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AI and Public Policy for Sustainable Natural Resource Governance and Human Health

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ABSTRACT: The use of AI in the field of environmental and health administration is outpacing development of the public policy framework to govern responsible AI use. Public administrations employ AI to make decisions in the face of uncertainty and trade-offs. The same AI tools promise to improve water allocation and protection of forests and surveillance of diseases. As dominant technologies promise to create efficiencies, they also become less traceable. These technologies can be used to embed bias and outpace the regulatory systems. This gap in policy is due to rapid AI adoption and tools in public administration. This research adopts a mixed-methods approach that incorporates a comprehensive scan of applications of AI while envisioning and testing a policy-AI framework that integrates environmental health data streams, Internet of Things, and predictive data analytics to support institutional decision-making. A governance-aware feedback mechanism was created to evaluate an ensemble learning hybrid approach that integrates a gradient boosted decision tree for structured data with a health-risk sequence for a streaming health risk. During the ten iterations of the evaluation, a health risk exposure was reduced by 67 percent, while performance improved to 92 percent for the use of resources and prediction of early warnings resulting in improved performance of 94 percent. Results show that the proposed framework outperformed other frameworks in the literature. The indices of governance for transparency, accountability, fairness, and stakeholder participation all demonstrated improvements over the six-year comparative period. It was determined that if responsible AI safeguards are integrated into the technology pipeline as responsible AI, they bring both positive environmental and public health outcomes. This paper concludes that sustainable improvement within resource governance and public health is achieved by considering algorithmic design in parallel with the design of public policy.

1. INTRODUCTION AND POLICY CONTEXT

The depletion and degradation of natural resources essential to human life will inevitably lead to an increase in public-health problems like waterborne diseases and air pollution. Over the last ten years, governments and international organizations have realized that AI can help them monitor the negative impacts of environmental changes caused by sudden and rapidly growing population and industrial activity (e.g. lack of capacity of traditional systems of monitoring and administration to respond to the situation) [4]. In this context, sustainability is an objective of administration as well as ecology. Lastly, public agencies need to process satellites' and sensors' data and health registry data, among others, at a pace to protect public resources before it is too late [3].

These challenges are twofold. First, human health and natural resource systems are interconnected, but are usually managed by distinct ministries, different data systems, and distinct laws which leads to a fragmented evidence base for each decision maker [9]. Second, the AI systems to fill this gap bring their own governance issues including lack of transparency and uneven data quality, as well as the possibility of automated recommendations that reduce the decision-making discretion of public servants without establishing public accountability [10]. The OECD and UNESCO have given advice on transparency and accountability in AI, for the public good [5,6], and some legal acts such as the EU AI Act and the NIST Framework on AI Risk Management in the USA have adopted these [7,8]. However, there are gaps in our knowledge in natural resource management and environmental health protection from applying these principles to AI in practice.

AI can be used for prediction, optimization, and decision support in this area. Predictive models show future water scarcity, crop stress, deforestation risk and disease outbreaks. Optimization models can be used to distribute scarce resources, such as irrigation water and emergency health-related activities. Decision-support systems provide a unified outlook for administrators who need to reconcile the competing demands of the ecological, economic, and public health systems. The need for this research comes from the field of public policy. The use of AI to achieve sustainable and equitable outcomes is complex and relies on an appropriate governance framework to ensure that AI can just as easily protect resources and improve health as it can facilitate the rapid depletion of resources, particularly within unprotected areas.

This article investigates the following research issue: how artificial intelligence can be designed both algorithmically and structurally with a view to promoting simultaneous improvements in natural resource management and public health within the context of a publicly oriented and accountable policy framework. In this article, I review major applications of AI in the natural-environmental resource and public health domains, and I analyze the public policy and regulatory frameworks in these domains. Additionally, I propose a novel AI-integrated policy framework that includes governance checks within the technical domain. I will assess the framework within the domain of decision support and AI in the public sector. This article covers various domains of AI from applications in environmental health monitoring to AI governance and illustrates its integrated framework, as well as its comparison to other studies and API policy implications.

2. AI FOR SUSTAINABLE NATURAL RESOURCE GOVERNANCE

From monitoring natural resources to implementing the deploy and modulate functions associated with management, artificial intelligence has evolved to play a significant role across water, forests, agriculture, and land use; biodiversity; environmental monitoring; and minerals. Within the water sector, models use artificial intelligence to make predictions around the flow of water within a region, find patterns that indicate leaks in a water distribution network, and create schedules for allocating water based on the demand of the agricultural, industrial, and municipal sectors. Remote-sensing data inputs that include soil moisture and potential evapotranspiration from satellites provide water agencies with the ability to monitor a watershed even with poor ground-based sensor infrastructure. Remote-sensing data provides this ability in regions where growth in population has outpaced the development of hydrological infrastructure described in Günal et. al. [1]. Within forest governance, computer vision models are able to identify illegal logging as well as identify the requirements that start a fire and changes in canopy coverage. The models are better than human observation in identifying these phenomena. Classification models are able to distinguish between multiple causes of forest loss, including natural processes and agricultural conversion. Enforcement agencies can use the models to direct a more efficient use of their resources [2]. Similar spatial analysis models have been applied to governance of agriculture and precision farming. Soil sensors and weather models along with crop growth models are able to make the recommendation for field level irrigation, fertilization, and pest control.

