data was self-reported, and the water used by households in the sample was not tested for contamination. Other tests may be added in future assessments.

How can you use it?

- The indicator can track progress toward the UN's SDG Target 6.1, that aims for universal and equitable **access to safe and affordable drinking water** for all.
- Self-reported data on the prevalence of **water-borne diseases** can provide a more nuanced picture of the state of water quality in a village.
- The data on **the quality of irrigation water** may be useful in planning interventions in areas with high salinity.

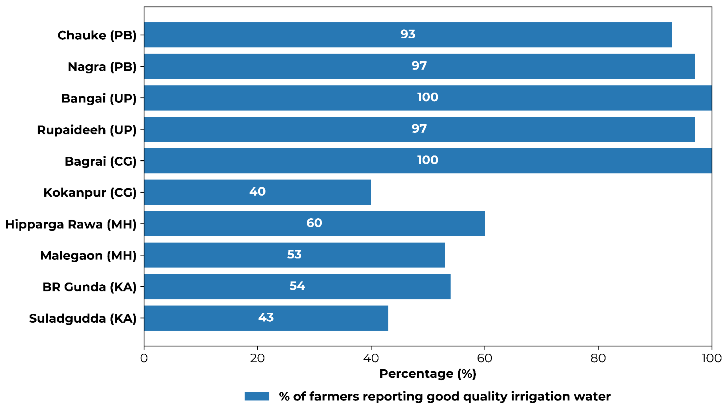
Limitation:
The data is based on perceived water quality. Although perception in water quality is very important, it may not be realistic. Thus, future plans include testing for Total Dissolved Solids (TDS) using handheld devices during assessments.

Findings from the pilot



Key takeaways

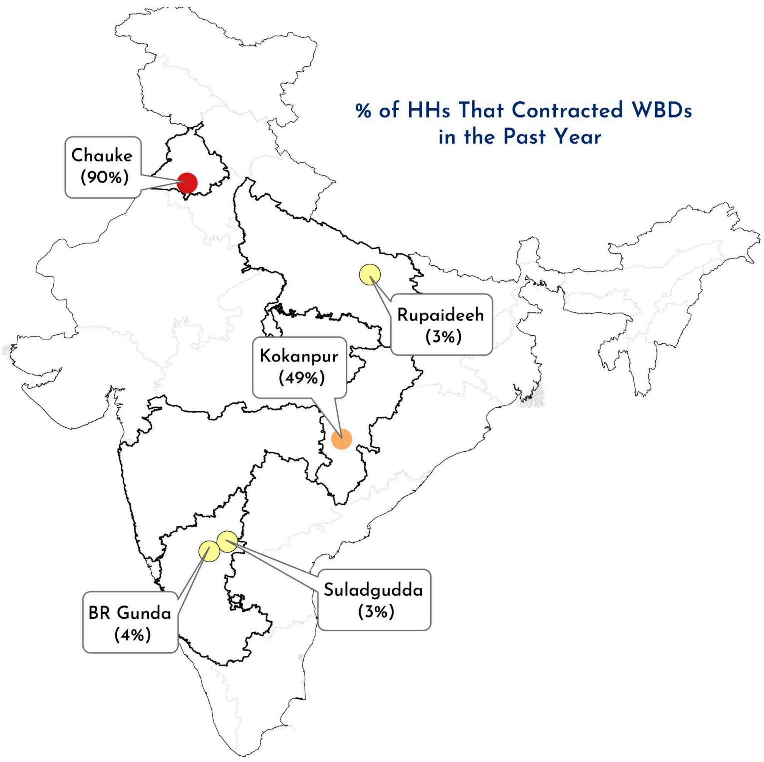
Access to clean water for domestic use from primary source: Overall, the villages in Maharashtra reported the highest access to clean water for domestic use. Among those who reported being unaware of water quality, most reported using the water as is, while some strained or boiled it.



Access to good quality of water from irrigation source(s): The villages in UP and Punjab had 100% farmers reporting that water quality is good for irrigation.
However, many people surveyed in two of the four villages reported that it was not good enough for drinking.

5 of 10 villages reported some incidence of water-borne diseases in the last one year.
Typhoid, diarrhea, and cholera were the top three diseases reported. Nagra (PB), Bagrai (CG), Bangai (UP), Malegaon (MH) & Hipparga Rawa (MH) reported 0% incidence.

Across villages, **no clear relationship emerged between water quality reported and incidence of waterborne diseases.**



Dimension: Productivity

Indicator: Crop Water Productivity

Selection criteria scorecard

Outcome-oriented

Highly sensitive
to work on the ground

Highly relevant
to stakeholders & geographies

Ease of capturing

Moderate
(Primary Data)

What does the indicator tell us?

The indicator measures the **average revenue** (in INR) that a farmer in a village earns **per m3 of water** required for the crops grown per year. It takes into account crop choices made by each farmer in the sample, and provides an INR/m^3 value that can be used to track **how productively water is being used** by the village towards enhancing farmer earnings.

How was it calculated?

For each farmer, the **average water productivity** in *kharif* and *rabi* season is calculated using this formula:

Average revenue per acre across all crops (avg yield x avg price) in INR

———————————————————

Average crop water requirement per acre across all crops (m^3)

The INR/m^3 for kharif and rabi are added for each farmer, then averaged across all farmers in the village-level sample to get a single INR/m^3 value for each village.

What data sources were used?

For the *kharif* and *rabi* seasons, the average yield (in quintals) per acre, average price per quintal, and crop choice data are self-reported, and were collected through **primary surveys** with farmers.

Crop water requirement (in mm) was sourced from Indian Agricultural Statistics Research Institute **(IASRI).**

How can you use it?

- It can be used to **track crop choice** as a balance between farmer income and water use. Crop choice is a key determinant that determines the balance between economic development and sustainability.
- This indicator provides a clear communication tool to ground the conversation on inducing more **productive use of water for agriculture.**
- It is especially useful to look at crop choice behaviour in water-scarce areas, which can be used for **crop water budgeting** (seen in the graph on the next page). Ideally, high-revenue and low-water-use crops may be prioritised. A participatory exercise with farmers can list all common crops of the area and show which crops may be most beneficial for the community as a whole.

