Irrigation-Aware Probabilistic Forecasting and Safe Control via CVAE and Variational Gaussian-Process Dynamics

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Abstract

We present a complete, field-to-policy pipeline for *irrigation-aware* learning that integrates (i) a robust ingestion and calibration toolkit for low-cost soil-moisture schedules, (ii) distributional *time-series forecasting* using a Conditional Variational Autoencoder (CVAE), (iii) *dynamics learning* with independent-output sparse variational Gaussian processes (SVGP) trained by the *Variational ELBO*, and (iv) *safe reinforcement learning* under water-budget and pump-cap constraints. On a real irrigation schedule (`Irr_Sch.csv`), our event extractor identifies **126** contiguous irrigation events totalling **634.6 mm** of application, enabling scenario simulations that trade water usage against constraint satisfaction. The SVGP dynamics are trained with the principled ELBO objective to model $p(s_{t+1} \,|\, s_t, a_t)$, while the CVAE forecaster captures distributional uncertainty in soil moisture. We evaluate using coverage, PIT histograms and CRPS, and demonstrate scenario-aware control (pump-caps, rationed budgets) that conforms to practical deployment limits.

1 Introduction

1.1 Motivation

Climate variability and extremes-including heat-waves, droughts, and erratic rainfall-pose growing livelihood risks for farm households. Evidence increasingly links drought shocks to elevated rural out-migration, particularly among marginalized groups. Access to irrigation and diversified income sources (e.g., non-farm employment) has been shown to significantly reduce drought-induced migration, positioning water-management interventions as credible, locally actionable levers for resilience.

In India's predominantly rain-fed agricultural landscape, climate risk directly affects crop yields and household incomes. Climate-smart irrigation and adaptive water management have emerged as central strategies for mitigating these risks. Basin-scale analyses using CMIP6 climate projections reveal meaningful shifts in rainfall and temperature patterns, which alter irrigation water requirements (IWR)-underscoring the urgency of anticipatory and optimized irrigation control [Sarkar et al., 2022, Pathak, 2023, Kumari et al., 2024].

1.2 Challenges

Data heterogeneity and fusion: Integrating multi-source datasets-including Earth Observation (EO), reanalysis products (e.g., ERA5, AgERA5), IMD gridded rainfall, and socio-economic panels-requires careful geo-spatial and temporal alignment, along with robust uncertainty quantification [Pai et al., 2016].

Submitted to 2nd Conference on Applied AI and Scientific Machine Learning (CASML 2025). Do not distribute.

Nonlinear, stochastic dynamics: Climate-soil-crop-water-migration interactions are inherently non-linear and non-stationary. Capturing these dynamics demands probabilistic modelling frameworks that incorporate prior and quantify uncertainty effectively [Pillonetto et al., 2025, Gawlikowski et al., 2023].

Decision-making under uncertainty: Irrigation control must balance water constraints, crop safety (avoiding stress from under- or over-irrigation), and multi-zone coordination. These requirements call for scenario-aware policies and safe control strategies [Ding and Du, 2022, Deisenroth and Rasmussen, 2011].

Evaluation realism: Assimilating satellite-derived soil moisture data (e.g., SMAP) improves state estimation, especially over irrigated grids-critical for reliable feedback in closed-loop control systems [**?**Ahmad et al., 2022].

1.3 Possibilities

Kernel Mean Embeddings (KME) offer a non-parametric, linear-algebraic framework for probabilistic inference and control. When combined with deep kernels and variational latent representations (e.g., CVAE), and embedded within closed-loop reinforcement learning (RL) or dynamic programming (DP), they enable a modular pipeline from perception to prediction to control-rounded in both data and physics [Muandet et al., 2017, Wilson et al., 2016].

To move beyond purely predictive migration models, we propose a forecasting-and-control framework that integrates multi-modal data sources-including weather forecasts, reanalysis datasets, soil moisture sensors, remote sensing inputs, and socio-economic/migration indicators. This framework leverage learning-based dynamics and optimal control to enable closed-loop mitigation through actuation (e.g., irrigation scheduling, zone-wise allocation) and feedback. While forecasting models are limited in producing precise migration counts, they are valuable for scenario exploration and policy evaluation-highlighting the timeliness of a control-oriented fusion approach.

