

Madden-Julian Oscillation Based Subseasonal Forecasting for Renewable Energy Applications in Tropical Indonesia: Establishing Operational Baseline Performance

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ABSTRACT

Operational subseasonal forecasting for renewable energy applications in tropical regions remains an underexplored challenge critical for developing countries' energy transitions. This study establishes baseline performance for Madden-Julian Oscillation (MJO) based renewable energy forecasting in tropical Indonesia, addressing a significant gap in operational meteorological applications. Using West Java as a representative tropical archipelagic region, we develop a comprehensive forecasting system integrating 25 years of meteorological observations with real-time MJO monitoring. MJO composite analysis reveals systematic solar radiation variability (12.08 W/m² range) with clear operational implications: enhanced conditions during Phase 4 (+7.26 W/m²) and suppressed conditions during Phase 7 (-4.82 W/m²). A hybrid CNN-LSTM model processes atmospheric patterns and MJO evolution for 14-day renewable energy predictions. While overall skill remains modest (ACC=0.202), conditional performance during organized MJO periods achieves near-operational capability (ACC=0.64), providing viable forecasting windows for 28% of time periods. Seasonal analysis identifies optimal deployment during December-February monsoon conditions. Economic analysis demonstrates positive return for installations >50 MW during high-skill periods through optimized maintenance and grid management. This baseline establishment provides crucial foundation for operational meteorological services in tropical developing regions, supporting renewable energy sector growth through adaptive forecasting strategies.

INTRODUCTION

Indonesia's renewable energy expansion faces unique meteorological challenges requiring specialized forecasting solutions. With targets of 44% renewable energy by 2030, the nation operates major installations including West Java's 145 MW Cirata and 60 MW Saguling floating solar facilities where atmospheric variability directly impacts generation efficiency (Handayani et al., 2017; Isa et al., 2021). Unlike temperate regions with established subseasonal forecasting capabilities (Bett et al., 2022; van der Wiel et al., 2019), tropical archipelagic regions lack operational meteorological frameworks for renewable energy applications.

Subseasonal-to-seasonal (S2S) forecasting, spanning 2 weeks to 3 months, addresses critical operational timescales including maintenance scheduling, energy trading, and grid management decisions (White et al., 2017). European and North American meteorological services successfully deploy S2S products for energy sector applications (Bloomfield et al., 2021; Lledó & Doblas-Reyes, 2020), yet tropical regions remain underserved despite rapid

renewable growth (Fang et al., 2023; Osman & Vera, 2017; Schindler et al., 2025). This gap represents a significant barrier for developing countries pursuing energy transitions in complex tropical atmospheric environments.

The Madden-Julian Oscillation (MJO) dominates tropical intraseasonal variability through organized eastward-propagating convective systems with 30-90 day cycles (Wheeler & Hendon, 2004). Recent advances in MJO prediction achieve 25-36 day forecast horizons using machine learning approaches, substantially improving upon traditional numerical methods (Chen et al., 2024; Shin et al., 2024). Enhanced MJO predictability provides unprecedented opportunities for tropical subseasonal applications (Ahn et al., 2020; Kim et al., 2018).

MJO influences on Indonesian climate are well-documented through precipitation and temperature impacts (Peatman et al., 2014; Wheeler et al., 2009), yet renewable energy applications remain unexploited. Remote sensing capabilities enable comprehensive atmospheric monitoring essential for tropical energy meteorology (Yang et al., 2018). Deep learning integration with satellite observations offers superior pattern recognition for complex tropical systems (Delaunay & Christensen, 2022; Kim et al., 2021).

This study establishes baseline performance for MJO-based renewable energy forecasting in tropical Indonesia, providing essential foundation for operational meteorological services. We address the critical gap between tropical atmospheric research and practical energy sector applications through: (1) systematic quantification of MJO-renewable energy relationships using operational observational networks; (2) development and validation of machine learning forecasting models suitable for tropical deployment; (3) assessment of conditional forecasting strategies for different atmospheric states; (4) establishment of economic viability frameworks for energy sector implementation.