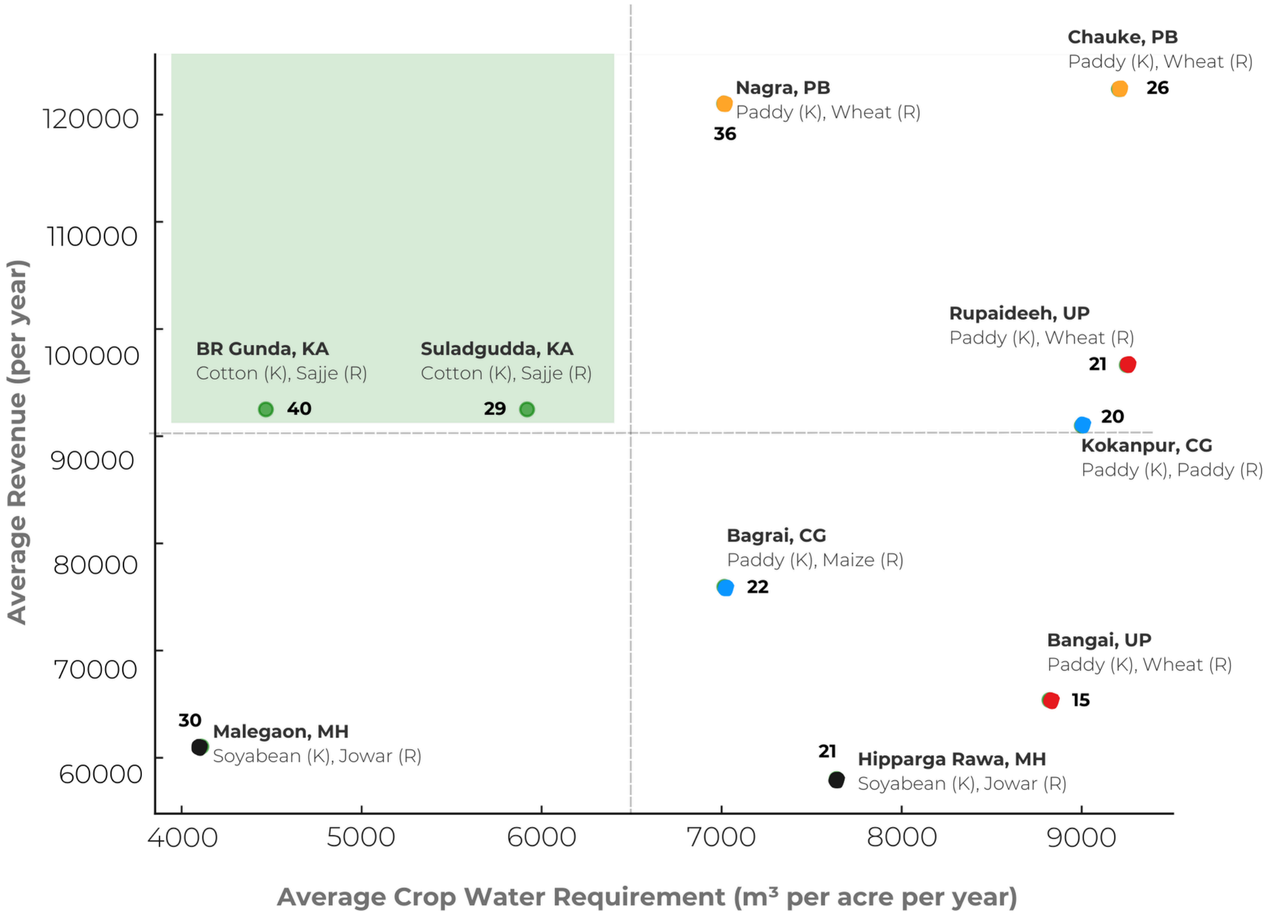
Limitations:

Average yield and price data is self-reported and has not been triangulated by the research team. Average crop water requirement is an estimate sourced from secondary data. The actual water usage by each farmer in the sample may differ, but collecting this was beyond the scope of this pilot.

Findings from the Pilot

Key takeaways

- Average water productivity in INR/m³ value for a village is influenced by its average crop water requirement (CWR) and the average revenue earned by its farmers.



Water productivity in INR/m³ is plotted alongside most common crops reported in kharif and rabi in the graph above.

- We saw that **most sample villages either fell in the High CWR-Low Revenue quadrant, or the High CWR-High Revenue quadrant.** However, from a water productivity perspective, the ideal quadrant for a village to be in is the top left one: High Revenue-Low CWR**.**

- For example, Chauke had the highest average revenue in the sample, but since its average CWR is also the highest, its crop water productivity is INR 26/m³ — which was lower than that of other villages in this cohort.

- Such an indicator can help us understand the **connections between crop choice, water productivity, and farmers' income.** In Phase 2, we plan to refine this indicator by collecting additional data that will help us better estimate crop wise water requirement and farmer profit.

Dimension: Resilience

Indicator: Variation In Cropping Intensity

Selection criteria scorecard

Outcome-oriented

Moderately sensitive to work on the ground

Partially relevant to stakeholders & geographies

Ease of capturing data

Easy (Ground-truthed remote sensing data)

What does the indicator tell us?

It looks at how **rainfall variability significantly impacts cropping systems,** affecting their outcome and stability[7].

This indicator shows the **reduction in cropping intensity in low rainfall years.** High levels of variation in cropping intensity may imply that the region has low water storage, as in the case of hard rock areas.

How was it calculated?

It was calculated by measuring the **average reduction in crop area** from the maximum crop area, during deficient rainfall years. *(Deficient rainfall was considered as < 20% of long-period average, for kharif and rabi seasons separately)*

Seasonal rainfall consideration: June–July for kharif, June–September for rabi.

Resilience rating: Reduction of: <10%—very high,
10% to 25%—high,
25% to 40%—moderate,
40% to 60%— low
> 60% —very low.

What data sources were used?

Natural Resources Census: NRSC LULC at 1: 250,000 (Bhuvan);

IMD gridded rainfall data (IMD).

How can you use it?

- These variations provide insights into how sensitive farmers are to low rainfall years. This can be used for **identifying vulnerable regions** where crop area reduction is significant and farmers may be more affected by possibly more frequent and severe droughts in the coming decades.
- It helps in **designing and prioritising interventions** based on whether the intervention (e.g., increased storage) will lead to more resilience or not.
- It can be a metric for **impact assessment** to see whether an intervention is leading to more climate resilience or not.

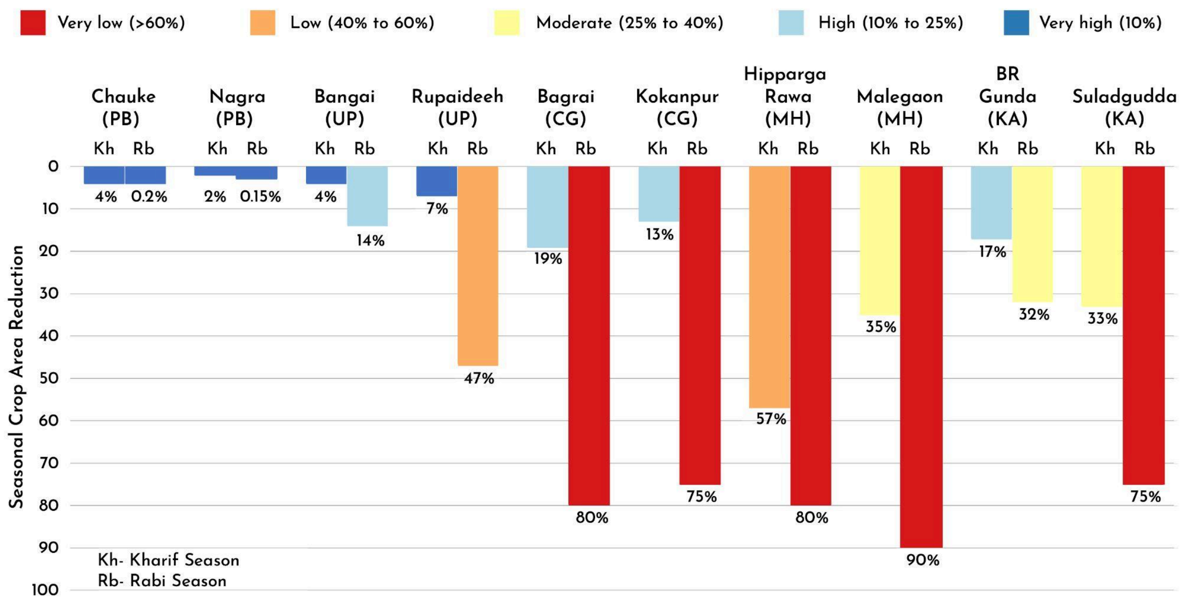
Limitations:
Data was not collected for crop yields for major crops in this phase, but this may be included in the future as this could be a major climate resilience indicator.