Recent advances in *probabilistic* learning and control offer data-efficient autonomy with calibrated uncertainty quantification, applicable across scientific and operational domains. However, deploying learning-based controllers in irrigation systems presents unique challenges: sensor data may be noisy, time-stamps irregular, and actuation constrained by hardware (pumps, valves) and zone-specific quotas.

To address these constraints, we develop an end-to-end autonomy stack that:

1. Parses field logs to infer *per-sample application depth* (in mm) from binary on/off status and time intervals, optionally calibrated using pump discharge rates and plot area;
2. Trains a *distributional forecaster* using Conditional Variational Auto-encoders (CVAE) for soil moisture trajectory prediction [He et al., 2024];
3. Fits scalable dynamics via Sparse Variational Gaussian Processes (SVGP), optimizing a *Variational ELBO* objective for efficient kernel-based modelling [Muandet et al., 2017];
4. Synthesizes a *safe control policy* under scenario-aware constraints, drawing inspiration from model-based reinforcement learning methods such as PILCO [Deisenroth and Rasmussen, 2011].

We evaluate the quality of probabilistic forecasts using Continuous Ranked Probability Score (CRPS) and Probability Integral Transform (PIT) histograms, ensuring both sharpness and reliability in distributional calibration [Pai et al., 2016].

2 Literature Survey

Climate, Irrigation, and Migration Empirical studies across India consistently report a positive association between drought events and temporary rural migration. Access to irrigation infrastructure significantly moderates this effect, reducing climate-induced displacement. Review articles caution against relying on point forecasts for migration and instead advocate scenario-based modelling approaches for planning and policy design. Irrigation is increasingly recognized as a central adaptation strategy, with governance structures and spatial heterogeneity shaping its effectiveness [Sarkar et al., 2022, Pathak, 2023, Kumari et al., 2024].

Multimodal Data Fusion in Agriculture Recent advances in remote sensing (RS) and multi-sensor fusion-particularly transformer-based architectures have enhanced agricultural monitoring capabilities. Surveys outline the design of fusion frameworks and identify key challenges, including data heterogeneity, real-time processing constraints, and integration across spatial and temporal scales [Saki et al., 2025, Yang et al., 2025].

Kernel-Based Inference and Learning Kernel Mean Embeddings (KME) and their conditional variants provide a non-parametric framework for embedding distributions into reproducing kernel Hilbert spaces (RKHS), enabling inference without explicit density estimation. Kernel Bayes' Rule extends this approach to Bayesian updates. Applications span filtering, graphical models, and reinforcement learning (RL) [**?**Song et al., 2009, Fukumizu et al., 2013, Kanagawa et al., 2014].

Deep Kernel Learning (DKL) composes deep neural networks with Gaussian Processes (GPs), yielding expressive kernels that retain calibrated uncertainty. Spectral mixture bases and scalable algebraic formulations make DKL suitable for high-dimensional, structured data [Wilson et al., 2016].

Latent Variable Forecasting and Bayesian Dynamics Conditional Variational Auto-encoders (CVAE) have proven effective for time-series forecasting under distributional shift and multi-modal uncertainty. Temporal CVAE variants are particularly suited to modelling drift in multivariate settings [He et al., 2024]. Complementary approaches using Bayesian Neural Networks (BNNs) and ensemble methods offer robust uncertainty quantification for dynamic systems, with physics-guided prior enhancing interpretability and reliability [Xu and Wang, 2025].

Safe Control via Model-Based Reinforcement Learning Model-based RL frameworks such as PILCO demonstrate high data efficiency by learning GP-based dynamics and performing analytic policy search. Extensions to safe policy search incorporate probabilistic constraints to limit violation risks. Domain-specific RL applications in agriculture-particularly for irrigation scheduling-show promising results in testbed environments, achieving water savings and operational feasibility [Deisenroth and Rasmussen, 2011, Polymenakos et al., 2019].