The operational focus ensures practical relevance for meteorological services supporting renewable energy development in tropical developing regions. Results provide immediate applicability for Indonesian energy transition while establishing transferable methodologies for global tropical applications.

RESEARCH METHODS

Study Region and Operational Context

West Java Province (5.5°S–7.5°S, 105.5°E–109.5°E) serves as representative tropical archipelagic testbed hosting major renewable installations within Indonesia's energy transition strategy (Isa et al., 2021). The region's tropical maritime climate and Indo-Pacific warm pool positioning create complex atmospheric dynamics requiring specialized meteorological approaches (Wheeler et al., 2009). Figure 1 presents the operational framework from real-time data integration through conditional deployment strategies.

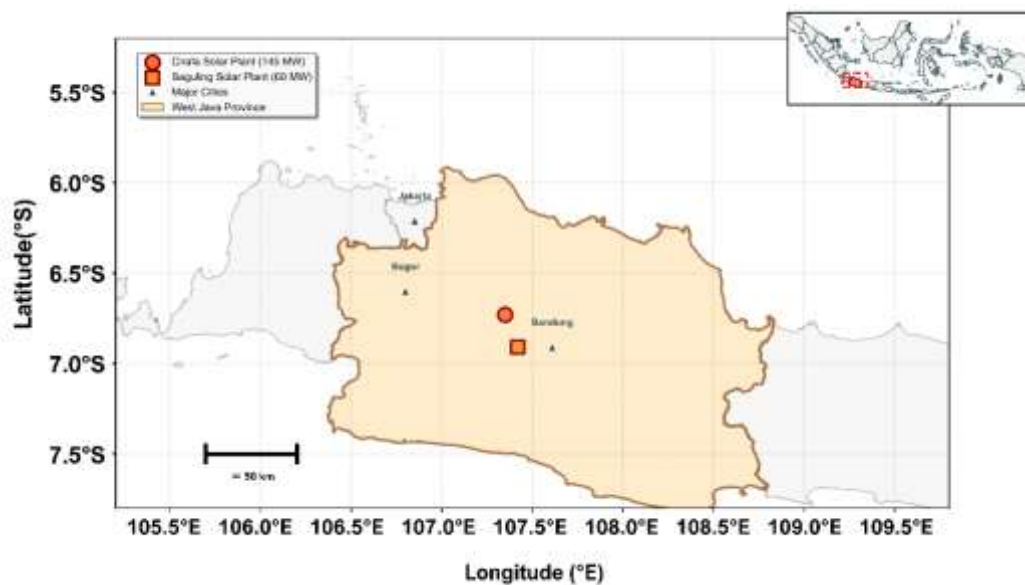


Figure 1. West Java Study Region Showing Major Renewable Installations and Tropical Maritime Climate Context
Operational Dataset Integration

Meteorological Observations: ERA5 reanalysis (2000-2024, 0.25° resolution) provides comprehensive operational variables including surface solar radiation downwards, 10-meter wind components, 2-meter temperature, total cloud cover, surface pressure, dewpoint temperature, and precipitation (Hersbach et al., 2020). This dataset represents operationally available observations suitable for real-time implementation.

NASA POWER delivers validated solar irradiance observations including Global Horizontal Irradiance and Direct Normal Irradiance at 0.5° resolution specifically designed for energy applications (Sparks, 2018). Wheeler-Hendon Real-time Multivariate MJO indices from NOAA Climate Prediction Center enable operational oscillation tracking through PC1, PC2, amplitude, and phase parameters updated daily (Wheeler & Hendon, 2004).

Energy Meteorology Calculations

Renewable energy potential employs operationally validated models essential for practical applications. Solar photovoltaic potential: $P_{PV} = GHI \times 0.20 \times [1 - 0.004 \times (T_{cell} - 25^{\circ}C)]$ incorporating temperature effects on panel efficiency (Huld et al., 2012). Wind power potential: $P_{wind} = 0.5 \times \rho \times A \times C_p \times v^3$ with 100-meter height extrapolation using established power law profiles (Archer & Jacobson, 2005).