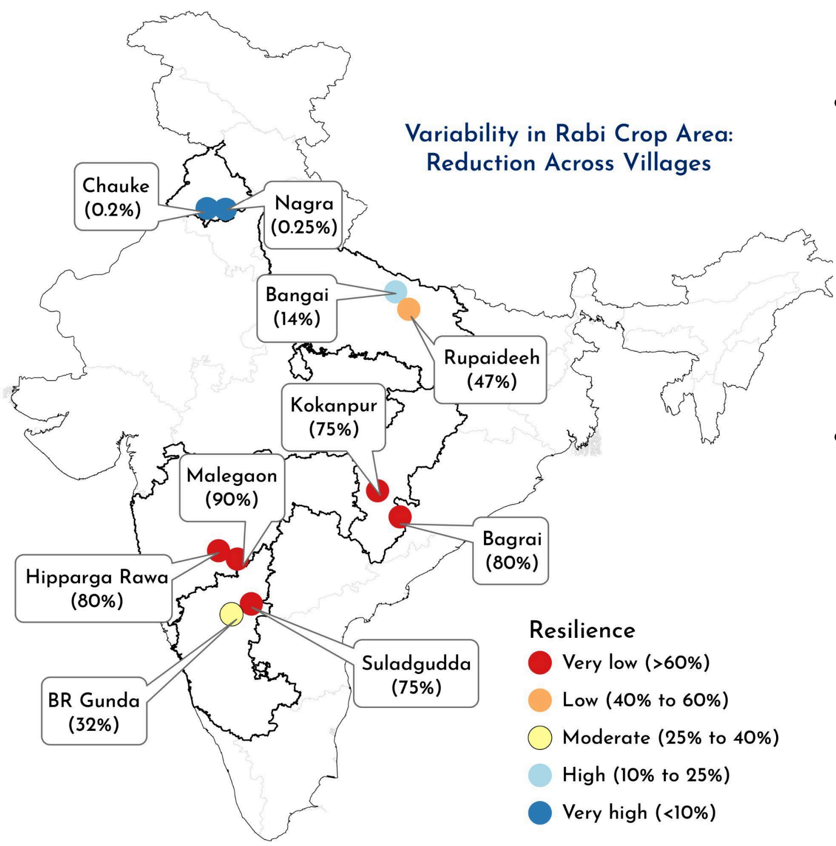
[7] IPCC. (2012). *Managing the Risks of Extreme Events & Disasters to Advance Climate Change Adaptation.* Retrieved from https://www.ipcc.ch/site/assets/uploads/2018/03/SREX_Full_Report-1.pdf.

Findings from the Pilot

Key takeaways

- Villages that experience a **significant reduction in cropped area during deficient rainfall years have lower resilience**, indicating greater dependence on rainfall and limited water access for sustaining agriculture.





- Villages in **Chhattisgarh maintained high resilience in *kharif*** but lacked irrigation support or water retention capacity for significant *rabi* cropping.
- Villages in **Punjab exhibited very high resilience in both *kharif* and *rabi* seasons**, likely due to extensive canal or groundwater irrigation.

Dimension: Resilience

Indicator: Propensity To Droughts (Meteorological)

Selection criteria scorecard

Input-oriented

Least sensitive
to work on the ground

Highly relevant
to stakeholders & geographies

Ease of capturing

Easy
(Purely secondary data)

What does the indicator tell us?

Meteorological droughts are said to occur when there is a **significant decrease from normal precipitation** over an area (i.e., more than 10%). It is typically defined by the degree of dryness and the duration of the dry period.

This indicator tells us the **areas that are experiencing long-term decline in rainfall** due to climate change and variability.

How was it calculated?

Standardised Precipitation Evapotranspiration Index (SPEI) data from the Drought Atlas of India was analysed over a 30-year period.

The total number of years with **SPEI < –1.3** was counted for each village. Based on drought frequency, villages were categorised into five categories from **Very Low** (≤2 years) to **Very High** (≥10 years) frequency.

What data sources were used?

12-month SPEI time series data from 1991-2020 from the **Drought Atlas of India**

How can you use it?

- Meteorological drought frequency helps assess **long-term climate risks** and water security. It can be used in identifying drought-prone areas, as high frequency indicates regions vulnerable to water scarcity
- The indicator helps understand and communicate the **impact of climate change** on long-term total rainfall.
- It helps inform **water resource management.** Areas with a high propensity to droughts should be encouraged to work towards more water storage and higher drought-resistant crops.

Limitations:

The SPEI derived from the Drought Atlas of India has limitations due to residual biases that may persist that could affect drought accuracy. Interpolation and correction techniques can introduce random errors in precipitation and temperature data. Additionally, fixed drought classification thresholds may not capture regional hydrological and soil moisture variability, limiting SPEI's applicability across diverse climates.

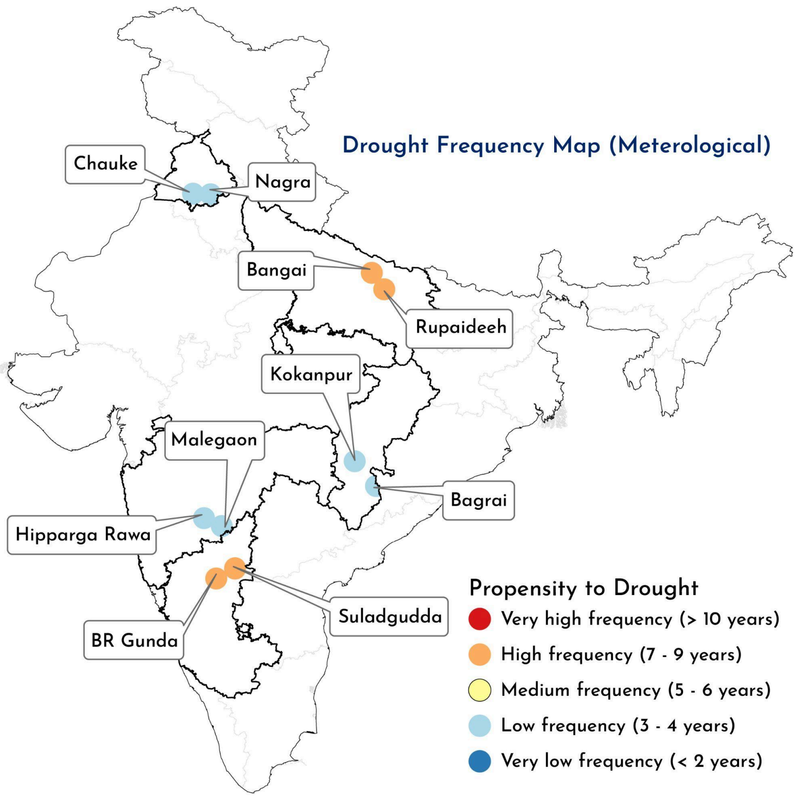
Findings from the Pilot

Key takeaways

- **Karnataka and Uttar Pradesh showed high drought frequency**, experiencing 7 years with SPEI < -1.3.
- **Maharashtra, Chhattisgarh, and Punjab** had villages with **fewer drought** years (≤ 4 years).
- This was consistent with the current understanding of climate change impacts that the **total rainfall is decreasing in UP and Bihar and increasing in northwestern India.**[8]

Frequently of drought conditions in the villages over the past 30 years

Standardised Precipitation Evapotranspiration Index	Drought Categories
-2.0 to -3.0	Exceptional
-1.6 to -2.0	Extreme
-1.3 to -1.6	Severe
-0.8 to -1.3	Moderate
-0.5 to -0.8	Abnormal
> -0.5	Normal



[8]MoES, Govt of India. (2020). (rep.). *Assessment of Climate Change over the Indian Region*. Retrieved from https://link.springer.com/book/10.1007/978-981-15-4327-2

Dimension: Resilience

Indicator: Propensity To Droughts (Agricultural)

Selection criteria scorecard

Input-oriented

Least sensitive
to work on the ground

Highly relevant
to stakeholders & geographies

Ease of capturing

Easy
(Purely remote sensing data)

What does the indicator tell us?

Meteorological droughts may or may not turn into agricultural droughts. The latter is defined to occur when there is insufficient water availability, hampering vegetation growth, causing crop stress, and potentially leading to yield losses.

The indicator essentially tells us the severity and frequency of drought conditions across different seasons.

How was it calculated?

Assessed using the Vegetation Condition Index (VCI)[9], derived from the Normalised Difference Vegetation Index (NDVI) in Google Earth Engine.

VCI = (NDVImax − NDVImin / NDVI − NDVImin) × 100

ESA LULC masked croplands. VCI was computed separately for *kharif* (Jun-Oct) and *rabi* (Nov-Apr) seasons, counting years per village with **VCI < 35%** (severe drought).

What data sources were used?

