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Low-Cost Water Quality Monitoring Using IoT Sensors for Rural Areas

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Abstract : *Safe drinking water depends on knowing what is in it, and in many villages nobody can check often enough. Laboratory testing is accurate but slow. Every sample has to be carried to a town, so a source can change for weeks before anyone notices. This paper describes the design of a low-cost Internet of Things (IoT) node for monitoring rural water sources. An ESP32 microcontroller reads four inexpensive sensors (pH, turbidity, total dissolved solids, and temperature), filters and calibrates the readings, and sends them over Wi-Fi or a 4G hotspot to a cloud dashboard. On the device, a small rule set compares each reading with the Bureau of Indian Standards limits for drinking water and labels the source Safe, Caution, or Unsafe.*

The node runs on a small solar panel and a Li-ion cell, keeps readings in flash memory when the network is down, and is estimated to cost roughly ₹4,000 to ₹8,000 in parts. We describe the hardware, wiring, calibration procedure, data processing, and a validation plan that compares the node with reference instruments and laboratory results. No field measurements are reported here, and the performance tables are marked for later evaluation. The system is a screening tool. It cannot detect bacteria, fluoride, arsenic, or nitrate, so it does not replace certified laboratory testing. Its contribution is a documented, reproducible design that a student team or a village committee can build and check for itself.

Key Words: Water quality monitoring, Internet of Things, IoT sensors, ESP32, pH, turbidity, TDS, temperature, rural areas, real-time monitoring, low-cost design.

I. INTRODUCTION

Having a water source is not the same as having safe water. A borewell, tank, or handpump can look and taste normal while its pH drifts, silt washes in after heavy rain, or dissolved salts build up through a dry season. In rural areas these changes often go unnoticed, simply because nobody is measuring.

The usual answer is laboratory testing. It gives detailed results, but it needs someone to collect the sample, a trip to a town laboratory, and a wait for the report. In practice, a village source may be tested a few times a year, and each result describes a single moment. Earlier work on rural monitoring names the same obstacles: high operating and transport costs, and the time that manual testing takes [2].

IoT research has tried to close this gap. Jabbar et al. built a solar-powered LoRaWAN node for rural water sources that measures pH, TDS, turbidity, and temperature and sends the data to cloud platforms [1]. Alipio developed a system for rural households in which sensor nodes report to a base station that classifies potability with ensemble learning [2]. Shete, Bongale, and Dharrao described a calibrated pH, temperature, and dissolved-oxygen setup for aquaculture [3].

These systems work, but they lean on infrastructure that a small team or a village may not have: a LoRaWAN gateway, a base station, or specialised probes. We wanted something simpler. The design in this paper uses one ESP32 board, four low-cost sensors, and whatever internet link the village already has, even a phone hotspot. It measures pH, turbidity, TDS, and temperature at a fixed interval, checks the values against national drinking-water limits, and shows the result on a dashboard that anyone with a phone can open.

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We are equally clear about what it does not do. Consumer-grade sensors drift and need regular calibration. None of the four parameters says anything about microbial contamination or about chemicals such as fluoride, arsenic, and nitrate, which matter a great deal in many Indian districts. The node is therefore a screening tool. Its job is to notice change early and to tell people when a proper laboratory test is worth the trip.

The objectives of this work are:

- to design a low-cost, solar-capable ESP32 node that measures pH, turbidity, TDS, and temperature;
- to define a calibration and data-processing routine that makes cheap sensors as trustworthy as they can be;
- to classify each reading against BIS drinking-water limits and present it remotely;
- to set out a validation plan against reference instruments and laboratory results.

II. RELATED WORK

IoT-based water monitoring has been studied with many sensor sets, radio links, and analysis methods. Three studies are closest to our setting.

Jabbar et al. [1] designed WQMS-LoRaWAN for rural regions. An Arduino Uno board with a LoRa shield reads pH, TDS, turbidity, and DS18B20 temperature sensors, and the node is solar powered and waterproof. Readings travel to a LoRaWAN gateway and then to The Things Network and ThingSpeak. The authors also compared the system with laboratory measurements on different water samples. Their work is the most direct precedent for ours, and we use the same four parameters. The main difference is the link: LoRaWAN gives long range but needs a gateway, while Wi-Fi or 4G needs no extra hardware where coverage exists.

Alipio [2] built portable sensor nodes for rural household water sources. The nodes send physicochemical readings wirelessly to a base station, which classifies potability using ensemble learning and sends the result to households over 2G/3G. A follow-up study [6] used pH, turbidity, TDS, and temperature with a hard-voting ensemble of k-nearest neighbours, naive Bayes, and a decision tree, and reported 97% accuracy for the voting classifier. Classification is attractive, but it needs labelled training data that a new site may not have. Fixed regulatory limits, as we use here, need none.

Shete, et al. [3] targeted aquaculture and measured temperature, pH, and dissolved oxygen with an Arduino Uno. Their pH calibration uses three standard buffers at 4.01, 7.00, and 10.01, and we adopt the same three-point scheme. Aquaculture has different water-quality needs from drinking water, so the parameters and limits differ.

Limits for drinking water come from the Bureau of Indian Standards, IS 10500:2012 [4], with the WHO guidelines [5] as an international reference. Both are summarised in Section 5.4.

Table I: Comparison of IoT-Based Water Quality Monitoring Approaches - 5

Sr. No.	Approach	Main Parameters	Major Advantage	Major Limitation
1	LoRaWAN-based rural monitoring [1]	pH, TDS, turbidity, temperature	Long range; solar powered; tested against laboratory results	Needs a LoRaWAN gateway and coverage
2	IoT potability classification [2], [6]	pH, turbidity, TDS, temperature	Gives households a direct potable / not potable result	Needs a base station and labelled training data
3	Aquaculture IoT monitoring [3]	pH, temperature, dissolved oxygen	Documented calibration; low human intervention	Built for fish farming, not drinking water
4	Proposed low-cost ESP32 node	pH, TDS, turbidity, temperature	Few parts; direct Wi-Fi/4G uplink; rule-based BIS status	Needs network coverage; sensors need frequent calibration
5	Laboratory testing	Wide range, including microbial and chemical tests	Detailed and certified results	Slow, costly, infrequent

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Taken together, these studies show that IoT can make water testing more frequent and easier to reach. They also show that calibration and comparison with reference measurements decide whether the numbers can be trusted.