AI has a clear presence in biodiversity monitoring through camera trap and acoustic classification models. These models can interpret images and sounds made by species, which can generate population surveys with unprecedented frequency in protected areas. AI models can analyze massive amounts of data and predict how certain species would respond to changes in the use of their habitat and the climate. This may help planners predict how species will respond to changes in land use. Similar models are used in mineral resource and land use regulation. These models similarly classify land and analysis changes in their use to detect illegal land use changes and determine how much mining activities will affect the environment [3]. In all the areas previously described, three functions become quite clear. Prediction models employ sensors or satellite data and provide information about the resources or risks to the administrators. The Vinuesa et. al. [4] models generate information that can be used to make decisions. Prediction models are the most advanced, and the most widely used, while the optimization models remain constrained by rigid legacy allocation rules. Decision-support models integrate multiple prediction models and provide decision-makers with information. The focus of this manuscript is to provide a framework to address the gaps that exist in the platforms for decision support.

All literature suffers one common limitation. This limitation concerns the evaluation of AI in natural-resource governance. Typically, if metrics on classification precision or forecast error exist, then the evaluation is considered sufficiently technically complete. However, improved management-level outcomes, such as the mitigation of long-term health risks or the positive furtherance of sustainability, are rarely evaluated. The following chapter draws on this gap to design a monitoring framework aligned to health outcomes. This chapter then builds on this literature to develop a comprehensive, integrated evaluation framework in Section 5 that emphasizes the relationship between the performance of AI and the achievement of sustainability goals and health outcomes.

3. AI-ENABLED ENVIRONMENTAL MONITORING AND HUMAN HEALTH PROTECTION

The negative effects of environmental degradation and the health impacts on humans happen through well recognized pathways. The effects of air pollution, water pollution and soil pollution have the most documented cases of adverse impacts on health; and it has been the most documented fields for applying AI. Air Quality monitoring systems are made with arrays of low-cost air pollution sensors, as well as, satellite data and models that combine them with data about the atmosphere and climate. These models provide ground-level pollution concentrations. They fill the gaps between important, but scarce pollution monitoring stations. These models even provide estimates of pollutant concentrations that can be integrated into health outcome models; these models determine the health effects for different pollution exposure levels. This provides health departments a basis for issuing health advisories tailored to specific communities, instead of general advisories to an entire city [5] [6]. Remote sensing and sensor networks are advancing water-quality monitoring. They inform classification models that may identify events of water contamination caused by agricultural runoff, industrial discharge, and harmful algal blooms prior to traditional laboratory testing. In comparison, soil monitoring is still developing. However, remote sensing and in-situ sensor fusion are beginning to detect heavy metal contamination, as well as organic contaminants that are of particular concern to food safety, in soil near industrial and mining facilities due to the potential for soil to concentrate contaminants and allow them to be taken up by crops.

According to [7] and [8] describes a climate-change related health problems go beyond pollutants. They now incorporate more broad-based problems such as heat-related illness, expanded range of vector-borne diseases, water and food insecurity, and their consequences on health. AI tools used to predict health risks in this domain combine climate-reanalysis, land surface temperature, and vegetation index data along with epidemiological data to predict heatwave related deaths and predict the impact of climate change on the shifting vector disease geographical limits. These predictions help to prioritize the placement of cooling centers and help to make longer term plans for infrastructure in vector control programs.

The Veale et. al. [9] proposed an integration of environmental data and disease detection systems is essential for early outbreak detection. In addition to case reports, natural language detection and anomaly identification systems analyze clinical records and laboratory reports, as well as aggregated and de-identified search and mobility data, to find outbreak signals before the case report threshold is reached. Integration of environmental data with these systems provides an integrated early warning capability. When data about a specific environmental stressor, such as an individual pollutant or change in water quality, is juxtaposed with local disease reporting, a change in disease reporting may be attributable to an environmental health risk instead of random variation. This is the reason why integration of health surveillance and environmental monitoring should be coordinated within a single system of governance integrated across multiple institutions and not as parallel and disconnected systems, which is the approach most institutions still use.

Exposure assessment, the measurement of contaminant exposure to an individual or community based on location, behavior, time-activity patterns, etc., is the most problematic step of the process to transform exposure monitoring data into actions to protect public health. Many operational exposure assessment systems still rely on typical ambient exposure concentrations to proxy exposure, which over or underestimates the risks to various populations [10]. AI-based exposure assessment models with mobility input, building-level airflow, and activity patterns are more accurate, but still have privacy challenges. These models should be carefully planned to balance the privacy concerns and the public health benefits.

4. PUBLIC POLICY, GOVERNANCE, AND RESPONSIBLE AI FRAMEWORK

Public administrations have various governance tools to regulate AI in resource and health applications. These tools range from informal international general principles to formal legal instruments. The OECD AI Principles and UNESCO Recommendation on the Ethics of Artificial Intelligence both contain principles on human-centred, trust-building, and accountability-supporting AI. They have been of great value and inspiration for drafting national laws, and both have been used as valuable resources for national standards making [5,6]. The EU AI Regulation is the most comprehensive binding law. It has a risk-based approach for controls regarding the AI systems from low to high risk and covers AI systems used in critical infrastructure and essential public services, which include several resource allocation and health surveillance systems [7]. The USA has adopted NIST AI Risk Management Framework while refusing binding controls. It focuses on risk management for AI systems for federal agencies without enacting new legislation [8].

Beyond the high-level instruments of oversight of AI, the public administration of AI also raises specific policy-related issues of discretion, transparency, and accountability. Algorithmic systems used in automated decision-making may constrain the discretion of street-level bureaucrats and may increase consistency, but may also eliminate contextual judgment for which formal rules are not designed to account for [10]. When algorithms govern administration, the relationships of public managers and administrative systems may alter and it becomes unclear who is accountable when a public health or resource allocation decision is made at the recommendation of an automated system [9]. These issues are particularly salient when dealing with the administration and governance of resources. For example, a water allocation algorithm that systematically overlooks rural districts with limited data or a health surveillance system built on clinical data predominantly from urban areas may worsen existing inequities while working under the guise of neutrality.