MODIS NDVI 500 m data processed in Google Earth Engine.

European Space Agency **ESA LULC** Dataset for agricultural land masking.

How can you use it?

- Agricultural drought monitoring helps evaluate crop vulnerability and food security risks. It can be used in **monitoring crop health** by identifying vegetation stress due to soil moisture deficits.
- It can help identify **historical drought trends**, aiding long-term agricultural planning and adaptation strategies.
- It can **guide irrigation planning** and help optimise water use based on drought severity.
- It can help in **informing policy and relief measures**, drought mitigation strategies and resource allocation.

Limitations:

VCI, derived from MODIS data, has coarse spatial resolution and may miss localised vegetation stress, and reliance on NDVI makes it sensitive to soil background and non-vegetative cover, potentially skewing drought severity.

VCI also lacks consideration of crucial factors like soil moisture, crop type, and irrigation. While VHI adds LST for a broader perspective, its 1 km resolution limits village-level applicability, making VCI a more practical, though imperfect, choice.

[9] Alito & Kerebih (2024). Spatio-temporal assessment of agricultural drought using remote sensing and ground-based data indices in the Northern Ethiopian Highland. *Journal of Hydrology: Regional Studies*, Vol. 52, DOI: https://doi.org/10.1016/j.ejrh.2024.101700.

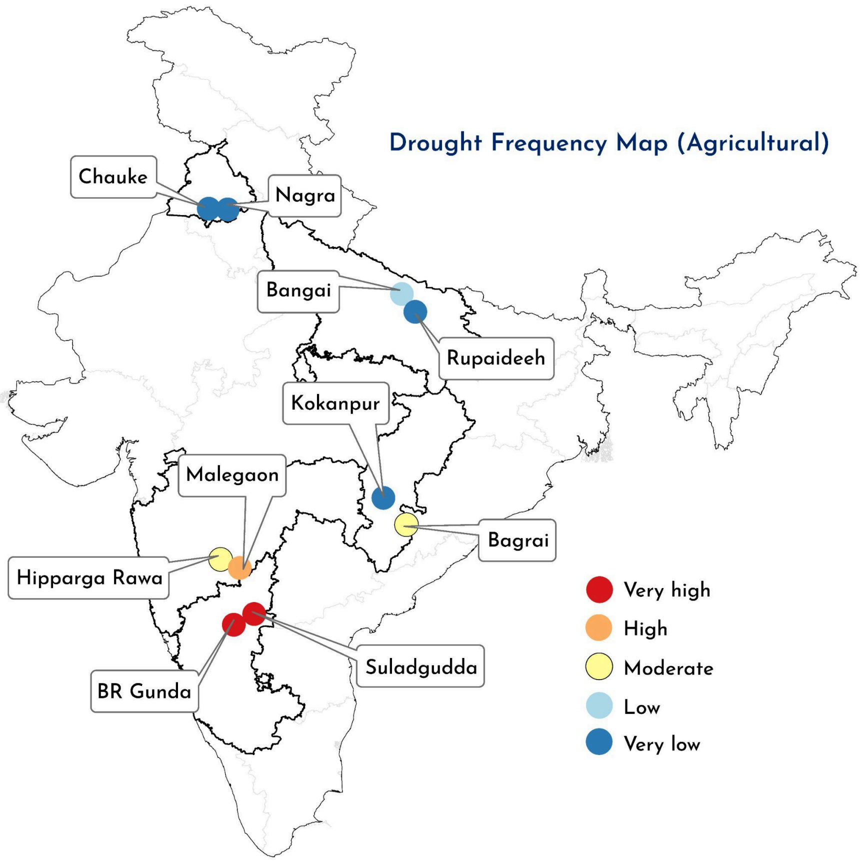
Findings from the Pilot

Key takeaways

- **Karnataka** exhibits **high drought vulnerability during *kharif*.**
- **UP and Punjab** show **low vulnerability**, with Rupaideeh and Nagra experiencing no drought years, possibly due to the presence of good water storage.

Frequency of agricultural drought conditions over the past 18 years

State	Village	No. of seasons with VCI < 35%	Percentage of drought-affected seasons
PB	Chauke	1	3 %
	Nagra	0	0%
UP	Bangai	2	6 %
	Rupaideeh	0	0 %
CG	Bagrai	3	8 %
	Kokanpur	1	3 %
MH	Hipparga Rawa	4	11 %
	Malegaon	5	14 %
KA	BR Gunda	6	17 %
	Suladgudda	7	19 %



Dimension: Resilience

Indicator: Propensity To Floods

Selection criteria scorecard

Input-oriented

Least sensitive
to work on the ground

Highly relevant
to stakeholders & geographies

Ease of capturing

Easy
(Purely secondary data)

What does the indicator tell us?

It measures the **likelihood of an area experiencing flooding** based on rainfall patterns, land characteristics, and drainage capacity. Unlike flood prevention which is not entirely possible, this indicator assessed flood propensity is a practical approach that aids in risk evaluation, preparedness, and mitigation planning. [10,11]

How was it calculated?

Data integration: Historical rainfall data, runoff potential, terrain characteristics, drainage density, water bodies and slope classification.

Generation of Flood Vulnerability Index (FVI): The National Remote Sensing Centre(NRCS) uses the Saaty's scale[12] to combine a set of inputs with different weightage in a multi-criteria evaluation within a spatial decision support system to generate the FVI.

What data sources were used?

The **Flood Vulnerability Index** (FVI) from NRCS, which is also used by agencies such as National Disaster Response Force.

How can you use it?

- The indicator can help in **agricultural risk management** through the selection of flood-tolerant crops, adjusting planting schedules, and implementing water management strategies.
- It can aid **disaster preparedness and early warning** by identifying high-risk areas, allowing timely flood warnings and better emergency response planning.
- It can support **infrastructure and land-use planning** and the design of flood-resilient infrastructure.

Limitations:

The FVI offers relative rankings without quantifying differences between areas[13]. It does not differentiate between fluvial, pluvial, or coastal flooding, limiting insight into specific risks. FVI also overlooks recent local mitigation efforts due to its reliance on static historical data[14], reducing its relevance for dynamic flood scenarios.

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[10] Falah et al (2019). 14 - Artificial Neural Networks for Flood Susceptibility Mapping in Data-Scarce Urban Areas. *Spatial Modeling in GIS and R for Earth and Environmental Sciences*, pp. 323-336, URL: https://doi.org/10.1016/B978-0-12-815226-3.00014-4.

[11] Tien Bui et al (2016). Hybrid artificial intelligence approach based on neural fuzzy inference model and metaheuristic optimization for flood susceptibility modeling in a high-frequency tropical cyclone area using GIS. *Journal of Hydrology*, pp. 317-330. DOI: https://doi.org/10.1016/j.jhydrol.2016.06.027.

[12] Hammami et al (2019). Application of the GIS based multi-criteria decision analysis and analytical hierarchy process (AHP) in the flood susceptibility mapping (Tunisia). *Arab J Geosci* 12, 653. https://doi.org/10.1007/s12517-019-4754-9.