III. RESEARCH GAP

Reading across the literature, we see four gaps that matter for a small rural deployment.

First, several systems depend on infrastructure that adds cost and setup effort, such as gateways, base stations, and chains of cloud services. That is reasonable for a funded project. It is harder for a student team or a village committee.

Second, sensor sets differ from study to study. A rural node needs a small set of parameters that say something useful about drinking water while keeping the bill of materials low. Dissolved-oxygen probes, for example, are valuable in aquaculture but are not needed for a first drinking-water screen.

Third, showing a number is not the same as showing a reliable number. Readings from low-cost probes shift with calibration, temperature, ageing, and the sample itself. Many papers stop at displaying values without a clear plan for checking them.

Fourth, raw readings are hard for non-specialists to act on. A villager does not know whether a TDS of 830 mg/L is a problem. A status label tied to a published standard, with a clear next step, is easier to use.

The proposed system addresses these gaps with a minimal, directly connected ESP32 node, a defined calibration and validation routine, and an on-device Safe / Caution / Unsafe rule based on BIS limits.

IV. PROPOSED SYSTEM

4.1 Design Rationale

The node is a compact unit that measures four parameters. Each was chosen because it is informative, cheap to sense, and covered by a national standard or useful for interpreting the others.

- pH shows acidity or alkalinity. BIS gives an acceptable range of 6.5 to 8.5 [4].
- Turbidity measures cloudiness from suspended particles. It often rises after rain and can shelter microorganisms from disinfection.
- Total dissolved solids (TDS) estimates dissolved salts from electrical conductivity. High values point to salinity or mineral loading.
- Temperature has no health limit of its own. We log it because conductivity readings must be temperature-compensated and because it explains seasonal trends.

An ESP32 was chosen as the controller because it combines a dual-core processor, a 12-bit analog-to-digital converter, and Wi-Fi on one inexpensive board. It samples the sensors, applies calibration, classifies the status, and uploads the result. Figure 1 shows how the blocks fit together.

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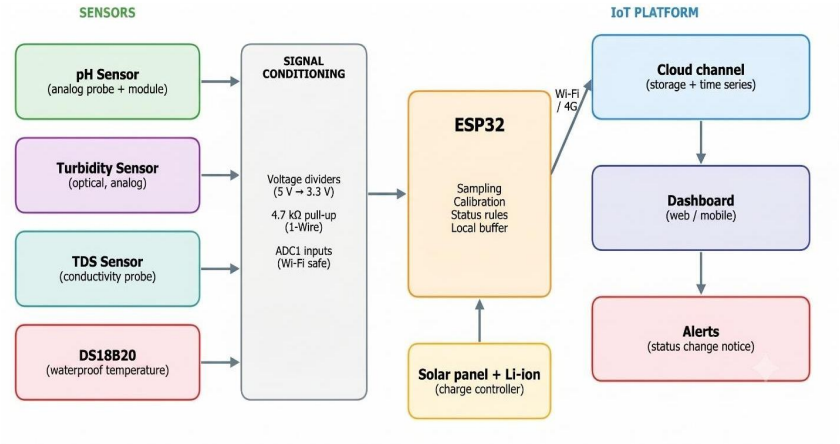


Fig. 1. Proposed system block diagram of the low-cost IoT water quality monitoring node.

4.2 Hardware Architecture

Table II lists the components and their roles. Figure 2 groups them into four layers: sensing, processing, communication, and cloud application.

Table II: Hardware Components and Functions - 12

Sr. No.	Component	Function in System
1	ESP32 DevKit	Sensor sampling, calibration, status rules, Wi-Fi connectivity, local buffering
2	Analog pH sensor kit (probe and interface board)	Measurement of water pH
3	Analog turbidity sensor	Optical measurement of suspended particles
4	Analog TDS sensor (conductivity probe)	Estimation of total dissolved solids
5	DS18B20 waterproof temperature sensor	Water temperature and TDS compensation
6	Resistor dividers and 4.7 kΩ pull-up	Level shifting to 3.3 V; 1-Wire bus pull-up
7	6 V solar panel	Recharging in off-grid locations
8	18650 Li-ion cell and charge controller	Energy storage and safe charging
9	IP65 enclosure with cable glands	Protection of electronics from water and dust
10	Wi-Fi router or 4G hotspot	Internet uplink
11	Cloud IoT platform (for example ThingSpeak)	Data storage, charts, dashboard, alerts
12	Reference instruments (pH meter, EC/TDS meter, turbidimeter, thermometer)	Used for calibration and validation only, not part of the node

Cost was a design constraint, not an afterthought. Figure 3 gives an indicative price range for each part based on typical Indian retail prices for hobby-grade modules. The total comes to roughly ₹4,000 to ₹8,000 per node, and the pH probe is the single largest item. These are planning estimates. The final bill of materials should be taken from actual invoices.