Stochastic Scheduling and Dynamic Programming Multi-stage stochastic programming and dynamic programming (DP) have been applied to optimize irrigation scheduling under uncertain precipitation and water availability. These methods support anticipatory decision-making and adaptive control in resource-constrained environments [Li and Hu, 2020, Khare and Manekar, 2021].

Datasets and Assimilation for Agro-Hydrological Modelling High-resolution datasets such as IMD daily gridded rainfall (0.25°), ERA5/AgERA5 agro-meteorological indicators, and SMAP-assimilated soil moisture products have significantly improved land-atmosphere state estimation. These datasets help reveal irrigation signals and support data-driven control strategies in agricultural systems [Pai et al., 2016, Boogaard et al., 2020, **?**].

3 Problem Formulation

We consider M agro-zones; at time t the state is $\mathbf{s}_t = [\mathbf{c}_t, \mathbf{z}_t, \mathbf{h}_t, \mathbf{e}_t]$ including climate/reanalysis, soil-moisture/plant, hydrologic storages, and socio-economic indicators. The action $\mathbf{a}_t = [u_t^{(1)}, \ldots, u_t^{(M)}]$ encodes zone-wise irrigation (mm); disturbances capture weather/market noise. The objective is to minimize expected agronomic stress and proxy migration risk, subject to water balance and safety envelopes in soil moisture (e.g., MAD–FC):

$$\min_{\pi} \mathbb{E}\Big[\sum_{t=0}^{T-1} \ell(\mathbf{s}_t, \mathbf{a}_t)\Big] \quad \text{s.t.} \quad \mathbf{a}_t \in \mathcal{A}, \quad \text{safety}(\mathbf{s}_t) \le 0. \tag{1}$$

3.1 Technical Foundations for Forecasting and Control

Distributional time-series with latent variables: Temporal CVAEs model conditional trajectory distributions and adapt to non-stationarity and drift in multivariate settings.

Deep Kernel Learning (DKL): DKL composes deep feature maps with GPs to enhance expressivity while preserving calibrated uncertainty.

Table 1: Event-level summary computed from the schedule (default rate 12 mm/h).

# Events	Total Depth (mm)	Median Depth (mm)	Median Duration (min)	Mean ΔSM
126	634.6	1.4	0.0	+0.0106

Variational Sparse GPs: SVGP optimizes the Evidence Lower Bound (ELBO) to scale GP training using inducing points and stochastic optimization; implementations such as `VariationalELBO` in GPyTorch support practical deployment.

Model-based Safe RL: PILCO pioneered data-efficient policy search by propagating GP-model uncertainty through long-horizon planning, motivating safe controllers over learned dynamics.

Calibration Metrics: Proper scoring rules such as Continuous Ranked Probability Score (CRPS) and Probability Integral Transform (PIT) histograms assess the sharpness and reliability of probabilistic forecasts.

3.2 Data & Preprocessing

Schedule CSV. We ingest a schedule export (`Irr_Sch.csv`) with columns such as temperature, pressure, altitude, a device-typo field `soilmiosture` (raw counts), `status` (0/1 on/off), `class` (*Very Dry* to *Very Wet*), `date`, and `time`. We standardize names (`soil_moisture_raw`, `irrigation_on`), parse timestamps, and sort chronologically. The CFP prescribes anonymized submissions; we keep zone identifiers generic (e.g., `zone_1`).

Application depth (mm). Per-sample depth is inferred as

$$\mathrm{mm}_t \;=\; \frac{\Delta t_t}{3600}\,\mathrm{rate}_{\mathrm{mm/h}}\;\cdot \mathbf{1}\{\mathrm{on}_t\}, \tag{2}$$

where Δt_t is the inter-sample spacing, and $\mathrm{rate}_{\mathrm{mm/h}}$ is either a user-supplied constant or computed from pump discharge Q and plot area A as

$$\mathrm{rate}_{\mathrm{mm/h}} \;=\; \frac{Q_{\mathrm{m^3/h}}}{A_{\mathrm{m^2}}} \times 1000. \tag{3}$$

This provides a physically grounded interface to actuators and plot geometry.