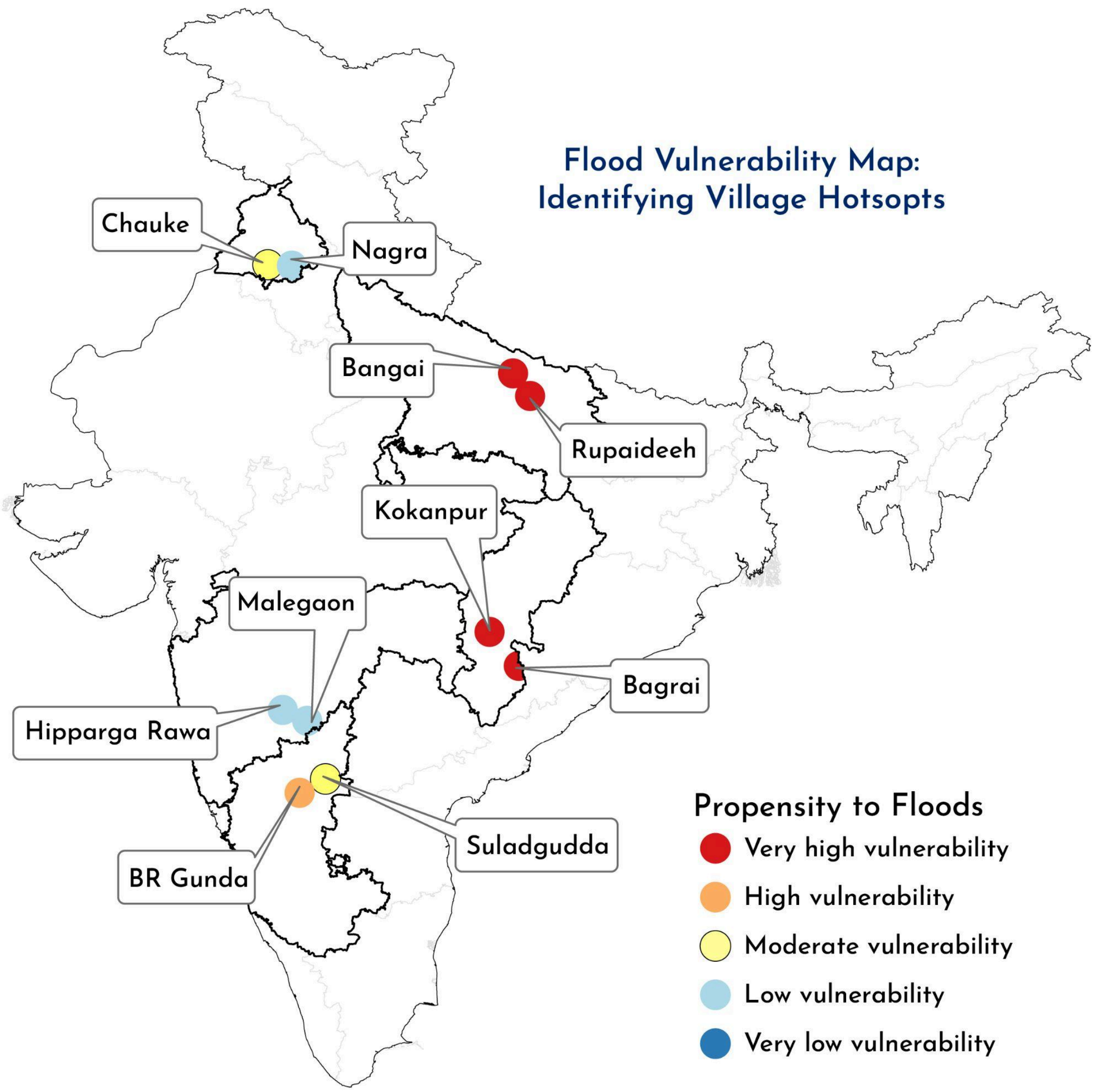
[13] Nasiri, H., Mohd Yusof, M.J. & Mohammad Ali, T.A. An overview to flood vulnerability assessment methods. Sustain. Water Resour. Manag. 2, 331–336 (2016). https://doi.org/10.1007/s40899-016-0051-x

[14] Mwalwimba, I.K., Manda, M. & Ngongondo, C. Flood vulnerability assessment in rural and urban informal settlements: case study of Karonga District and Lilongwe City in Malawi. Nat Hazards 120, 10141–10184 (2024). https://doi.org/10.1007/s11069-024-06601-5

Findings from the Pilot

Key takeaways

- **Rupaideeh, Bangai, Kokanpur, and Bagrai** face very **high flood vulnerability** due to factors like being close to a major stream, terrain, runoff characteristics, etc. They may require action on drainage improvements, flood-resilient infrastructure and early warning systems to protect livelihoods and water security.
- This indicator may be more **relevant to states like Bihar and Assam** to assess the variability of more or less vulnerable areas in those regions.



Dimension: Governance

Indicator: Local Water Governance

Selection criteria scorecard

Output-oriented

Moderately sensitive to work on the ground

Partially relevant to stakeholders & geographies

Ease of capturing

Difficult (Primary data)

What does the indicator tell us?

It measures how many households in the **village report** that their community or village has a **water governance institution**, which could be any formal or informal institution, committee or group that decides how water will be shared among village residents, especially during water-stressed years.

This indicator is important because it assesses **community participation** in managing their water resources sustainably and equitably.

How was it calculated?

The WISER scorecard shows the percentage of **households** in the village that **reported that there is a local institution** (formal or informal) in their village that decides how water will be shared among village residents, especially during water-stressed years.

Other variables of interest captured for this indicator are whether the village has clear water-sharing rules, and if households think having a local water governance institution will be helpful.

What data sources were used?

Primary data from household-level surveys across 10 villages in 5 states (n=300)

The data was **self-reported.** In this phase, we did not triangulate this government or other data.

How can you use it?

- The indicator can track **community participation** in water and sanitation management in accordance with the UN's SDG Target 6b.
- Data about local institutions can help in suitably **design participatory watershed management programmes.**
- The National Water Policy, 2012 prioritises drinking water over needs for livelihoods. The existence and functioning of such institutions can help implement such **initiatives during water-stressed years** or in areas where such prioritisation requires enforcement. .

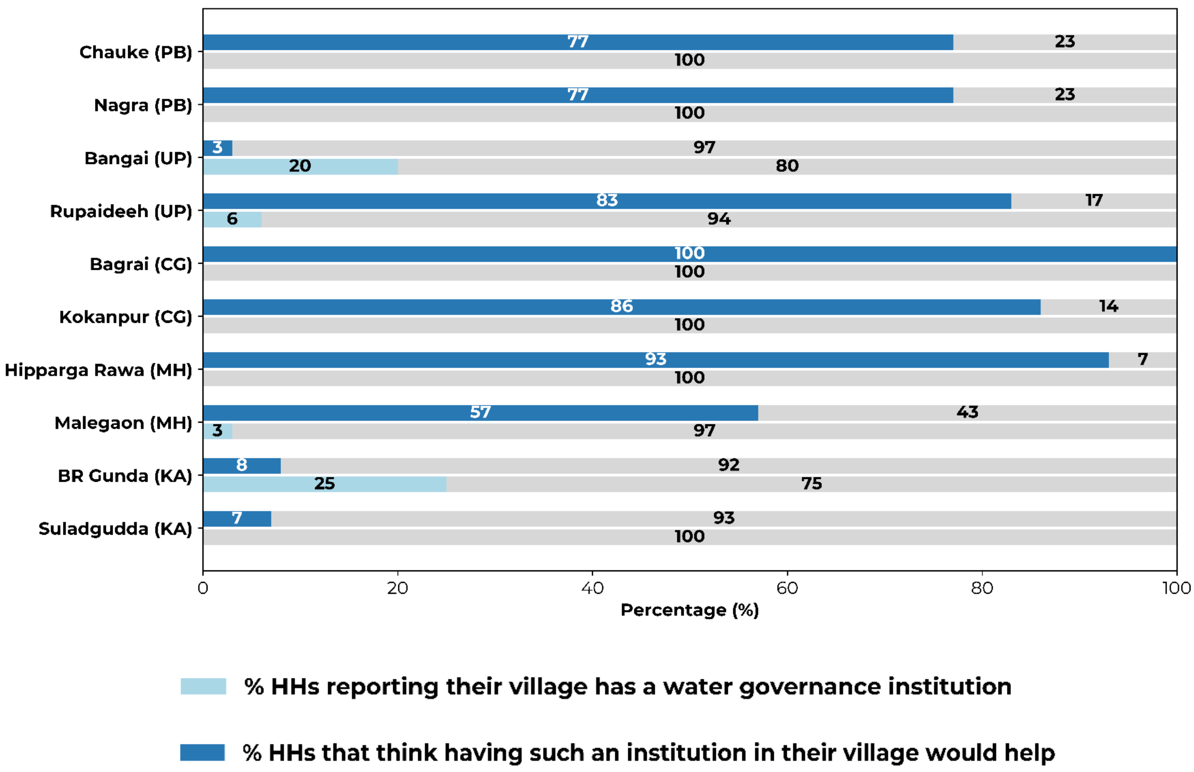
Limitations:

In the current phase of the project, we asked exploratory questions to test if households could provide a nuanced picture of water governance. In future phases, we plan to add further questions related to water use during the dry season and user fees charged by such institutions, to get a more accurate picture about the existence and functioning of institutions.