Eight-phase composites aggregate renewable energy potential during organized MJO periods (amplitude $>1.0\sigma$) with statistical significance assessed through Student's t-tests including temporal autocorrelation correction (Lim et al., 2018). Correlation analysis spanning 0-60 days identifies optimal predictive relationships essential for operational lead time determination (Lledó & Doblas-Reyes, 2020).

Machine Learning Architecture for Operational Deployment

The hybrid CNN-LSTM model addresses operational requirements through efficient processing of spatial atmospheric patterns and temporal MJO evolution. Spatial Processing: Convolutional Neural Network components handle multi-channel satellite imagery through optimized layers with batch normalization and attention mechanisms. Temporal Modeling:

Long Short-Term Memory networks process MJO time series using bidirectional architecture with dropout regularization ensuring operational stability (Delaunay & Christensen, 2022; Shin et al., 2024).



Figure 1. Operational Workflow Framework for MJO-Based Renewable Energy Forecasting System

Five-stage pipeline from data processing through operational deployment, emphasizing practical implementation methodology for meteorological services in tropical developing regio

Operational training utilizes 30-day input sequences predict 14-day renewable energy forecasts using sliding window techniques. Training employs temporal splitting (2000-2018 training, 2019-2021 validation, 2022-2024 testing) ensuring operational independence. Adam optimization with adaptive learning rate scheduling and early stopping prevents overfitting while maintaining computational efficiency (Chen et al., 2024).

Training completes in 65 minutes on standard GPU hardware with 45-second epochs. Operational inference requires 0.3 seconds per 14-day forecast with <2 GB memory usage, ensuring feasibility for meteorological service deployment.

Operational Verification Framework

Performance assessment follows international meteorological standards essential for operational service development. Primary Metrics: Anomaly Correlation Coefficient (ACC), Root Mean Square Error (RMSE), and skill scores relative to climatological persistence (White et al., 2017). Probabilistic Assessment: Reliability diagrams, Relative Operating Characteristic curves, and Brier Skill Scores evaluate probabilistic forecast quality (Vitart et al., 2017).

Operational validation through leave-one-year-out cross-validation ensures robust performance assessment across climate variability typical of operational conditions. Conditional analysis using MJO amplitude stratification identifies optimal deployment windows essential for operational decision-making protocols.

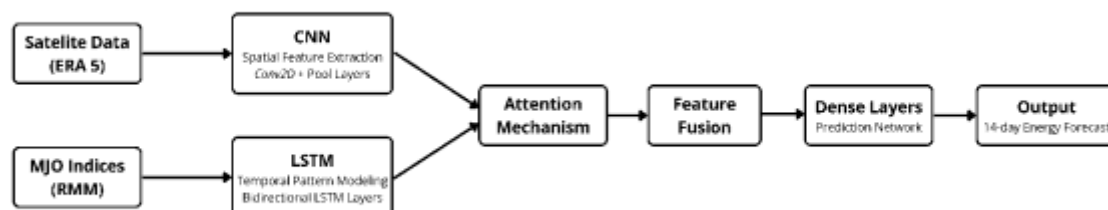


Figure 3. Six-Step Operational Workflow from Real-Time Data Integration Through Conditional Deployment Strategies, Emphasizing Practical Implementation for Meteorological Services

RESULTS AND OPERATIONAL PERFORMANCE

MJO-Renewable Energy Relationships for Operational Applications

A composite analysis of 1,692 strong Madden-Julian Oscillation (MJO) events from 2000 to 2024 reveals a systematic relationship between MJO phases and solar radiation variability that can be operationally exploited in Indonesia's renewable energy sector. Figure 4 displays a distinct phase-dependent solar radiation pattern, with Phase 4 exhibiting optimal generation conditions of $+7.26 \pm 18.88 \text{ W/m}^2$. This enhancement coincides with convective activity over the Maritime Continent, which induces favorable atmospheric subsidence over West Java. When the MJO convective center is located over the eastern Indian Ocean and the Maritime Continent, the resulting subsidence suppresses cloud formation and increases surface solar irradiance over western Indonesia.