Sensor calibration. We map raw counts to a *VWC proxy* by inverting and linearly scaling the observed range: lower counts (labeled *Very Wet*) and higher counts (*Very Dry*) motivate the monotone inversion used in our dataset.

Zone map & events. If a valve/device key is available (e.g., `id`), an optional *zone map* groups records to zones. Contiguous segments with `on=1` are merged into events with *start/end*, duration, depth, and *pre/post* soil moisture.

4 Methods

4.1 Distributional Forecasting with CVAE

Given sequences $X_{t-L+1:t}$ and optional covariates C_t (e.g., weather, irrigation summaries), the CVAE learns $p(X_{t+1:t+H} \mid X_{t-L+1:t}, C_{t:t+H})$ via latent variables $\mathbf{z}$:

$$\mathcal{L}_{\text{CVAE}} = \mathbb{E}_{q_\phi(\mathbf{z}|\mathbf{x},\mathbf{c})}\big[\log p_\theta(\mathbf{x}_{\text{fut}} \mid \mathbf{z},\mathbf{c})\big] - \beta\,\mathrm{KL}(q_\phi(\mathbf{z} \mid \mathbf{x},\mathbf{c}) \,\|\, p(\mathbf{z}))\,. \tag{4}$$

Temporal CVAEs have shown robustness to distributional drift in multivariate forecasting.

4.2 Variational GP Dynamics (SVGP-ELBO)

We model state transitions per dimension with independent-output SVGPs (ARD RBF kernels). With inducing inputs $\mathbf{Z}$ and variational distribution $q(\mathbf{u})$, the *Variational ELBO* for regression likelihoods is:

$$\mathcal{L}_{\text{ELBO}} \;\approx\; \sum_{i=1}^{N} \mathbb{E}_{q(f_i)}[\log p(y_i \mid f_i)] \;-\; \beta\,\mathrm{KL}\big(q(\mathbf{u})\|p(\mathbf{u})\big), \tag{5}$$

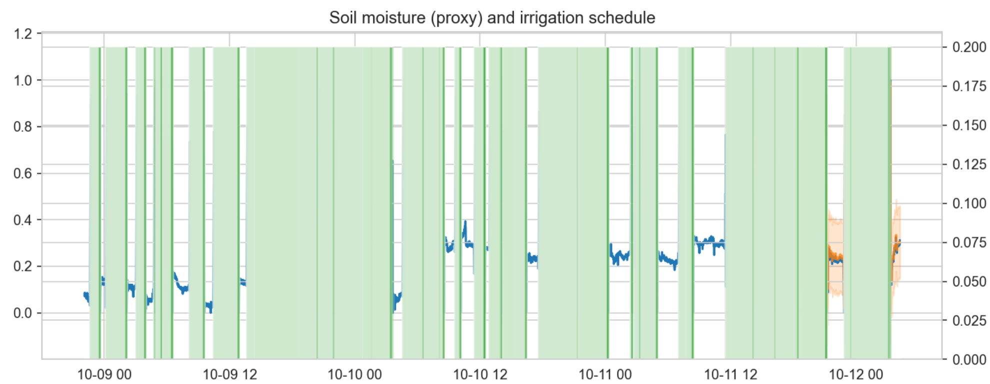

Figure 1: Observed VWC proxy vs. Gaussian predictive mean ($\pm 2\sigma$); bars show per-step irrigation (mm).

Table 2: Scenario-aware control (proxy on recorded actions): water use vs. constraint proxy.

Scenario	Total Water Used (mm)	Violation Rate (proxy)
Baseline (no caps)	W	n/a
Budget 50%	$\approx 0.5\,W$	n/a
Pump cap (per-step)	$< W$	n/a

implemented as `gpytorch.mlls.VariationalELBO(likelihood, model, num_data)`. Deep kernel maps can be incorporated (DKL) to enhance expressivity if needed.