Findings from the Pilot

Key takeaways

- **Awareness about the existence of any formal/informal local water governance institution was minimal.**
- Across the sample villages, we found that there were **no clear water-sharing rules.** Agreements among residents if any were voluntary, unsaid, mutual agreements.
- Most households across the sample either said their village did not have a local water governance institution that decided how water would be shared among residents, especially during water-stressed years, or that they were unaware of the existence of such an institution.
- In most such villages, **over 70% of households said having such an institution in their village would help.**



Dimension: Water Ecosystem and Health

Indicator: Ambient Water Quality

Selection criteria scorecard

Outcome-oriented

Moderately sensitive to work on the ground

Highly relevant to stakeholders & geographies

Ease of capturing data

Moderate (Primary data)

What does the indicator tell us?

This indicator provides **insights into the water quality** and ecological health of lakes in villages by assessing the presence of eutrophication and fish populations.

Eutrophication may indicate **nutrient pollution** and possible water quality degradation, while the presence of fish suggests a balanced aquatic ecosystem. This indicator serves as a proxy measure for lake water health.

How was it calculated?

Surveys were conducted in the pilot villages on the following:
Presence of eutrophication in the lake (Yes/No)
Presence of fishes in the lake (Yes/No)
The **water quality was categorised** based on the responses into three categories:

Good: No eutrophication + Presence of fish
Moderate: Some eutrophication + Presence of fish
Poor: Large eutrophication + No fish

What data sources were used?

Primary Data: Field surveys were conducted in villages, where respondents reported on the presence of algal patches and fish populations in local lakes.

How can you use it?

- This indicator can help provide an **overview to stakeholders** on what are the regions with better or worse water quality, especially in the aftermath of the increased return flows from the Jal Jeevan Mission water supply.
- Bio-indicators like eutrophication and the presence of fish are simple but effective methods of testing for the **ecosystem health of lakes** and identification of the lakes that need intervention.
- It can help track **ecological trends over time** by repeating the survey annually.

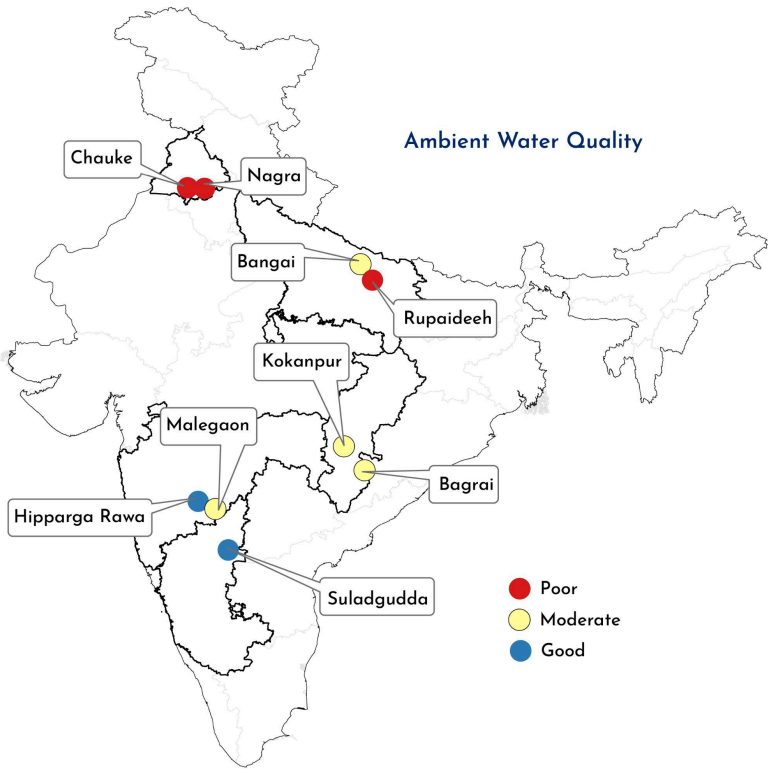
Limitations:
The present phase did not use any testing and relied on survey participant responses, but in the future phases, we plan to include the testing of total dissolved solids (TDS) and other in-situ tests.

Findings from the Pilot

Key takeaways

- Most of the surveyed villages exhibit **moderate to poor ambient water quality**, primarily due to widespread eutrophication and a low presence of fish.

- **Good ambient water quality** is observed only in Hipparga Rawa (MH) and Suladgudda (KA). Both these villages are in **upstream areas**, suggesting that return flows from villages may be worsening the water quality in other villages.



State	Village	Free from eutrophication	Presence of fish	Ambient water quality
PB	Chauke	No	No	Poor
	Nagra	No	No	Poor
UP	Bangai	No	Yes	Moderate
	Rupaideeh	No	No	Poor
CG	Bagrai	No	Yes	Moderate
	Kokanpur	No	Yes	Moderate
MH	Hipparga Rawa	Yes	Yes	Good
	Malegaon	No	Yes	Moderate
KA	BR Gunda	No lakes		
	Suladgudda	Yes	Yes	Good

WISER Results Summary Matrix for Pilot Villages with Primary Data (n=10)

Dimension	Indicators	Metric	Interpreting indicator values	Pilot villages									
				PB		UP		CG		MH		KA	
				Chauke	Nagra	Bangai	Rupaideeh	Bagrai	Kokanpur	H. Rawa	Malegaon	Suladgudda	BR Gunda
BALANCE	Groundwater levels	Change in groundwater level (in meters) between 2005 and 2021, calculated as the difference between 2021 and 2005 values for the same season[15]	Closer to zero or more than zero is better	-12.93	-15.63	0.1	0.72	-1.55	2.79	0.9	-1.44	2	-0.48
	Surface water extent	Percentage reduction in surface water extent between post-monsoon (November) and peak summer (May).	Lower the better (Range: 0-100%)	80%	97%	95%	49%*	55%	80%	93%	69%	98%	No water bodies
	Water stress	Balance between groundwater availability and extraction	Range: Safe to Overexploited	Over exploited	Over exploited	Safe	Safe	Safe	Safe	Safe	Safe	Safe	Safe
ACCESS	Cropping intensity	Average cropping intensity calculated over the period 2010-11 to 2022-23, representing the sustained level of agricultural activity across years[16]	Higher the better	192%	198%	176%	152%	84%	97%	54%	49%	72%	168%
	Domestic water access	Percentage of households who have adequate access to water for drinking & domestic use all year round, especially in the summer	Higher the better (Range: 0-100%)	100%	100%	53%	100%	33%	71%	77%	100%	83%	67%
	Domestic water quality	Percentage of households that report they have access to clean water for domestic use (no visible contamination, foul smell, bad taste, etc.)	Higher the better (Range: 0-100%)	87%	10%**	97%	30%**	93%	57%	93%	100%	83%	38%**
PRODUCTIVITY	Crop water productivity	INR per m^3 that farmers earn on average in the village (factors in crop choice and revenue per crop)	Higher the better	26	36	15	21	22	20	30	21	29	40

[15] Since differences between different aquifer typologies are not comparable, the values have not been graded on a scale of severity.
[16] Values <100% indicate single cropping, while >100% reflect multiple cropping cycles within a year.
***** Only for the year 2023-24.
******>60% of HHs in these villages were unaware of the quality of the water they used, but most of them reported using the water as is, indicating adequate water quality.