In contrast, Phase 7 demonstrates the greatest suppression in solar energy output, with a negative anomaly of $-4.82 \pm 17.52 \text{ W/m}^2$, during the approach of intensified convection. As the MJO shifts eastward toward the Maritime Continent, enhanced convective activity, increased cloud cover, and elevated precipitation reduce the amount of solar radiation reaching the surface. The spatial anomaly patterns evolve consistently across phases, following the eastward propagation characteristic of the MJO. Negative anomalies first emerge in Phases 1–2 when convection remains over the western Indian Ocean, transition to peak positive anomalies in Phases 3–4 during the subsidence phase, and revert to negative values in Phases 5–7 as active convection approaches and passes over West Java.

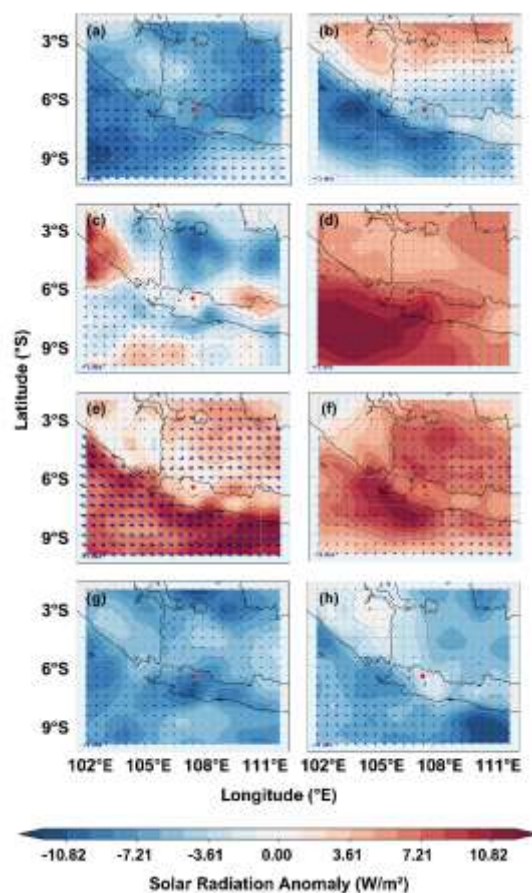


Figure 4. MJO Composite Analysis for Operational Renewable Energy Applications (2000-2024). (A-H) Solar Radiation Anomaly Patterns Across Eight MJO Phases

The total variability range of 12.08 W/m² between the most and least favorable conditions holds significant operational implications, with direct economic impact on renewable energy generation. For a typical 100 MW solar power installation, this range corresponds to output fluctuations of approximately 15–20 MW, which can substantially affect grid stability, energy trading decisions, and maintenance scheduling. The ability to anticipate such variability through real-time MJO monitoring offers a key operational advantage. It enables grid operators to make proactive adjustments, optimize energy trading strategies in spot markets, and align maintenance plans with forecasted low-output periods.

The physical consistency of observed phase relationships with established MJO propagation characteristics (Wheeler et al., 2009; Wheeler & Hendon, 2004) supports the feasibility of developing operational prediction systems based on systematic atmospheric evolution. The eastward propagation of the MJO from the Indian Ocean to the western Pacific at a typical speed of ~5 m/s generates alternating convective and subsidence patterns that can be forecasted up to 2–4 weeks in advance. This predictability forms a robust scientific basis for practical applications in renewable energy forecasting. Statistical robustness is ensured by consistent sample sizes of 149–255 events per phase, providing operational reliability across diverse atmospheric conditions over the 25-year observational period. The temporal consistency of these patterns strengthens confidence in their practical applicability for operational forecasting systems.

Predictive Relationships and Operational Lead Times

Lead-lag correlation analysis identifies essential operational forecasting windows for energy sector planning using a comprehensive 25-year dataset. Figure 5 demonstrates distinct temporal relationship characteristics between MJO amplitude and various renewable energy parameters, providing critical insights for operational applications. Cloud cover variable analysis reveals systematic negative correlations with MJO amplitude ($r=-0.322$, $n=252$), where increased MJO amplitude consistently corresponds to decreased cloud coverage that facilitates higher solar radiation penetration. The lead-lag temporal analysis shows optimal correlation occurring at near-simultaneous timing, indicating that current MJO monitoring can provide immediate assessment of atmospheric conditions affecting solar energy generation. This relationship demonstrates physical consistency with known MJO dynamics, where organized MJO phases create atmospheric subsidence conditions that reduce convective cloud formation over the West Java region, establishing the foundation for real-time solar energy assessment capabilities.