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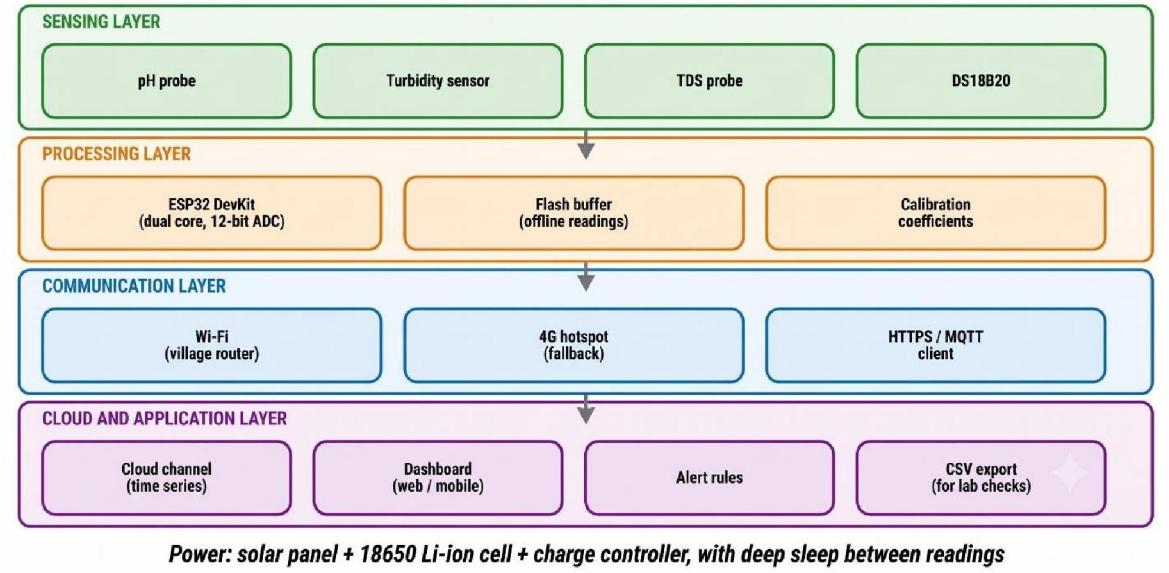


Fig. 2. Layered hardware architecture of the proposed node.

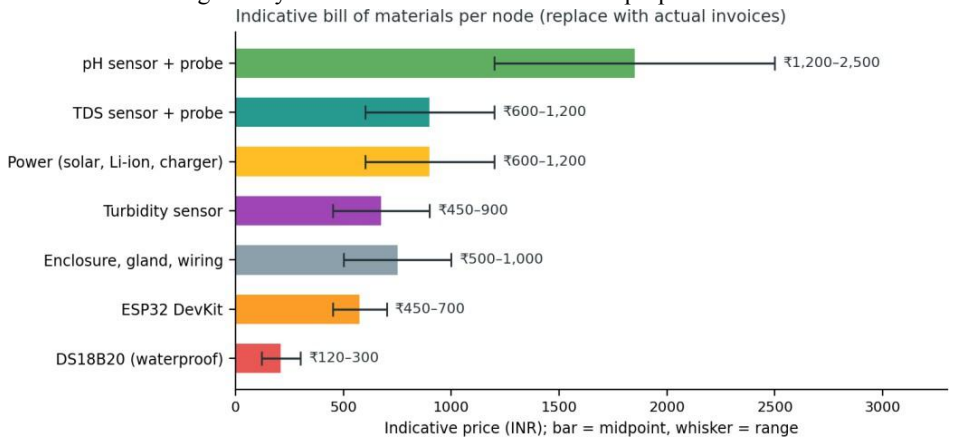


Fig. 3. Indicative cost breakdown of one monitoring node (planning estimates, not quotations).

4.3 Sensor Placement

The electronics sit above the water line inside the enclosure, and only the probes go into the water. The pH and TDS probes hang at least 5 cm apart, because probes placed close together are known to disturb each other's readings. For the same reason the TDS probe is powered only while it is being read. The DS18B20 sits between them so it reports the temperature the other two probes actually see.

Turbidity is measured in a small side cell shaded from sunlight, because ambient light corrupts an optical reading. Every probe tip stays fully submerged and clear of the container wall.

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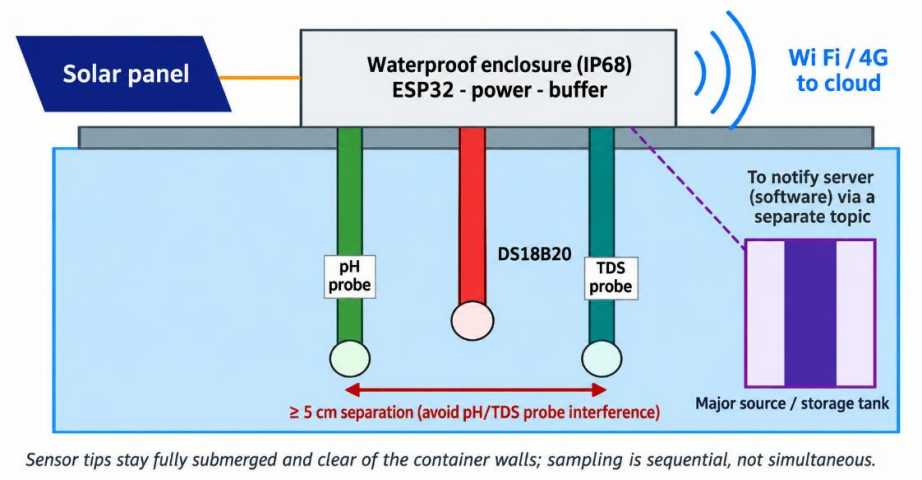


Fig. 4. Proposed sensor placement arrangement (cross-section).

4.4 Circuit Connection and Data Acquisition

The three analog sensors go to ADC1 pins on the ESP32. This is deliberate: the ADC2 channels cannot be used while Wi-Fi is active. Several sensor modules output up to 5 V, which would damage a 3.3 V input, so a resistor divider sits between each such module and its pin. The DS18B20 uses the digital 1-Wire bus with a 4.7 kΩ pull-up. Table III gives the proposed pin map. Pin numbers should be checked against the exact board used.

Table III: Proposed ESP32 Pin Assignment - 4

Sensor	Signal	ESP32 Pin	Interface Note
pH module	Analog voltage	GPIO34	ADC1; resistor divider if module output exceeds 3.3 V
Turbidity module	Analog voltage	GPIO35	ADC1; resistor divider (output can reach about 4.5 V)
TDS module	Analog voltage	GPIO32	ADC1; supply switched through GPIO25
DS18B20	Digital (1-Wire)	GPIO4	4.7 kΩ pull-up to 3.3 V

At each measurement cycle the node wakes from deep sleep, warms the sensors, and reads them one at a time. It then calibrates and classifies the readings, uploads them, and goes back to sleep until the next interval.