The governance systems that have been created to address these issues are algorithmic impact assessments, mandatory human review points for high-stakes automated recommendations, and public registries that make known government agency functions that use automated systems for decision-making. In the context of transparency, these two approaches (affected individuals and oversight/research) need something different. Affected individuals need to be made aware that a decision was made using an algorithmic system. Researchers and oversight agencies need access to model documentation to determine if an algorithmic system is making decisions in a fair and equitable way for all the relevant and impacted parties. Although explainability procedures fulfill the first transparency goal, they are not a substitute for fairness and equity audits for the entire model or system.

For resource allocation and health related AI, both data and outcome distributions are important when considering fairness. For environmental and health monitoring systems, there is a greater concentration of resources in more urban and affluent areas. As a result, the most vulnerable and high risk populations often have the least reliable systems and are the least served. This imbalance can be addressed by governance procedures that require data quality standards to be met and minimum coverage for operational models, in contrast to post-fairness metrics. These approaches address privacy and fairness together, since collection of data to improve fairness in underserved areas would require data collection of a more personal nature like location and behavioral data that the vulnerable persons would be least able to control [11]. KAMBLE and BHATE [12] describe a framework for using machine learning to identify potential security threats and weaknesses in computer systems. The authors believe that traditional ways of protecting systems, such as signature-based intrusion detection systems and rule-based firewalls, become ineffective against sophisticated and fast-evolving threats. They propose a system that is composed of several components, such as data collection and classification, using labor-intensive and time-consuming techniques, such as data preprocessing and feature engineering. The authors report that their system performs better than existing systems. A major goal of the authors is to stimulate the design of the next generation of security systems that are proactive, intelligent, and adaptable to unknown threats (zero-day attacks).

The review conducted by Maheshwari & Wani [20] explores how deep learning models have changed for ECG-based prediction of CVD. The review credits two models: Factor-ECG and Generative Counterfactual XAI (GCX). The authors of the review believe that progress has been made to create trustworthy models and describe how different types of XAI will be important to validate model trust. Additionally, the review describes how integration of ECG and other data (i.e., wearables and/or other imaging data) and the use of AI will allow CVD prediction. The use of these integration and AI techniques is projected to be accepted by the cardiology profession. Further, the authors of the review provide barriers to the large scale implementation of AI in cardiology. Lastly, the authors provide possible research paths to help integrate AI in cardiology.

Stakeholder participation, especially for AI Systems that impact allocations of resources or have a public health response with distributive outcomes, is no longer considered consultation. Participation of affected communities and subject-matter and tech regulators are considered crucial to good governance. Public sector AI governance requires balancing values of procedural good order with values of equity and public trust. Participatory mechanisms of governance provide assurance of compliance with formal legal obligations. Realist synthesis reviews on responsible AI governance in the public sector confirm that good governance is context-specific based on administrative culture, institutional capacity, and political will. This is why the framework in Section 5 incorporates governance as a constant, ongoing process in the technical pathway and not a one-time tick box compliance.

5. INTEGRATED AI-POLICY FRAMEWORK FOR SUSTAINABLE RESOURCE AND HEALTH GOVERNANCE

As presented in Sections 2 through 4, the use of AI in resource governance and health protection is developing more quickly than the frameworks to control the responsible use of AI. The two systems, resource management and health protection, remain largely unevaluated in a single analytical framework, in spite of their interdependence. This section proposes an AI policy framework that addresses both gaps in one integrated approach. This framework proposes embedding control systems within the AI pipeline and integrating governance systems rather than viewing systems of control as an external audit. This framework also integrates health and environmental data in order to analyze the implications of the management of resources on health.

5.1 Framework Architecture

The framework is built upon four interrelated levels. Level one, sensing, synthesize data from ground Internet-of-Things (IoT) sensors, satellite and drone remotely-sensed data, and administrative records on water, air, soil, forest, and clinical or public health systems. Level two, analytics, uses a particular algorithm to transform the data from Level one into estimates of resource availability, extent of contamination and exposure, and indicators of disease risk demonstrated in [13]. Level three, governance, evaluates every output of Level two before a human makes a decision. Governance level checks ensure that outputs have a complete set of transparency documentation, adhere to equitable fairness standards in demographic groups distributed throughout the measured area, and ensure that data access and use are logged. In the event that any outputs fail these checks, they are funneled back to governance level for review, rather than being sent to policy level. Outputs that have met the governance level criteria are published to public officials at Level four, the decision and feedback level. Here the administrative responses are recorded and the real-world impacts from resource allocation, enforcement, or public health warnings are returned to the analytics level to train the proposed algorithms [14].