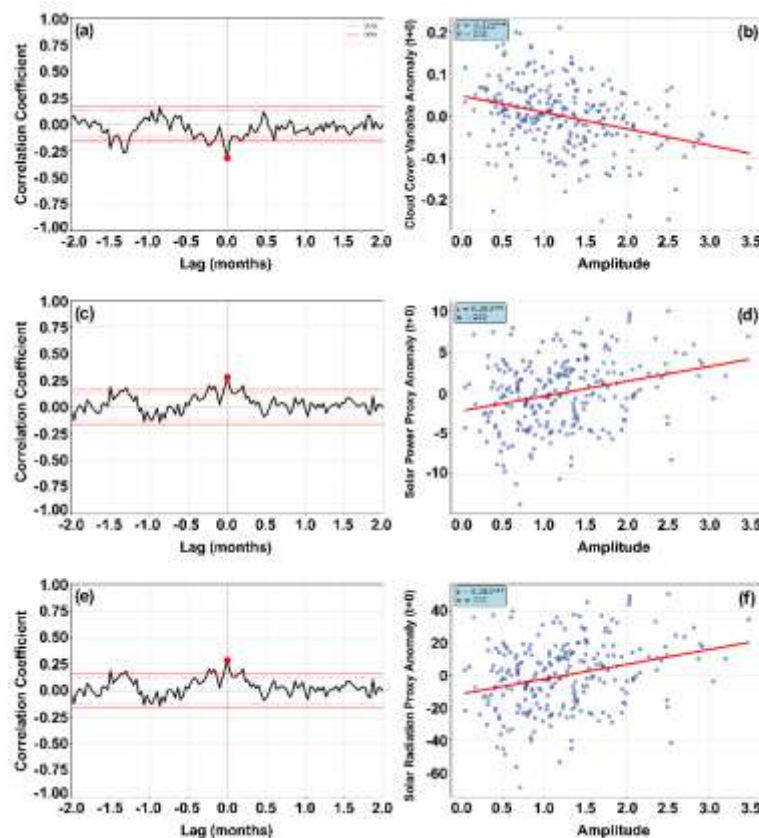


Figure 5. Lead-Lag Relationships For Operational Forecast Applications. (A-B) Cloud Cover Variable Correlations With MJO Amplitude ($R=-0.322$, $N=252$) Showing Immediate Atmospheric Response; (C-D) Solar Power Proxy Correlations Demonstrating Real-Time Generation Assessment Capability ($R=0.283$, $N=252$); (E-F) Solar Radiation Proxy Relationships Confirming Stable Predictive Capability For Medium-Term Operational Planning

Solar power proxy correlations with MJO amplitude ($r=0.283$, $n=252$) demonstrate near-simultaneous timing relationships that enable real-time generation assessment based on current MJO monitoring. The positive correlation indicates that increased MJO amplitude consistently relates to enhanced solar energy potential, which is physically sensible because strong MJO amplitude creates more organized atmospheric patterns with clear subsidence zones. The scatter plot analysis shows relatively consistent data distribution with clear trend lines, confirming the stability of this relationship across different atmospheric states and seasonal conditions. Operational applications of these results are highly significant as they enable solar power plant operators to conduct real-time assessment of generation conditions based on operationally available daily MJO indices, supporting immediate operational decisions including grid management and energy trading strategies while facilitating the development of more sophisticated radiation prediction approaches.