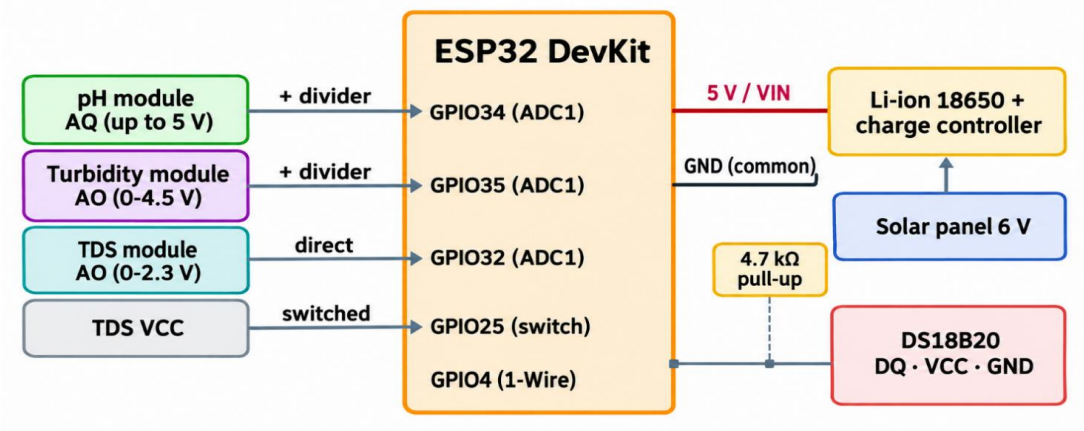


Fig. 5. Circuit connection and sensor interfacing architecture.

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4.5 System Data Flow

Figure 6 traces a reading from the water to the dashboard. The raw ADC values are averaged, converted with the stored calibration coefficients, and checked against the limits before upload. If the link is down, the record is kept in flash with its timestamp and sent later.

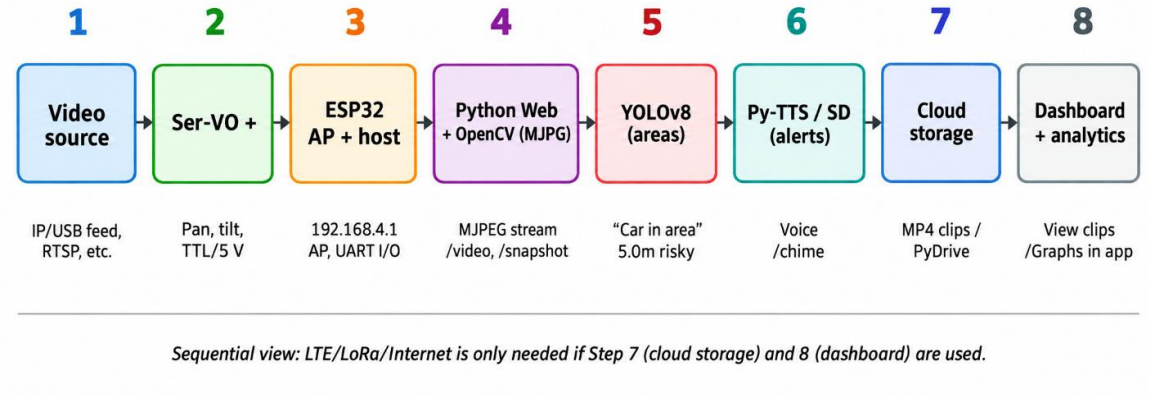


Fig. 6. System data-flow pipeline from water sensing to IoT visualization.

4.6 Rural Deployment Scenario

Figure 7 shows how we expect the node to be used. It sits at a community tank or well, connects to a local router or a phone hotspot, and reports to a cloud dashboard that a villager, the Gram Panchayat, or a health or water officer can open. The node flags problems. A periodic laboratory test remains the way to confirm them, and the only way to check for microbial and many chemical contaminants.

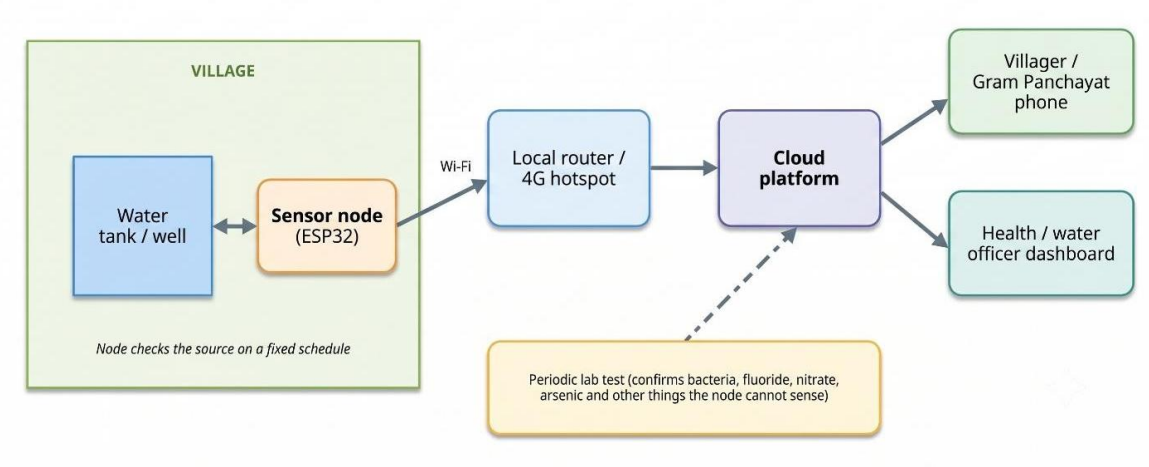


Fig. 7. Proposed rural deployment scenario.