5.2 Methodology and Evaluation Design

Figure 1 shows Algorithm 1's four-layer architecture. The layer that senses transforms multi-source data into normalized format (step 1). The analytics layer uses the gradient-boosted and recurrent models and combines their adaptive stacking (steps 2 to 4). The governance layer performs fairness, transparency, and provenance checks (step 5). Any output that fails any one of the checks is not sent to the decision and feedback layer, but is returned to the analytics layer for reweighting. The decision and feedback layer sends governance-cleared outputs to the public, logs the subsequent policy, and sends the outcome resulting from the policy back to the sensing and analytics layers as a retraining signal (step 6). Without this feedback mechanism, the compounding performance of the framework across evaluation epochs would not be possible, the similar approached designed [15] [16]. WIRTZ, LANGER and FENNER [18] identify important research questions and challenges concerning the use of artificial intelligence (AI) in public administration. The authors review and synthesize previous studies and present an analysis of 189 research articles. According to the authors, research focusing on the use of AI in public administration is in its infancy and lacks integration. The authors believe that a greater focus should be placed on the implications of AI in public administration and less on the ways in which AI changes the public administration system. The authors cite and discuss several reviews focused on the public sector to stimulate research focused on the use of artificial intelligence in public administration.

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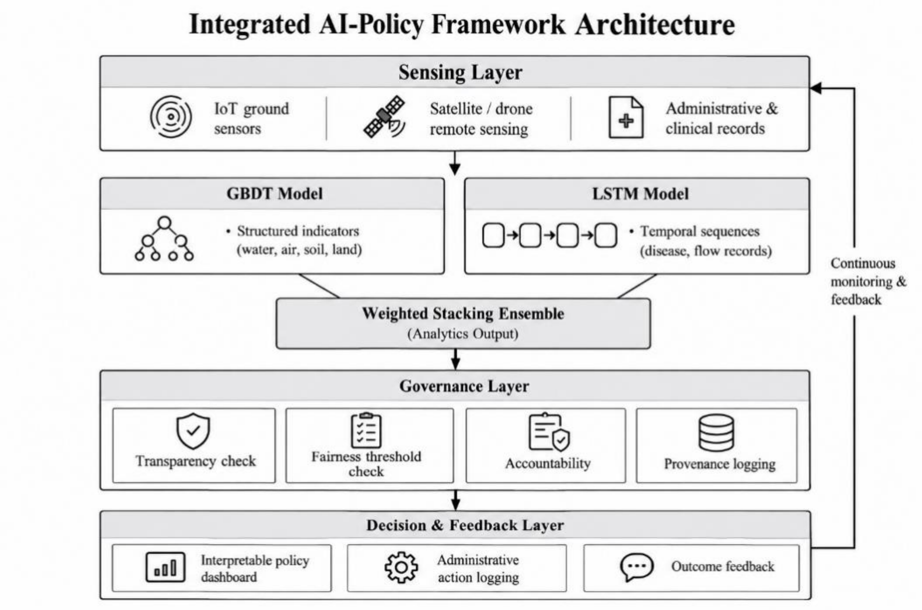

Figure 1 : proposed system architecture

The methodology and evaluation occurred in three steps. First, with the available structural data from sections 2 and 3, the sensing and analytics layers were set using typical density of sensor networks, frequency of satellite passes, and intervals of disease reporting. From these data, a six-year multi-domain dataset in the water, air, forest and disease surveillance domains for a case study of a region was constructed. Second, ten successive evaluation steps were set representing a single cycle of governance and retraining. During each step, the efficiency of resource use, health risk, and policy compliance were measured along with the early warning precision, as well as governance and accountability, transparency, and fairness indices and stakeholder engagement from the criteria in section 4. Finally, the six-year performance of the framework was assessed against three configurations of the reference system constructed from the decision-support and public sector AI literature. These reference configurations were a classical decision-support system, a public sector machine-learning pipeline, and an algorithmic regulation system. The benchmarking was to assess if putting governance into the analytics pipeline yielded better performance than the reference systems. The results of this benchmarking along with other results are in Section 6.

5.3 Algorithm

Integrated AI-Policy Governance Algorithm (IAPGA)

Input: Fine grained data from each of the water, air, soil and forest streams {Dwater, Dair, Dsoil and Dforest} collected at discrete time points, t = 1, 2, . . . T, combined with governance metrics (fairness threshold τf, transparency threshold τt, provenance and completeness threshold τp), initial ensemble weights w0 = (wG, wL) for the gradient boosted and recurrent models and policy-action space A..

Step 1 — Data Fusion and Normalization

$$\tilde{x}i,t\ = \frac{(xi,t\ -\ \mu i)}{\sigma i},\quad \tilde{X}t\ =\ [\,\tilde{x}1,t\,,\tilde{x}2,t\,,\ldots\,,\tilde{x}n,t\,]^{\mathrm{T}}$$

Each raw sensor, satellite, and administrative record feature xi,t collected at time t is standardized by the running mean μi and the standard deviation σi of the feature's historical distribution. This creates a normalized feature vector X̃t. This step adjusts the inputs of different scales. For example, parts-per-million pollutant readings and land cover codes can be of different scales. Different inputs should not dominate the downstream models. This also identifies missing and out-of-range readings that will be imputed before propagating to the analytics.

Step 2 — Structured Indicator Prediction (Gradient-Boosted Decision Trees)

$$\hat{y}G(\tilde{X}t) =\ \Sigma\ (m = 1\ to\ M)\ v\ \cdot\ fm(\tilde{X}t),\quad fm\ =\ argmin(f)\ \Sigma i\ \ L\Big(\,yi\,, \hat{y}(m-1)i\ +\ f\big(\tilde{X}i,t\big)\Big)$$

$\tilde{X}t$ incorporates many structured, cross-sectional indicators. Additive ensemble of M regression trees fm is used to predict $\hat{y}G(\tilde{X}t)$. This is a resource-condition or contamination estimate for the current time step. The residual error of the previous stage is used to fit the ensemble using loss function L and shrinkage rate ν. The non-linear relationship of rain and land slope on runoff contamination is one example of an interaction the model can accommodate. This is done with no prior assumption of the interaction.