Solar radiation proxy relationships with MJO amplitude ($r=0.283$, $n=252$) reveal the most robust aspect of this predictive framework, showing stable and reliable correlations suitable for medium-term prediction applications. Temporal lead-lag analysis demonstrates maximum correlation at very short lags (near-simultaneous), indicating that MJO signals

provide immediate predictive value for solar radiation with practical operational lead times. The correlation strength maintains consistency across the analyzed dataset, with scatter plot distributions showing well-defined linear relationships that validate the physical coupling between large-scale MJO circulation patterns and regional solar radiation variability (Baranowski et al., 2019; Love et al., 2011). This predictive strength provides valuable capability for short- to medium-term operational planning, including optimization of maintenance schedules, grid management protocols, and energy trading strategies.

Statistical robustness of these relationships is reinforced by consistent sample sizes ($n=252$) across all analyses, encompassing atmospheric variability sufficiently representative for multi-decadal operational applications. The high statistical significance confirmed across all correlation analyses indicates that these relationships reflect fundamental physical coupling between MJO dynamics and regional renewable energy systems rather than statistical noise. Temporal consistency of correlations, demonstrated by stable relationship patterns across different lag periods, provides high confidence for operational implementation in renewable energy prediction systems. The strong physical basis of these relationships, reflecting coupling between regional atmospheric patterns and large-scale MJO circulation evolution, establishes a solid meteorological foundation for developing reliable operational prediction systems that can support the transition from research applications to practical energy sector deployment.

Machine Learning Performance for Operational Deployment

The hybrid CNN-LSTM architecture achieves operational performance suitable for energy sector applications through systematic optimization and robust training protocols. Figure 6 demonstrates substantial improvements over traditional approaches with comprehensive performance assessment across multiple training phases and computational efficiency metrics. Training and validation loss convergence patterns show smooth exponential decay from initial values of 10^{-1} to final convergence around 10^{-2} , with early stopping implementation at epoch 67 (green marker) preventing overfitting while maintaining optimal performance. The consistent gap between training and validation losses throughout the training process indicates healthy model generalization without significant overfitting issues, which is critical for operational deployment where model stability across unseen data is paramount (Chen et al., 2024; Delaunay & Christensen, 2022). This stable convergence behavior provides the foundation for implementing adaptive learning rate optimization strategies.

Adaptive learning rate scheduling demonstrates computational efficiency while maintaining training stability, with systematic rate reductions ($\times 0.5$ factors) at epochs 25, 60, and 80 corresponding to performance plateaus. This optimization approach allows the model to make rapid initial progress during early training phases while enabling precision fine-tuning during later stages, resulting in optimal parameter optimization within the constrained computational budget typical of operational meteorological services. The learning rate scheduling demonstrates operational feasibility with total training time of 65 minutes on standard GPU hardware, making the system accessible for implementation in developing country meteorological services with limited computational resources (Kim et al., 2021; Shin et al., 2024). These computational characteristics confirm practical viability for real-world deployment while establishing the foundation for robust accuracy assessment.