V. METHODOLOGY

5.1 Data Collection Protocol

Data collection has three stages. The first is bench testing with controlled samples: tap water, tap water with a measured amount of fine soil (for turbidity), with dissolved salt (for TDS), and with small amounts of dilute acid or baking soda (for pH). This gives known changes in one parameter at a time. The second stage compares the node with a calibrated handheld meter and with an accredited laboratory on shared samples. The third is a field pilot at one or more real village sources.

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In the field, the node records every 15 minutes by default. Each record carries a timestamp, the four readings, battery voltage, and the status code. We also note the source type, recent rainfall, and any maintenance done. Test samples are never for drinking, and anyone handling buffers or standards follows basic laboratory hygiene.

5.2 Sensor Calibration

Low-cost sensors are only as good as their calibration, so this step gets its own procedure (Figure 8). The pH probe uses three buffers at 4.01, 7.00, and 10.01, following Shete et al. [3]. The TDS channel is scaled against a conductivity standard, with temperature compensation:

$$EC_{25} = EC / [1 + 0.02 (T - 25)], \quad TDS \approx k \times EC_{25}$$

Here T is the water temperature in °C and k is a conversion factor, commonly taken as 0.5 to 0.7 depending on the ionic composition. We start at 0.5 and adjust it against laboratory TDS. The turbidity sensor is calibrated with formazin standards, and its curve is fitted piecewise because its voltage falls as turbidity rises and the relationship is not linear across the range. Temperature is checked against a reference thermometer.

Table IV: Calibration References and Method - 4

Parameter	Reference	Method	Recalibration
pH	Buffers at 4.01, 7.00, 10.01	Three-point fit with temperature noted	Before deployment; then monthly during the pilot
TDS / EC	1413 µS/cm conductivity standard	Scale factor plus temperature compensation	Monthly; after probe cleaning
Turbidity	Formazin standards, 0 to 50 NTU	Piecewise curve of voltage against NTU	Monthly; if the window is fouled
Temperature	Reference thermometer	Offset correction	At setup

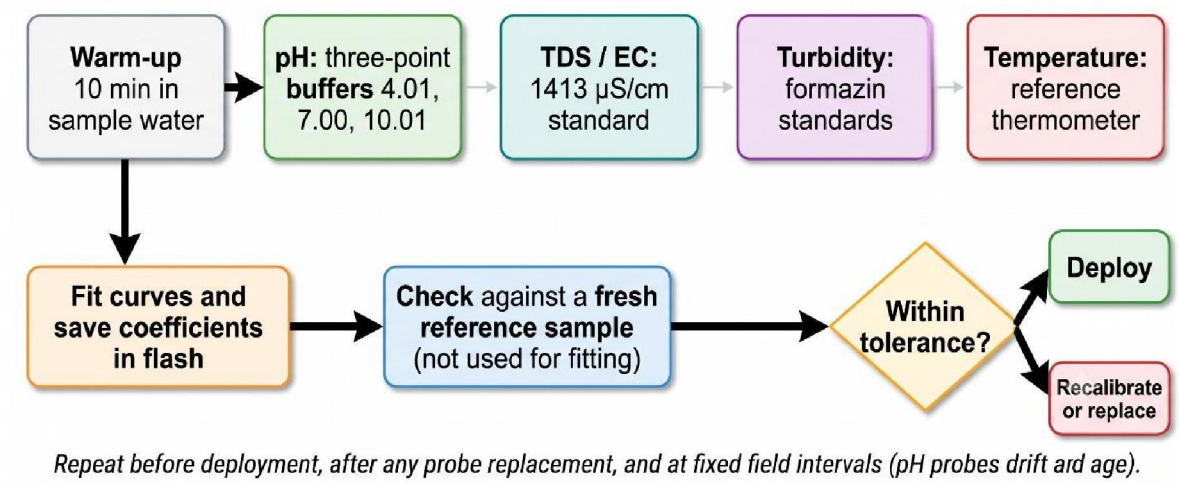


Fig. 8. Sensor calibration workflow.

5.3 Preprocessing

The ESP32's built-in ADC is noisy and bends away from linear near the ends of its range, so raw counts are not trusted directly. Each channel goes through the following steps.

- Sensors warm up for a short period in the sample before reading.
- Ten samples are taken per channel at about 100 ms spacing, and the median is used.
- Samples far from the median (by a median-absolute-deviation test) are discarded as outliers.

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- Range checks reject impossible values, for example a pH outside 0 to 14 or a disconnected probe.
- TDS is temperature-compensated using the DS18B20 reading.
- Calibration coefficients are applied, and the record is timestamped from network time.

Readings that fail the range check are flagged as sensor faults and are not classified. A dead probe should never look like clean water.

5.4 Water-Quality Assessment

The node compares each calibrated reading with the limits in IS 10500:2012 [4]. The standard gives an acceptable limit and, for some parameters, a permissible limit that applies when no alternative source is available. The WHO guidelines [5] treat pH and TDS mainly as acceptability issues (taste and corrosion) rather than direct health hazards and ask for low turbidity so that disinfection works. Because the Indian standard is the legal reference for our users, the rules follow BIS. Table V and Figure 9 show the limits.