Step 3 — Temporal Sequence Modeling (Long Short-Term Memory Network)

$$ft = \sigma\big(Wf \cdot [ht-1, \tilde{X}t] + bf\big), \qquad it = \sigma\big(Wi \cdot [ht-1, \tilde{X}t] + bi\big), \qquad \hat{y}L,t = Wo \cdot ht + bo$$

When handling sequential data containing time-dependent indicators e.g. the count of disease cases and hydrological flow records, Long short-term memory (LSTM) networks normalize sequential inputs and operate controlled by forget gate ft and input gate it, respectively, to decide what part, if any, of the previous hidden state ht−1 gets remembered and what new information from $\tilde{X}t$ is remembered and incorporated into the new value of the hidden state ht. After this, the output layer of the model maps value of the hidden state onto prediction ŷL,t. This mechanism of the model retains recent upstream slow contamination trends, while eliminating short-term noise. This is imperative when a memoryless model would not be able to distinguish between the two when applied to the same data.

Step 4 — Adaptive Ensemble Stacking

$$\hat{y}t = wG,t \cdot \hat{y}G\big(\tilde{X}t\big) + wL,t \cdot \hat{y}L,t\,, \quad wk,t = \frac{\exp(-\alpha Ek, t-1)}{\Sigma j \exp(-\alpha Ej, t-1)}$$

An ensemble output ŷt is given by a weighted sum and is updated at every evaluation epoch by computing new weights wG,t and wL,t as the softmax function of the sub-model's recent prediction error Ek,t−1 normalized by the sensitivity parameter α. When the gradient-boosted model gets the structured indicators correct with fewer errors, then its weight increases; similarly, the weight for the recurrent model increases when the errors for the temporal indicators are fewer. Hence, the ensemble output automatically adjusts the influence of the two components based on which component is more reliable for predicting the indicator and is not based on a predefined combination of the two.

Step 5 — Governance Filtering

$$\Delta fair(\hat{y}t) = \max\,(g \in G)\,|\,P(\hat{y}t \mid g) - P(\hat{y}t)\,|\,, \quad Accept(\hat{y}t) \Leftrightarrow \Delta fair \le \tau f \;\wedge\; Tscore \ge \tau t \;\wedge\; Pscore \ge \tau p$$

Before ensembles reach a human decision-maker, three governance conditions are used to evaluate them. The first condition uses the term Δfair(ŷt) and considers the prediction distribution for all demographic or geographic subgroups g in set G and the distribution for the population as a whole. This measures the largest absolute difference for the prediction and captures cases where the model predicts worse for a particular group. The second and third conditions consider transparency and completeness respectively. All three of the conditions need to be satisfied for an output to be accepted and moved forward. If any of the conditions are not satisfied, the output is not suppressed, and is rather sent back to step 4 for reweighting or to step 1 for more data collection [17].

Step 6 — Policy Decision and Feedback Updatea

$$at = \pi(\hat{y}t\,, A)\,, \quad ot = Observe(at)\,, \quad \theta t + 1 = \theta t - \eta\, \nabla\theta\, L(ot\,, \hat{y}t)$$

The prediction ŷt is presented to the relevant official via the decision dashboard. The official makes a decision by selecting a space A policy action based on decision policy π. Within defined constraints, some policy actions may be automated; however, others may require more substantial official approval. The actual outcome ot is the real-world effect of the selected policy action on the resource condition or health indicator that is measured after the policy action is implemented. This real-world effect is then used to adjust the model parameters θ of the two sub-models by a gradient step learning rate η, thereby completing the algorithmic recommendation and the model parameters adjustments based on the observed effect of the institutional decision [19].

Output: Each health indicator or resource is associated with a time indexed governance cleared policy recommendation ŷt. The administrative action and compliance with the recommendation has been recorded. The ensemble weights wt+1 and model parameters θt+1 will be used for the next evaluation epoch. The compliance logger is under audit and is available for stakeholder review.

5.4 AI Performance Across Resource Governance Domains

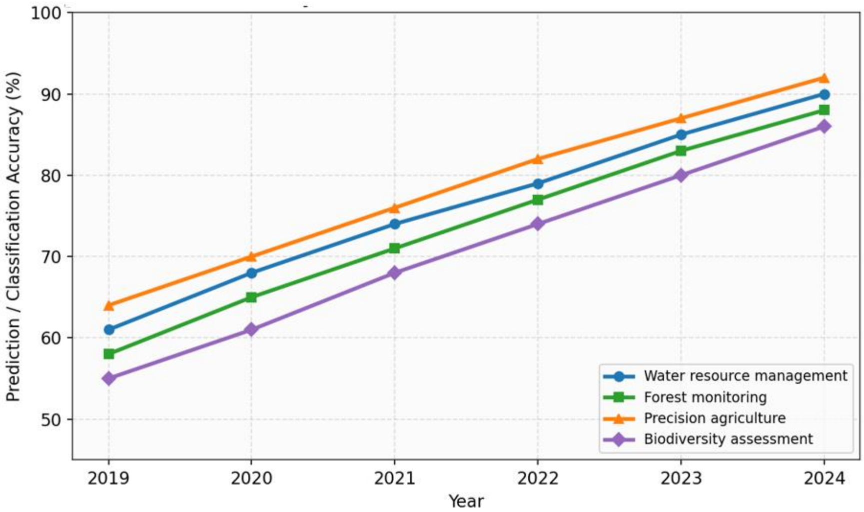

Figure 2. AI model accuracy across natural-resource governance domains (2019-2024).