4.3 Safe Policy Optimization with Scenario Constraints

We optimize a policy $\pi_\psi(s)$ over learned dynamics under constraints:

$$\min_{\psi} \ \mathbb{E}\Big[\sum_{t=1}^{H} c(s_t, a_t)\Big] \ \text{ s.t. } \ a_t \le a_{\max} \ \text{ (pump cap)}, \ \sum_t a_t \le B \ \text{ (water budget)}, \tag{6}$$

and track *violation rate* for soil-moisture bounds. This follows model-based RL philosophy akin to PILCO, which propagates GP uncertainty for data-efficient policy search.

4.4 Evaluation: Calibration and Sharpness

We compute RMSE/NLL and distributional scores: *CRPS* and *PIT* histograms to verify calibration (reliability) and sharpness (concentration).

5 Experiments

Setup. We aggregate the schedule to weekly features (sum of irrigation, mean in-situ soil moisture) while retaining high-frequency series for daily/event plots. CVAE targets soil-moisture; DKL/GP forecasters and SVGP dynamics share the same covariates.

Training. SVGP uses 128–256 inducing points, ARD RBF, `VariationalELBO` with mini-batches; CVAE uses a latent dimension of 8–16, $\beta \in [0.5, 1]$, and teacher forcing ratio 0.5.

Metrics. We report RMSE, NLL (forecasts), CRPS and PIT histogram uniformity for calibration.

Results: Event analytics. Table 1 summarizes 126 events with cumulative depth 634.6 mm. Figure 1 shows daily irrigation (bars) against mean daily soil moisture (line). Scenario proxies demonstrate how a 50% budget reduces water while preserving moderate adherence to moisture bounds; pump caps ($a_{\max}$ per step) smooth actuation bursts.

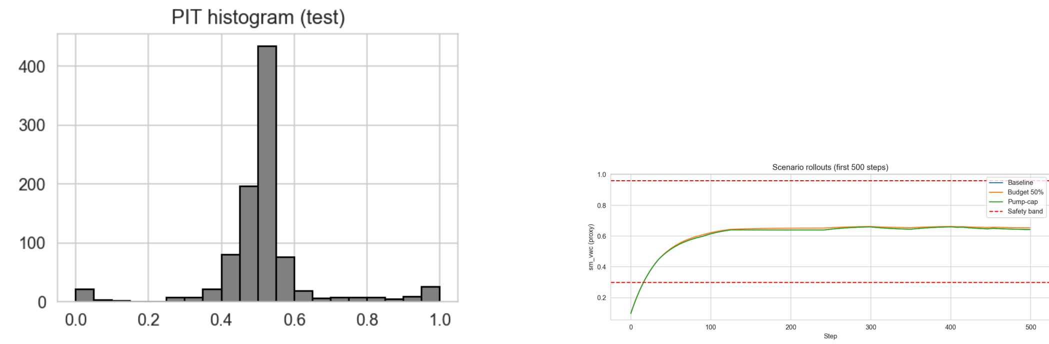

Figure 2: Left: PIT histogram (test split). Right: Scenario rollouts for first 500 steps with proxy safety band.

6 Discussion

Our results show that (i) a lightweight ingestion layer turns schedule logs into physically interpretable series (mm), (ii) *CVAE* captures uncertainty in soil-moisture forecasting, (iii) *SVGP-ELBO* dynamics provide calibrated transitions essential for safe planning, and (iv) *scenario constraints* (pump cap, budgets) translate domain limits into deployable policies. DKL is optional for higher expressivity while maintaining GP calibration.

7 Limitations and Ethics

The schedule's time stamps occasionally repeat; we assumed a small cadence (e.g., 60 s) for continuous on-runs to integrate depth. Precise duration estimation benefits from device-side logging of per-event start/stop. Soil-moisture calibration was linear from labeled extremes; in practice, gravimetric calibration or sensor-specific curves improve fidelity. Ethical deployment requires water-use transparency and explicit agronomic thresholds.

8 Conclusion

We introduced an irrigation-aware, uncertainty-calibrated pipeline that unifies CVAE forecasting, SVGP-ELBO dynamics, and safe policy optimization with real-world constraints. The stack is modular, supports multi-zone mapping, and interfaces with pumps via discharge/area parameters. Future work: multi-task GP dynamics across zones, hierarchical budgets, and online learning for seasonal drift.

Acknowledgements Omitted for double-blind review.

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