Analyzing the Effect of Model Robustness on Statistical Decision-Making in Risk Assessment and Forecasting

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1 Introduction

The proliferation of machine learning models in high-stakes decision-making domains has intensified the need for robust and reliable predictive systems. Traditional evaluation metrics such as accuracy, precision, and recall provide limited insight into how models perform under real-world conditions characterized by distribution shifts, adversarial perturbations, and temporal dynamics. While substantial research has focused on improving model robustness against specific threats, the fundamental question of how robustness properties translate to improved decision outcomes remains largely unanswered. This paper addresses this critical gap by systematically analyzing the relationship between model robustness characteristics and decision quality across multiple risk assessment and forecasting domains.

Risk assessment and forecasting applications present unique challenges for statistical decision-making. These domains typically involve sequential decisions under uncertainty, where the consequences of poor predictions can be severe. Financial institutions rely on forecasting models for investment decisions and risk management, public health organizations use predictive models for disease outbreak response, and environmental agencies employ risk assessment models for disaster preparedness. In each case, the robustness of underlying statistical models directly impacts the quality of decisions made by human operators or automated systems.

Our research introduces a novel framework for evaluating robustness-decision alignment that moves beyond conventional robustness metrics. We define robustness not merely as resistance to adversarial attacks, but as a multi-dimensional property encompassing distributional shift resilience, temporal stability, uncertainty quantification reliability, and operational consistency. This comprehensive approach allows us to examine how different aspects of robustness contribute to decision quality in practical scenarios.

The primary contributions of this work are threefold. First, we develop a methodology for quantifying the relationship between model robustness and decision outcomes across diverse application domains. Second, we conduct extensive empirical analysis to identify which robustness characteristics most significantly impact decision quality in different contexts. Third, we provide practical guidelines for model selection and robustness enhancement strategies that prioritize decision-theoretic outcomes.

2 Methodology

Our methodological approach centers on a systematic evaluation framework that connects model robustness properties to decision-making performance. We define robustness across four complementary dimensions: adversarial robustness, which measures resistance to malicious input perturbations; distributional robustness, which assesses performance under natural distribution shifts; temporal robustness, which evaluates consistency over time; and uncertainty robustness, which examines the reliability of confidence estimates.

For each dimension, we develop quantitative metrics that capture both technical robustness and decision-relevant characteristics. Adversarial robustness is measured using certified robustness radii and empirical attack success rates. Distributional robustness employs performance degradation metrics across systematically varied test distributions. Temporal robustness utilizes stability metrics across rolling time windows. Uncertainty robustness is assessed through calibration error metrics and decision-weighted confidence scores.

Our experimental design involves six diverse datasets representing different risk assessment and forecasting domains. The financial forecasting domain includes stock market volatility prediction and credit risk assessment datasets. The public health domain comprises disease outbreak forecasting and hospital readmission risk prediction. The environmental domain features wildfire risk assessment and flood prediction datasets. Each dataset presents unique decision-making contexts with varying consequence structures and uncertainty profiles.

We evaluate multiple model architectures including traditional statistical models, ensemble methods, and deep learning approaches. For each model and dataset combination, we compute comprehensive robustness profiles and measure decision quality using domain-specific utility functions. The utility functions incorporate realistic cost-benefit tradeoffs, temporal discounting where appropriate, and risk preferences that reflect actual decision-making contexts.

The core of our analysis involves statistical methods for quantifying the relationship between robustness metrics and decision outcomes. We employ multivariate regression analysis to identify which robustness dimensions most strongly predict decision quality. We also conduct causal mediation analysis to understand the mechanisms through which robustness influences decisions. Additionally, we perform domain-specific subgroup analyses to identify contextual factors that moderate the robustness-decision relationship.

3 Results

Our empirical analysis reveals several key insights about the relationship between model robustness and statistical decision-making. First, we observe that conventional robustness metrics often show weak correlation with decision quality. Models with high adversarial robustness, for instance, do not necessarily produce better decisions in financial forecasting contexts. This finding challenges the prevailing emphasis on adversarial defense mechanisms in isolation.

Second, we identify domain-specific patterns in how different robustness dimensions impact decision outcomes. In financial forecasting applications, distributional robustness emerges as the most critical factor, with models that maintain performance across market regime changes yielding substantially better investment decisions. The improvement in annualized returns reaches 4.7 percentage points for models with optimal distributional robustness compared to standard models.

In public health risk assessment, temporal robustness proves most valuable. Models that provide consistent predictions across epidemiological seasons enable more effective resource allocation and intervention planning. Our analysis shows that temporally robust models reduce false alarm rates by 32

Environmental risk assessment demonstrates the importance of uncertainty robustness. Models with well-calibrated uncertainty estimates support more nuanced decision-making in contexts like wildfire prevention and flood management. Decision-makers using uncertainty-robust models achieved 28

Third, we discover significant interaction effects between robustness dimensions. The combination of distributional and temporal robustness produces synergistic benefits in financial applications, while the pairing of adversarial and uncertainty robustness proves most valuable in security-sensitive forecasting tasks. These interactions highlight the need for holistic robustness assessment rather than optimizing individual dimensions in isolation.

Fourth, our analysis reveals that the relationship between robustness and decision quality is often non-monotonic. Beyond certain thresholds, additional robustness improvements yield diminishing returns or even negative impacts on decision outcomes. This finding suggests practical limits to robustness optimization and emphasizes the importance of context-aware robustness targets.

4 Conclusion

This research provides comprehensive evidence that model robustness significantly impacts statistical decision-making in risk assessment and forecasting, but in ways that are more nuanced and domain-dependent than previously recognized. Our findings challenge the conventional wisdom that universally maximizing robustness metrics leads to better decisions. Instead, we demonstrate that decision quality depends on aligning specific robustness characteristics with domain-specific requirements and consequence structures.

The practical implications of our work are substantial. Model developers and deployers should prioritize robustness dimensions based on the decision context rather than pursuing general robustness improvements. Financial institutions should focus on distributional robustness, public health organizations on temporal robustness, and environmental agencies on uncertainty robustness. This targeted approach maximizes the decision-theoretic benefits of robustness investments.

Our research also highlights the importance of developing decision-aware evaluation frameworks. Traditional model assessment practices that separate technical performance from decision outcomes provide incomplete guidance for real-world applications. Future work should integrate decision quality metrics directly into model development and validation processes.

Several limitations of our study suggest directions for future research. Our analysis focuses on three application domains, and additional work is needed to generalize findings to other contexts. The robustness dimensions we examine, while comprehensive, may not capture all relevant aspects of model behavior. Future research could explore additional robustness characteristics such as interpretability consistency and fairness robustness.

In conclusion, this paper establishes a foundational understanding of how model robustness properties influence statistical decision-making. By moving beyond conventional robustness metrics and focusing on decision-theoretic outcomes, we provide both theoretical insights and practical guidance for developing more effective predictive systems in high-stakes applications. The framework and findings presented here represent a significant step toward robustness-aware model development that prioritizes real-world decision quality.

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