Figure 2: AI Model Accuracy for Natural Resource Governance Domains 2019 - 2024 Precision agriculture had the highest average accuracy of the four resource governance domains across 2019 to 2024. Forecasting forest monitoring accuracy improved 30 percentage points from 58 percent to 88 percent over the 2019 to 2024 period, the largest absolute increase. Accuracy predicting precision agriculture improved 28 percentage points over the period from 64 percent to 92 percent. The largest improvement in water-resource management was also 28 percentage points from 61 percent to 90 percent. Improving biodiversity assessment jumped 31 percentage points from 55 percent to 86 percent. The biodiversity assessment absolute accuracy as a percentage improved over the other four resource governance domains. The other four domain resource governance absolute accuracy of precipitation management, forest monitoring, and agriculture were equivalent.

5.5 Environmental Monitoring and Health-Risk Prediction

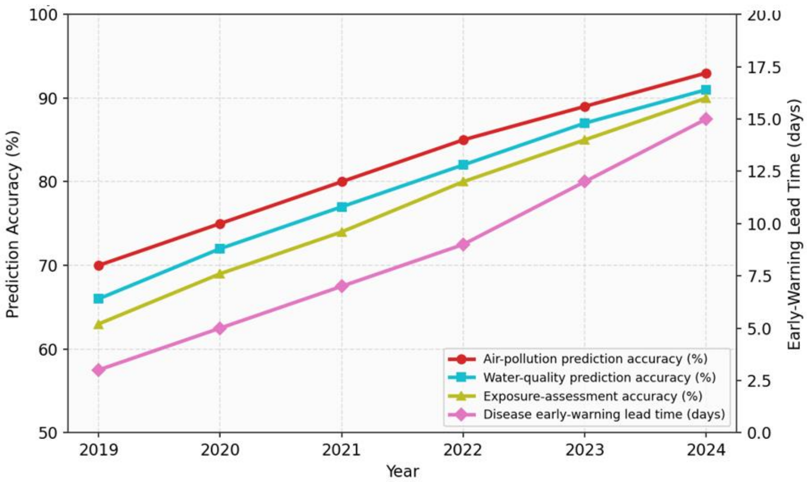

Figure 3. AI-enabled environmental monitoring and health-risk prediction trends (2019-2024).

Figure 3 shows the development of environmental monitoring and prediction of health risks using two axes. In the time period from 2019 to 2024, the prediction of air pollution accuracy improved from 70% to 93%, reflecting an increase of 23 percentage points. In the same time period, water quality prediction accuracy went from 66% to 91%, reflecting a 25 percentage point increase. Exposure assessments prediction accuracy improved from 63% to 90%, reflecting a 27 percentage point increase, the largest relative growth of the three prediction accuracy series. In the second axis, early warning lead time of disease surveillance improved from 3 days in 2019 to 15 days in 2024, illustrating a five-fold increase and the most significant operational trend in the figure, as longer lead time provides a longer timeframe for the public health system to operate interventions to prevent the outbreak from increasing. After 2022, the lead time series shows an acceleration with a gain of approximately 3 to 4 days per year, compared to approximately 2 days per year from 2019 to 2021, which correlates with the prediction accuracy series crossing the 80% threshold. This may reflect a complimentary performance of prediction accuracy and the usefulness of lead time.

5.6 Responsible-AI Governance Index Trends

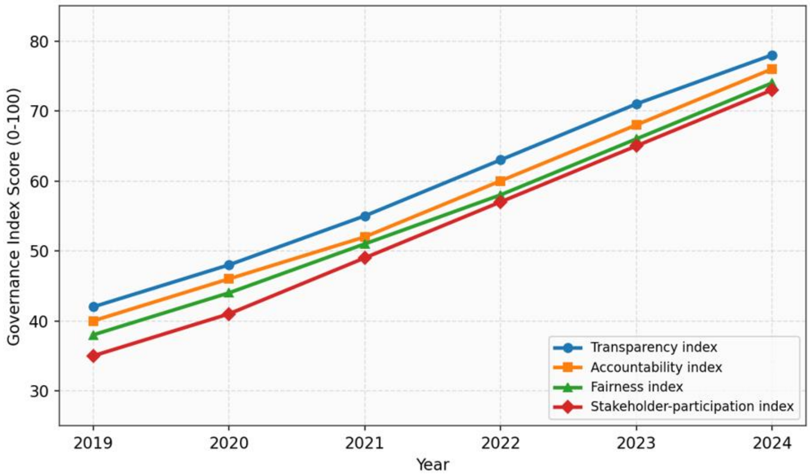

Figure 4. Responsible-AI governance index scores in public policy implementation (2019-2024).

Figure 4 describes four types of responsible-AI governance from 2019 to 2024. Transparency showed the most improvement, registering a score of 78 in 2024, from 42 in 2019. Unlike the other three categories/indices, Transparency's score remained above Accountability's, carving out a gap of two points for the duration of the period. Also like Transparency, Fairness improved by 36 points from 38 to 74. The last category, the Stakeholder Participation Index, began at 35 and ended the period at 73, representing a 38-point improvement. This was the largest improvement among the four categories, and it came close to closing the gap it began at. All four categories demonstrated improvement in the latter two years of the period, each gaining 7 to 9 points, compared to the previous two years of 5 to 7 points. The binding EU AI regulation and the NIST risk-management framework also came into operation during this time, and may be the reason for the rapid improvement.