Table V: Drinking-Water Limits Used for Status Classification - 4

Parameter	Acceptable	Permissible (no alternative source)	Status rule
pH	6.5 to 8.5	No relaxation	Inside 6.5 to 8.5: Safe; outside: Unsafe
Turbidity	1 NTU	5 NTU	Up to 1: Safe; above 1 to 5: Caution; above 5: Unsafe
TDS	500 mg/L	2,000 mg/L	Up to 500: Safe; above 500 to 2,000: Caution; above 2,000: Unsafe
Temperature	No limit	No limit	Logged only

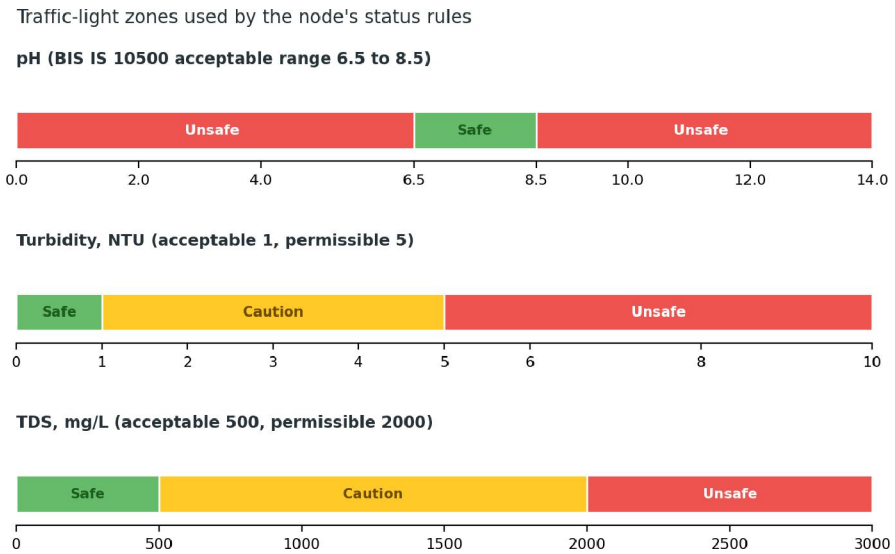


Fig. 9. Traffic-light zones for pH, turbidity, and TDS based on BIS limits.

The overall status is the worst of the three individual statuses. Figure 10 shows the logic, including the fault branch.

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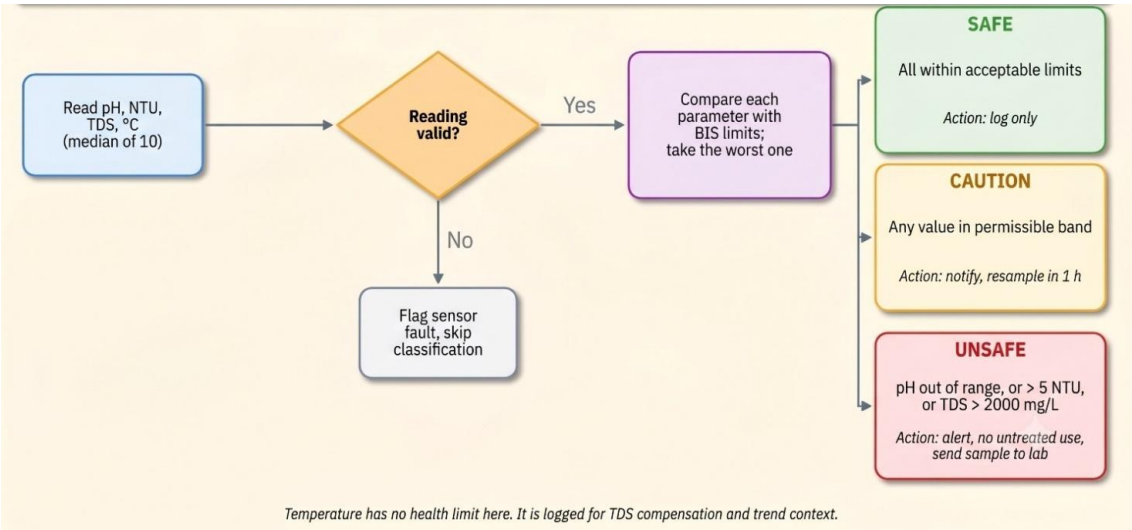


Fig. 10. Status decision logic executed on the node.

For trend charts, the dashboard can also show a weighted-arithmetic water quality index. It is a secondary indicator only, and the traffic-light status remains the primary output:

$$WQI = \Sigma(q_i\, W_i) / \Sigma W_i, \qquad q_i = 100\,(V_i - V_{i,ideal}) / (S_i - V_{i,ideal}), \qquad W_i = K / S_i$$

V_i is the measured value, S_i the standard limit, $V_{i,ideal}$ is 7 for pH and 0 for the other parameters, and K is a normalising constant. Commonly used bands run from 0 to 25 (excellent) through 76 to 100 (very poor), with values above 100 considered unsuitable.

5.5 IoT Data Transmission and Dashboard

The node uploads over HTTPS or MQTT to a cloud channel. A free-tier channel with eight fields is enough: pH, turbidity, TDS, temperature, status code, battery voltage, and WQI. Credentials stay out of the published source code. The node reconnects automatically after a Wi-Fi drop, and a watchdog timer restarts it if the firmware hangs.

Alerts fire on a change of status, not on every reading, so a source that sits at Caution for a day produces one notice rather than ninety-six. Figure 11 shows the intended dashboard layout. The values in it are placeholders.

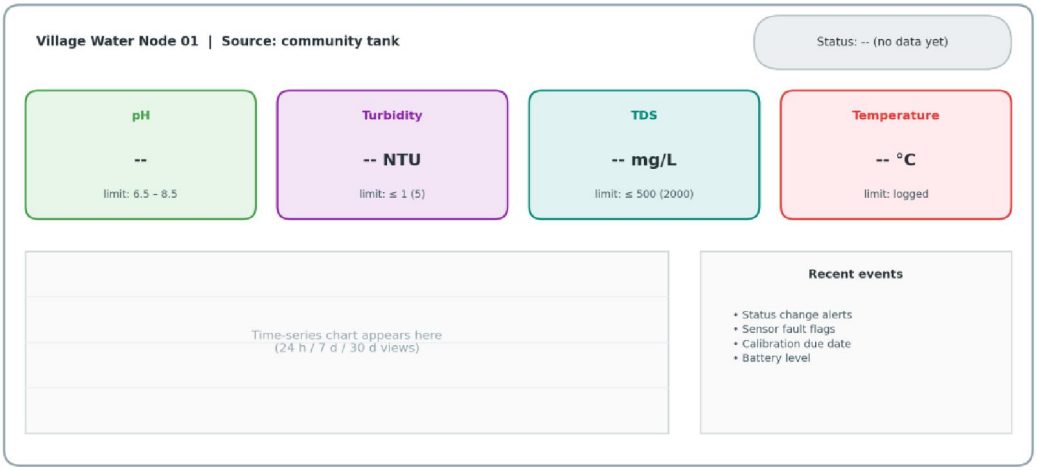


Fig. 11. Conceptual dashboard layout (placeholder values, not measured data).