Dimension	Indicators	Metric	Interpreting indicator values	Pilot villages									
				PB		UP		CG		MH		KA	
				Chauke	Nagra	Bangai	Rupaideeh	Bagrai	Kokanpur	H. Rawa	Malegaon	Suladgudda	BR Gunda
RESILIENCE	Variation in cropping intensity	Average reduction in cropped area during deficient rainfall years (with rainfall <20% of the long-term average)[17].	Higher the better	Very high resilience	Very high resilience	High resilience	Low resilience	Very low resilience	Very low resilience	Very low resilience	Very low resilience	Very low resilience	Moderate resilience
	Propensity to droughts	Meteorological: Count of years (1991-2020) where SPEI < -1.3, indicating significant rainfall deficiency.	Lower the better	Low frequency	Low frequency	High frequency	High frequency	Low frequency	Low frequency	Low frequency	Low frequency	High frequency	High frequency
		Agricultural: Percentage of cropping seasons between 2005-2022 where VCI < 35%, signaling severe vegetation stress	Lower the better (Range: 0-100%)	3%	0%	6%	0%	8%	3%	14%	11%	19%	17%
	Propensity to floods	Likelihood of an area experiencing flooding based on rainfall patterns, land characteristics, and drainage capacity	Lower the better	Moderately vulnerable	Less vulnerable	Very highly vulnerable	Very highly vulnerable	Very highly vulnerable	Very highly vulnerable	Less vulnerable	Less vulnerable	Moderately vulnerable	Highly vulnerable
GOVERNANCE	Local water governance	Percentage of households that report there is a local institution (formal or informal) in their village that decides how water will be shared among village residents, especially during water-stressed years[18]	Higher the better (Range: 0-100%)	0%	0%	20%	6%	0%	0%	3.30%	0%	0%	25%
WATER ECOSYSTEM & HEALTH	Ambient water quality	Provides insights into the water quality and ecological health of lakes in villages by assessing the presence of eutrophication and fish population	Range: Good to Poor	Poor	Poor	Moderate	Poor	Moderate	Moderate	Moderate	Good	Good	No water bodies

LEGEND	Worse				Better

[17]Measured separately for *kharif* and *rabi* seasons, relative to their respective maximum cropped area, using 12 years of data (2010-11 to 2022-23). Based on this reduction, a resilience class has been assigned to each village.

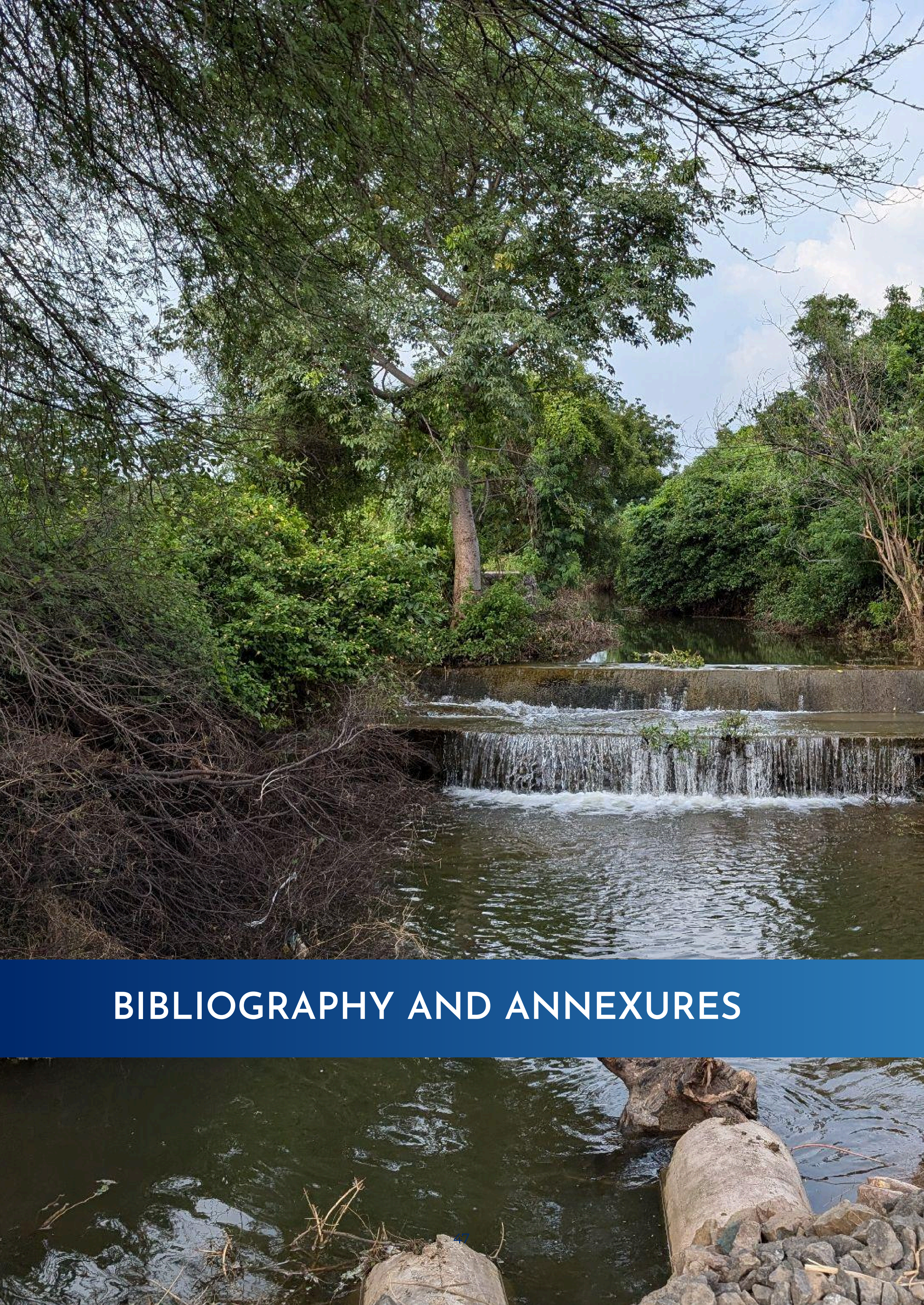
[18]Exploratory questions asked in Phase 1, hence these values may not be representative of the true state of water governance in the sample villages. This indicator will be sharpened to be more reliable in Phase 2.

WISER Results Summary for Pilot Villages with only Secondary Data (n=40)

State	District	Sub-district (Tehsil)	Block	Villages	GW Levels	Surface Water Extent	Water Stress	Cropping Intensity	Variation in Cropping Intensity	Meteorological drought	Agricultural drought	Propensity to Floods
				DIMENSION	BALANCE			ACCESS	RESILIENCE			
				Indicator	GW Levels	Surface Water Extent	Water Stress	Cropping Intensity	Variation in Cropping Intensity	Propensity to Droughts: Meteorological drought	Propensity to Droughts: Agricultural drought	Propensity to Floods
				How to interpret	Closer to zero or more than zero is better	Lower the better (Range: 0-100%)	Range: Safe to Overexploited	Higher the better	Higher the better	Lower the better	Lower the better (Range: 0 to 100%)	Lower the better
PB	Bathinda	Bathinda	Bathinda	Goniakalan	-5.94	NA[19]	Critical	190%	Very high	Low	5.56%	Moderate
			Sangat	Bandi	1.27	NA	Safe	180%	Very high	Low	0%	Low
		Talwandi Sabo	Talwandi Sabo	BangiRuldu	1.62	NA	Safe	194%	Very high	Low	11.11%	Moderate
				Giana	-0.98	NA	Safe	189%	Very high	Low	2.78%	Low
	Sangrur	Dhuri	Dhuri	Bardwal	-8.85	NA	Over exploited	187%	Very high	Low	8.33%	Moderate
			Sherpur	Ghanouri	-3.18	NA	Over exploited	198%	Very high	Low	2.78%	Moderate
		Lehra	Lehragaga	Bhaiki pishori	-3.27	NA	Over exploited	198%	Very high	Low	0%	Low
		Sangrur	Sangrur	Bhindran	-7.7	NA	Over exploited	196%	Very high	Low	0%	Moderate
UP	Gonda	Gonda	Jhanjhari	Madhaipur	-0.62	36 %	Safe	169%	Moderate	High	2.78%	Very high
			Mujhana	Jigna	0.19	73 %	Safe	165%	Moderate	High	2.78%	Very high
				Retwagarh	-0.03	47 %	Safe	151%	Low	High	8.33%	High
		Mankapur	Chhapia	Makuia	-0.82	90 %	Safe	178%	Moderate	High	2.78%	High
				Payarkhas	-0.82	30 %	Safe	152%	Moderate	High	8.33%	High
	Shravasti	Ikauna	Ekona	Bhojpur	0.5	99 %	Safe	159%	Very high	Very Low	8.33%	Very high
				Lalbojhi	-0.09	99 %	Safe	162%	Low	Very Low	5.56%	High
				Samgarha	-0.17	70 %	Safe	173%	High	Very Low	2.78%	Very high

[19] For the surface water extent values for villages in Punjab, these locations exhibited anomalously higher water pixel counts in summer. Further ground truth validation is needed to confirm that values generated here accurately reflect the ground reality.