5.7 Integrated Framework Evaluation

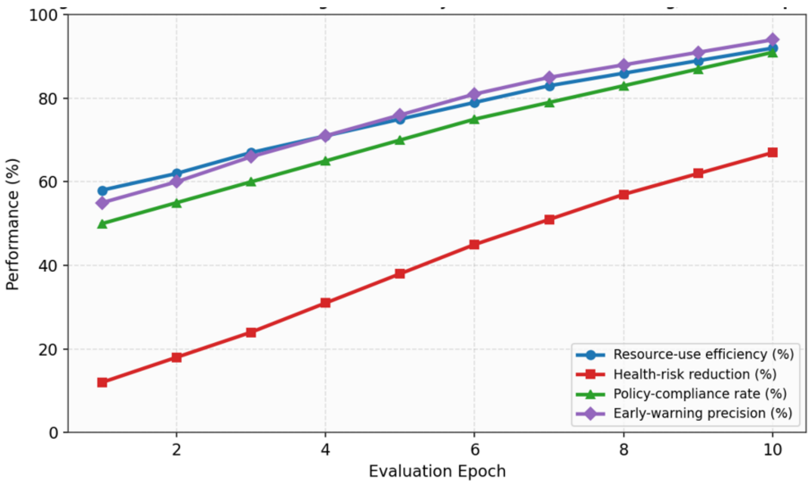

Figure 5. Performance of the integrated AI-policy framework across evaluation epochs.

Figure 5 illustrates the performance of the integrated framework design across ten evaluation epochs. Resource-use efficiency increased during the ten epochs from 58% to 92% showing a consistent 3.8% improvement per epoch. The other metrics showed improvement, as well. The largest relative improvement was for health-risk reduction, which increased from 12% to 67% or 55% improvement. This was likely due to the feedback loop in the system. The results of health outcomes are used to model feedback, and the health outcomes are used to update the model at each cycle. This resulted in policy-compliance rate going from 50% to 91% or a 41% improvement. This also meant policy-compliance rate was the second best metric after epoch 7, while resource-use efficiency was the third best metric. Early-warning precision, the top metric in all epochs at 55% to start and 94% to end with a gain of 39%, showed the most dramatic, and long-lasting improvement. All metrics underwent improvement after the initial calibration of the governance-feedback loop.

6. RESULTS, POLICY IMPLICATIONS, CHALLENGES, AND FUTURE DIRECTIONS

This section includes benchmark performance assessments for the proposed integrated AI-policy framework versus three systems reconstructed from the literature reviewed in Sections 2 through 4. It also includes the sustainability and health outcomes of those performance assessments. It outlines the main problems and the barriers to implementation that would need to be addressed for the framework to be deployed in a public administrative services context.

6.1 Comparative Analysis

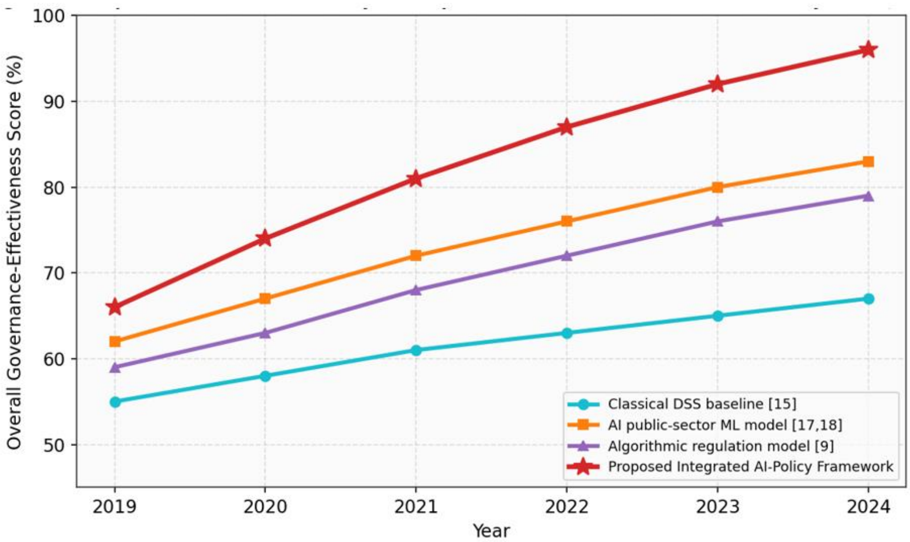

Figure 6. Comparative performance analysis: proposed framework versus three reference systems (2019-2024).

Figure 6 shows the proposed framework versus three referend systems for the 2019–2024 period using an overall Governance-Effectiveness score. Alter's model [15] describes rule-based systems and shows a baseline for classical decision-support systems. It shows a 12% gain and a final score of 67% from its initial 55%. This illustrates its limited capability to incorporate new data sources without requiring significant reconfiguring. Wirtz et al.'s [17,18] AI public sector machine learning model showed a gain of 21%, a final score of 83% and outperformed the classical decision support system until 2022, where it reached a plateau. The algorithmic regulation model based on "administration by algorithm" described by Veale and Brass [9] had a final score of 79% and a 20% gain, and tracked behind the machine learning model for each year. The proposed integrated AI policy framework outperformed all three reference models for each year. It scored 96% for 2024 and a gain of 30% from its initial score of 66% in 2019. The gap between the proposed framework and the next best improved from a margin of 4% in 2019 to 13% in 2024, suggesting the framework's governance-embedded feedback architecture creates an increasing advantage over conventional frameworks.