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5.6 Validation Methodology

Validation compares node readings with reference readings taken on the same sample at the same time. For each parameter we will report the mean absolute error, root-mean-square error, bias, coefficient of determination, and the share of readings inside the tolerance stated in Section 6.3:

$$\text{MAE} = (1/n)\ \Sigma\ |x_i - r_i|,\quad \text{RMSE} = \sqrt{[(1/n)\ \Sigma\ (x_i - r_i)^2]}$$

Here x_i is the node reading and r_i the reference. Repeatability comes from repeated readings of one stable sample, summarised by standard deviation. Drift is tracked by re-measuring reference samples across the pilot. For status, we will compute what the reference values would have classified and compare it with what the node reported. The count that matters most is how often an Unsafe sample was called Safe. System-level checks include upload success rate, uptime, and battery autonomy with and without sunlight.

5.7 Implementation Plan

We propose a 16-week schedule (Figure 12). Calibration overlaps with firmware work, and bench comparison is finished before the field pilot begins.

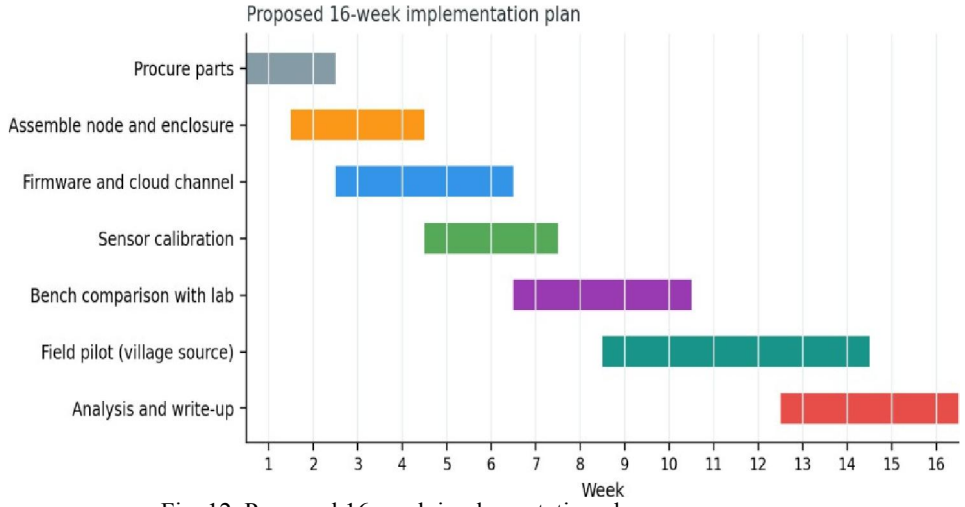


Fig. 12. Proposed 16-week implementation plan.

VI. RESULTS AND DISCUSSION

At this stage the paper reports a design, not a tested system, and we keep those two things separate. The sections below describe what the design provides. Numerical performance is left blank until real data exist.

6.1 Hardware-Level Result

The design fits four sensors, a microcontroller with Wi-Fi, solar charging, and an enclosure into a single node with an estimated parts cost of about ₹4,000 to ₹8,000 (Figure 3). Every part is a common off-the-shelf item, so the node can be assembled and repaired without special tools. Analog inputs are limited to ADC1, and TDS power is switched, which addresses two known ESP32 and probe-interference issues before they appear on the bench.

6.2 Software and Processing Result

The firmware design turns noisy analog readings into calibrated, labelled records. Median filtering and outlier rejection reduce single-sample spikes. Range checks separate sensor faults from real water changes. Flash buffering keeps records during outages. The rule-based status gives a result without needing training data, which is why we chose it over a learned classifier for a first version.

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6.3 Performance Evaluation

The tolerances below are proposed acceptance targets, chosen as reasonable goals for low-cost sensors. They are not results. If the measured errors exceed them, the calibration routine or the sensor choice needs to change.

Table VI: Proposed Performance Evaluation of Sensor Readings - 4

Parameter	Proposed tolerance	MAE	RMSE	R^2	Readings within tolerance (%)
pH	±0.2 pH	To be Evaluated	To be evaluated	To be evaluated	To be evaluated
Turbidity	±10% or ±0.5 NTU	To be Evaluated	To be evaluated	To be evaluated	To be evaluated
TDS	±10%	To be Evaluated	To be evaluated	To be evaluated	To be evaluated
Temperature	±0.5 °C	To be Evaluated	To be evaluated	To be evaluated	To be evaluated

Table VII: Proposed Evaluation of Status Classification - 4

Metric	Definition	Result
Overall agreement with reference-derived status	Matching samples / all samples	To be evaluated
Unsafe samples reported as Safe	Missed alarms / Unsafe samples	To be evaluated
Safe samples reported as Unsafe	False alarms / Safe samples	To be evaluated
Upload success rate and uptime	Delivered records / expected records	To be evaluated

Figure 13 is the plot template we will fill in. Points close to the diagonal and inside the shaded band would mean the node agrees with the reference.