State	District	Sub-district (Tehsil)	Block	Villages	BALANCE			ACCESS	RESILIENCE			
				DIMENSION	BALANCE			ACCESS	RESILIENCE			
										Propensity to Droughts		
				Indicator	GW Levels	Surface Water Extent	Water Stress	Cropping Intensity	Variation in Cropping Intensity	Meteorological drought	Agricultural drought	Propensity to Floods
				How to interpret	Closer to zero or more than zero is better	Lower the better (Range: 0-100%)	Range: Safe to Overexploited	Higher the better	Higher the better	Lower the better	Lower the better (Range: 0 to 100%)	Lower the better
CG	Bastar	Bakawand	Bakawand	Chhindgaon	1.03	72 %	Safe	84%	Low	Low	19.44%	Very high
				Kaundwawnd	-0.3	58 %	Safe	93%	Very low	Low	11.11%	Very high
				Pithapur	2.45	99 %	Safe	94%	Very low	Low	2.78%	High
	Kanker	Kanker	Kanker	Nawagaon Bhavgir	-0.7	52 %	Safe	102%	Very low	Low	2.78%	Very high
		Narharpur	Narharpur	Kanharpuri	-2.26	61 %	Safe	94%	Very low	Low	5.56%	High
		Kanker	Kanker	Sarangpal	2.64	86 %	Safe	113%	Very low	Low	5.56%	High
	Kondagaon	Kondagaon	Kondagaon	Mohlai	0.85	81 %	Safe	50%	Very low	Medium	22.22%	Very high
				Nilji	-0.68	71 %	Safe	89%	Very high	Medium	5.56%	Low
MH	Osmanabad	Kalamb	Kalamb	Hawargaon	-1.89	78 %	Safe	117%	Very low	Medium	13.89%	Moderate
				Nipani	-2.2	83 %	Safe	101%	Very low	Medium	5.56%	Moderate
		Lohara	Lohara	Hipparaga Sayyad	-4.9	89 %	Safe	64%	Very low	Low	19.44%	Moderate
				Mogha	-3.5	80 %	Safe	51%	Very low	Low	8.33%	Low
				Undergaon	-10.6	86 %	Safe	39%	Very low	Low	19.44%	Moderate
		Tuljapur	Tuljapur	Barul	-3.75	86 %	Safe	66%	Very low	Low	16.67%	Low
				Honala	-0.45	99 %	Safe	87%	Low	Low	11.11%	High
				Kati	-1.36	86 %	Safe	67%	Low	Low	2.78%	Moderate
KA	Raichur	Devadurga	Devadurga	Gajaldinne	1.21	No lakes	Safe	81%	Low	High	11.11%	High
				Gandhal	-1.1	No lakes	Safe	151%	Moderate	High	19.44%	High
				Muduvayya gadi	3.76	No lakes	Safe	165%	Moderate	High	8.33%	High
				Mukkanal	0	No lakes	Safe	115%	Moderate	High	11.11%	Moderate
				Mundalgudda	1.21	99 %	Safe	61%	Low	High	25%	High
				Mykaladoddi	-1.1	No lakes	Safe	186%	High	High	19.44%	High
				Parapur	0	12 %	Safe	126%	Moderate	High	8.33%	Moderate
				Somanmardi	3.76	No lakes	Safe	131%	Low	High	5.56%	Moderate



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Annexure A: Rationale for Selection Criteria Categories

CRITERIA	CATEGORIES	RATIONALE
Outcome-oriented / output-oriented / input-oriented	Outcome-oriented	The indicator is oriented to capture outcome(s) that are ends in themselves either for socioeconomic or biophysical conditions in the landscape
	Output-oriented	The indicator is oriented to capture the immediate output(s) of an intervention
	Input-oriented	The indicator is oriented to capture input(s) or contextual factors that can affect the output(s)/outcome(s) of an intervention
Sensitivity to work on the ground	Highly sensitive	The indicator will be very good at reflecting the change that occurs in the given parameter if the intervention is trying to actively address the parameter.
	Moderately sensitive	The indicator will be somewhat good at reflecting the change based on the intervention; however the indicator may be dependent on other factors which the intervention cannot change
	Least sensitive	The indicator will move very little or not at all to reflect the change that occurs in the given parameter, even if the intervention is trying to actively address the parameter.
Relevance to stakeholders / geography	Highly relevant	The indicator is highly relevant to all geographies and stakeholders across the country
	Partially relevant	The indicator may not be relevant to some geographies or stakeholders while it may not be relevant to others
Ease of capturing	Easy	This indicator is easy to capture because either a) the remote sensing product is already available,or b) it is relatively easy to consolidate existing databases to arrive at our indicator.
	Medium	This indicator is somewhat difficult to capture because either a) the remote sensing product is not yet available, or b) additional primary or secondary validation is required to arrive at our indicator.
	Difficult	This indicator is difficult to capture because either a) the methodology is complicated and requires building of workflows from scratch, or b) primary data at household level is required to arrive at our indicator.

Annexure B: Definitions

DEFINITIONS OF TECHNICAL TERMS	
Agricultural droughts	They occur when soil moisture is insufficient to support plant growth due to below-normal precipitation and/or above-normal temperatures and wind.
Aquifer system	It is a natural underground layer of rock/soil that stores and allows the movement of groundwater. It acts like a hidden reservoir beneath the surface, supplying water to wells and springs.
Baseflow	The portion of a stream's flow that is sustained between precipitation events (rainfall), and is fed to the stream by delayed pathways such as groundwater discharge.
Climatic Water	It refers to water that comes from weather-related sources like rainfall, snow, or humidity.
Cropping intensity	Percentage of Total Cropped Area over Net Area Sown
Eutrophication	A process that occurs when a body of water becomes enriched with nutrients, leading to an excess of plant and algae growth.
Evapotranspiration (ET)	Water evaporates from land and water surfaces and transpires, or is released, from plants and re-enters the atmosphere. This combined process is called evapotranspiration.
Hydrogeologic water	Groundwater stored and moved through underground layers of soil and rock.
Hydrological droughts	A period of time when a lack of precipitation (rainfall), including snowfall, impacts the water supply: streamflow, reservoir and lake levels, and groundwater table all decline.
Irrigation Efficiency Benchmarking	Productivity benchmarks are set using an agricultural database to make probability distributions. Each quartile is a benchmark.
Long Period Average (LPA)	LPA of rainfall is the rainfall recorded over a particular region for a given interval (like month or season), averaged over a long period like 30 years, 50-years etc.
Meteorological droughts	They refer to a prolonged period of below-average precipitation, causing water deficits.
Normalised Difference Vegetation Index (NDVI)	This is used to quantify vegetation greenness and is useful in understanding vegetation density and assessing changes in plant health.
Remote Sensing (RS)	Remote sensing refers to acquisition of information about an object or phenomenon without making physical contact.

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