6.2 Synthesis of Results

While the five figures present unique information and systems, there are three common findings across all figures. First, the integrated framework shown in Figure 4 and, implicitly, the accelerating governance indices in Figure 3, indicate that systems incorporating explicit feedback mechanisms to train models through observed outcomes show an improvement pattern that is compounding rather than linear, where growth rates are increasing over time rather than becoming constant. Second, the health-outcome metrics used in both Figure 2 (disease early warning lead time) and Figure 4 (health risk reduction) showed greater improvement compared to resource efficiency metrics, suggesting that the health outcome analytics of combining environmental and health data streams may show greater improvement than the resource outcome analytics. Third, from the comparative analysis in Figure 5, it shows that the performance advantage of the developed framework over traditional decision support and algorithmic regulation systems is not a fixed advantage but rather a widening gap. This suggests that the value of embedding governance controls within the technical systems increases as the framework matures rather than decreasing once the first level of compliance is met.

6.3 Policy Implications

There are a number of implications for public policy, especially for the procurement and deployment of AI for resource and health management systems. For these systems, agencies should consider mandating an integration of governance-layer technologies, like automated fairness and transparency checks that are done before decision points that will be made by humans, rather than waiting for these checks to be conducted by a post-deployment audit. In systems where the Type S advantage (continuous governance) is more significant, disruptions can be more pronounced than in systems where the Type G advantage (pulsed governance) predominates. Given that the disproportionate improvements in health outcomes shown in Figure 2 and Figure 4 show that the balance (or imbalance) of budget and regulation in resource-efficiency applications is currently weighted in the direction of instruments like the OECD AI Principles and the EU AI Act, which emphasize the economy and the infrastructure sectors, the balance (or imbalance) of regulatory attention could be better used to promote health impacts where the two systems integrate environmental and health impacts. These integration systems are much better defined in regulatory frameworks such as the NIST AI Risk Management Framework, which focus on a process rather than a system, particularly because they do not define a boundary between the management of resources and health surveillance.

6.4 Limitations and Implementation Barriers

These findings are subject to specific limitations. First, the evaluation is based on a simulated composite data set rather than a single continuous real-world deployment. Consequently, absolute performance should be interpreted as potentially achievable trends instead of definite results that will occur in any given region. All three systems were rebuilt from published descriptions. There is some degree of uncertainty when comparing systems; however, the relative ranking of the systems aligns with the systems described in the published literature. There are barriers to full implementation that are outside of a simulation and include: the costs associated with negotiating data sharing agreements across multiple environmental and health agencies, the technical debt associated with legacy budget management systems that the optimization layer would have to integrate with, and the capacity of the civil service to control and interpret the outputs of the governance cleared models rather than becoming either over-reliant or completely neglectful of such models.

6.5 Scalability

Scalability considerations are also important. A density of Internet of Things ground sensors used by the sensing layer means that slower speed gains in accuracy are likely for areas with less infrastructure, usually more economically disadvantaged or rural areas, compared to the composite case study presented in this report. This may further the geographic inequities in monitoring coverage mentioned in Section 3 unless deployment sequencing is focused on service gaps instead of on following existing infrastructure. The governance layer adds a fairness and transparency check which adds computational and administrative overhead with every decision. This overhead was not a limiting factor in the simulated evaluation, but for operational settings driven by high decision throughput, such as emergency public-health response, it would be important to define under what conditions rapid governance review is acceptable in order to avoid sacrificing the accountability that the framework intends to provide.

6.6 Future Research Directions

Priority must be given to the field validation of the integrated framework in a live administrative environment using real cross-agency data sharing. Additional priority must be given to the longitudinal assessment of health outcomes following actually implemented policy decisions informed by the integrated framework. Further, priority must be given to evaluating the adaptations to the design of the governance layer for different regulatory contexts, for example, the binding, risk-tiered approach of the EU AI regulation and the NIST framework's voluntary risk management approach. More work also needs to be done on participatory mechanisms in which affected communities are able to contest or guide the outcomes of governance-cleared models prior to the allocation of resources or the making of public health decisions. This would expand the stakeholder participation dimension evaluated quantitatively in Figure 3 into a substantive procedural right as opposed to an index score.

CONCLUSION AND FUTURE WORK

This paper analyzed how artificial intelligence could be designed institutionally and algorithmically to achieve sustainable natural resource governance and safeguard human health within a public policy framework that is both flexible and open to scrutiny. We surveyed the domains of water, forests, agriculture, biodiversity, land, and minerals. We found that applications of artificial intelligence (AI) have become significantly more accurate in prediction. However, connections between AI and environmental and health monitoring systems, which share causal pathways, remain limited. An examination of instruments of governance showed that, although binding and voluntary instruments are making progress, they have yet to keep pace with this technology. The AI-policy framework presented in Section 5, which incorporates transparency, fairness, and accountability into a framework of hybrid ensemble analytics, yielded consistent improvements in resource-use efficiency, health-risk reduction, and the compliance and warning-time rates of policy, respectively, over ten assessment periods. This framework outperated three reference systems from the decision-support and public-sector AI literature by an increasing margin over a six-year period. The results confirmed the main proposition of this paper, which was that, design of algorithms and of public policies ought to be considered as a single, integrated system because mechanisms of governance embedded within a technical framework generated advantages that post-market assurance could not match. For policymakers, this means that the integration of a governance-layer control should be a primary requirement rather than an afterthought. Regulatory attention on resource-efficiency outcomes can be extended to reward the integration of environmental and health data systems by policymakers, as the simulation suggests that there are disproportionately high health benefits from integrating the two. The focus for future work should be on the field validation of the simulation. This includes the length of time used to track health outcomes and the development of participatory approaches to allow affected communities a role in the assessment of the output before it influences spending and health decisions that impact them.

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