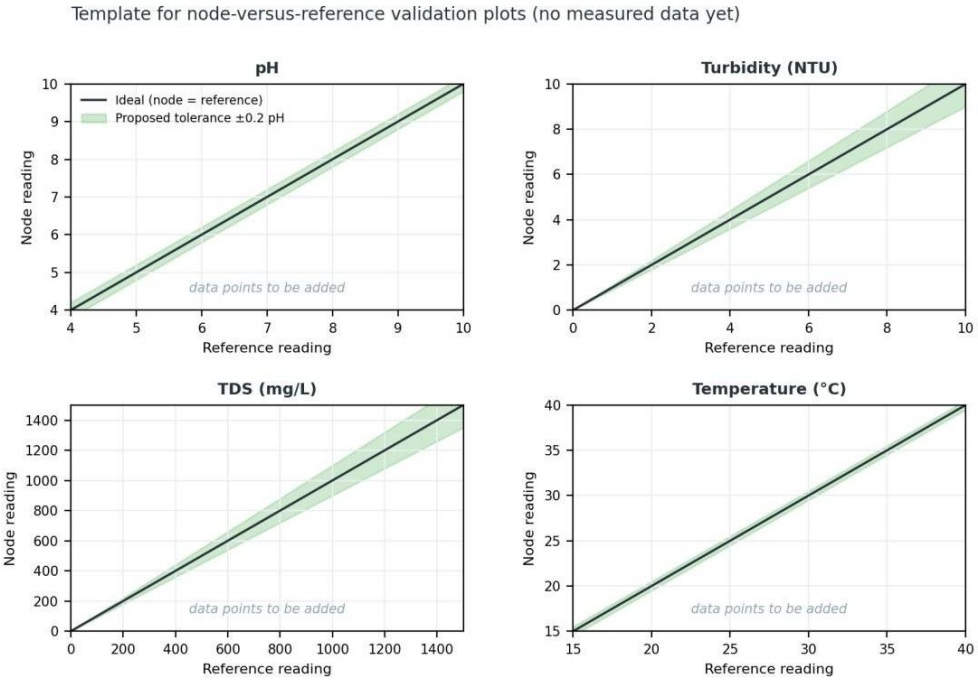


Fig. 13. Template for node-versus-reference validation plots (no measured data yet).

6.4 Discussion

Three design choices deserve comment. The first is Wi-Fi or 4G in place of LoRaWAN. Jabbar et al. [1] show that LoRaWAN works well for rural water monitoring, and it is the better option where no cellular or Wi-Fi coverage exists.

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Where a router or hotspot is available, though, our approach removes the gateway and lowers setup effort. Combining the two is a sensible extension.

The second is the reliance on hobby-grade sensors. This is where the design is most exposed. pH probes drift and age, turbidity windows foul, and TDS ignores which ions are present. The calibration schedule in Table IV is meant to manage this, but only field data will show how often recalibration is really needed. We expect this to be the main practical finding of the pilot.

The third is rule-based status in place of machine learning. Alipio [2], [6] shows that ensemble classifiers can perform well. Our rules cannot learn a local pattern, but they are transparent, need no training data, and trace directly to a published standard, so a village officer can see why a source was flagged. A learned model could be added once enough labelled data has been collected.

VII. LIMITATIONS

This work has clear limits. The main one is that no experimental data are presented. Every accuracy statement is a plan. The four measured parameters cannot detect bacteria, viruses, fluoride, arsenic, nitrate, pesticides, or heavy metals. A source can pass every rule on the node and still be unsafe to drink. For that reason the node must be described as a screening tool, and periodic laboratory tests stay necessary.

Low-cost sensors drift, foul, and age, and the calibration workload could be a burden for a village. Solar and battery performance in monsoon conditions has not been tested. Wi-Fi or 4G coverage is assumed, and it may not exist at every source. Finally, the pilot will cover only a few sources and a limited season, so the results will not represent every kind of rural water.

VIII. FUTURE SCOPE

Several extensions follow naturally. A LoRa or NB-IoT option would serve sites with no cellular coverage. Further sensors, such as electrical conductivity with a dedicated probe, oxidation-reduction potential, or an ion-selective probe for nitrate, would widen what the node can screen. With enough labelled data, a lightweight classifier or anomaly detector could complement the fixed rules, in the way Alipio [2] describes.

On the practical side, a self-cleaning turbidity window, automatic calibration reminders, and an offline local display would help in real villages. Multi-node deployments could map quality across a whole gram panchayat. Long-term, the design could be checked against a certified reference method with support from a water-testing laboratory.

IX. CONCLUSION

This paper presented the design of a low-cost IoT node for monitoring rural water sources. It measures pH, turbidity, TDS, and temperature with an ESP32, calibrates and filters the readings, labels each source Safe, Caution, or Unsafe using BIS limits, and reports remotely to a cloud dashboard. It can run on solar power and keep records through network outages.

The main contribution is a complete, documented design: hardware, wiring, calibration, processing, decision rules, and a validation plan, at an estimated parts cost of about ₹4,000 to

₹8,000. Performance is not yet measured, and the node cannot detect microbial or many chemical contaminants, so it should be treated as a screening prototype and not as a substitute for certified testing. The next steps are to build the node, calibrate it, compare it with laboratory results, and run the field pilot.

Author Contribution

The authors contributed to the work according to their project responsibilities.

Harsh Tambatkar: Designed the water-quality assessment and IoT layer, implemented the Safe/Caution/Unsafe rules based on IS 10500:2012, set up cloud transmission and the alert dashboard, and defined the water quality index for trend charts.

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Nadeem Shaikh: Developed the firmware and data-processing pipeline, designed the sensor calibration procedure, and implemented median filtering, outlier rejection, range checks, and flash buffering for offline records.
Kshitij Pinagale: Conceptualized the overall system, designed the hardware architecture (ESP32, four sensors, ADC1 pin map, 3.3 V level shifting), planned sensor placement, and prepared the node cost estimate.
Abhishek Pandit: Conducted the literature review and research-gap analysis, compiled the standards references (IS 10500:2012, WHO), and designed the validation methodology (MAE, RMSE, R^2) and the 16-week implementation plan.
Chinmay Deshpande: Prepared the figures, diagrams, and graphical abstract, wrote and formatted the manuscript, and coordinated the team and final review.

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Conflict of Interest
The authors declare no conflict of interest.

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