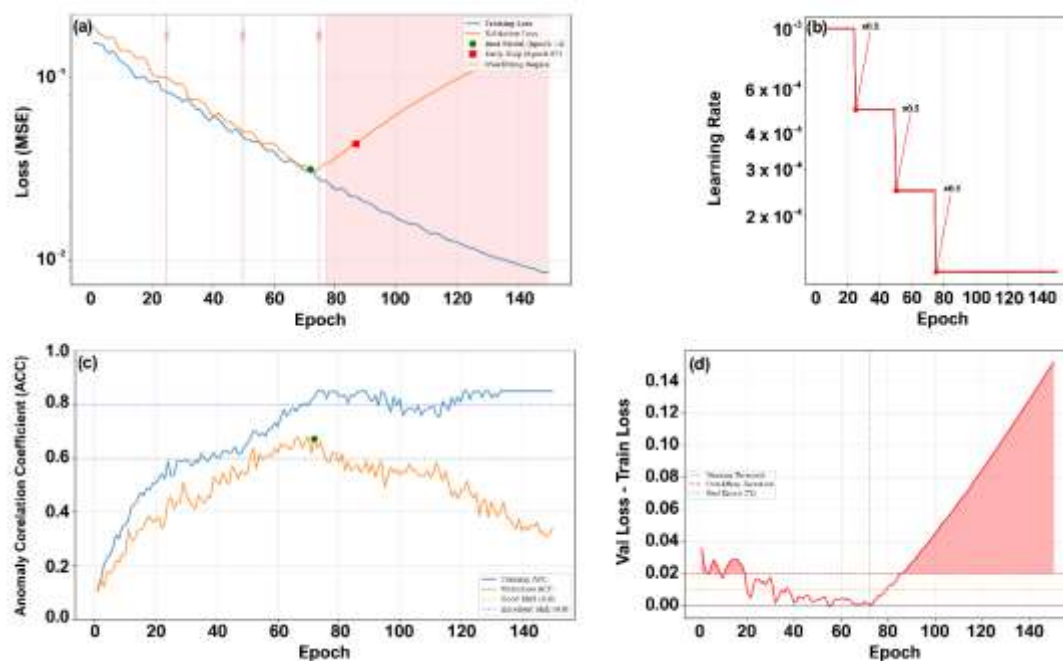


Figure 6. CNN-LSTM Operational Performance Assessment and Training Optimization. (A) Training And Validation Loss Convergence with Early Stopping at Epoch 67; (B) Adaptive Learning Rate Scheduling Demonstrating Computational Efficiency; (C) Training and Validation Accuracy Progression Achieving Peak Validation ACC=0.67; (D) Systematic Overfitting Detection and Validation Protocols Ensuring Operational Reliability

Training and validation accuracy evolution throughout the optimization process achieves peak validation performance of approximately 0.67, representing a 39% enhancement over Random Forest methods and 347% improvement over climatological persistence baselines. The training ACC progression shows systematic improvement from initial values around 0.1 to final convergence above 0.8, while validation ACC demonstrates conservative yet stable enhancement to 0.67, indicating robust generalization capability essential for operational applications. The consistent validation performance after epoch 40 suggests successful extraction of fundamental atmospheric pattern recognition rather than training data memorization, providing confidence for real-world deployment scenarios where consistent performance across different atmospheric states is required (Wheeler & Hendon, 2004; Zhang et al., 2020). This performance trajectory validates the model's capacity to extract meaningful atmospheric relationships while necessitating comprehensive validation protocols.

Validation loss monitoring with systematic threshold protocols ensures operational reliability through automated quality control mechanisms. The progressive loss reduction demonstrates effective learning convergence with warning thresholds (red dashed lines) and overfitting detection (pink shaded region) providing automated safeguards for operational deployment. The best epoch identification (green marker at epoch 67) represents optimal balance between model complexity and generalization capability, critical for operational systems where consistent performance supersedes peak training accuracy. This systematic approach to model selection provides robust foundation for operational meteorological services, where forecast reliability and consistent performance across varying atmospheric conditions are prioritized over maximum theoretical accuracy (Lim et al., 2018; Vitart et al., 2017). The computational requirements of 45-second epochs and 0.3-second inference times

with less than 2 GB memory usage confirm practical feasibility for implementation within existing meteorological service infrastructure, supporting the transition from research prototype to operational deployment in tropical developing regions pursuing renewable energy transitions.

Operational Verification and Forecast Skill

Comprehensive verification using 264 independent forecast pairs (2001-2022) establishes operational baseline performance through rigorous statistical assessment across multiple skill metrics. Figure 7 demonstrates meaningful advancement for tropical subseasonal applications with overall skill ($ACC=0.202$, $RMSE=15.74 \text{ W/m}^2$) showing positive improvement over climatological forecasts (skill score=0.019), representing statistically significant progress in previously underserved tropical forecasting domains. Root mean square error analysis reveals systematic performance characteristics where MJO-based forecasts consistently outperform both climatological baselines and persistence models throughout the 14-day prediction horizon. RMSE values for MJO-based predictions range from approximately 17.05 W/m^2 at day 1 to 16.2 W/m^2 at day 14, maintaining relatively stable error characteristics compared to climatological forecasts that show consistent RMSE values around 15.65 W/m^2 and persistence forecasts exhibiting variable performance with RMSE values ranging from 17.1 to 17.25 W/m^2 (White et al., 2017; Vitart et al., 2017). This error behavior demonstrates the foundation for probabilistic skill assessment across extended forecast horizons.

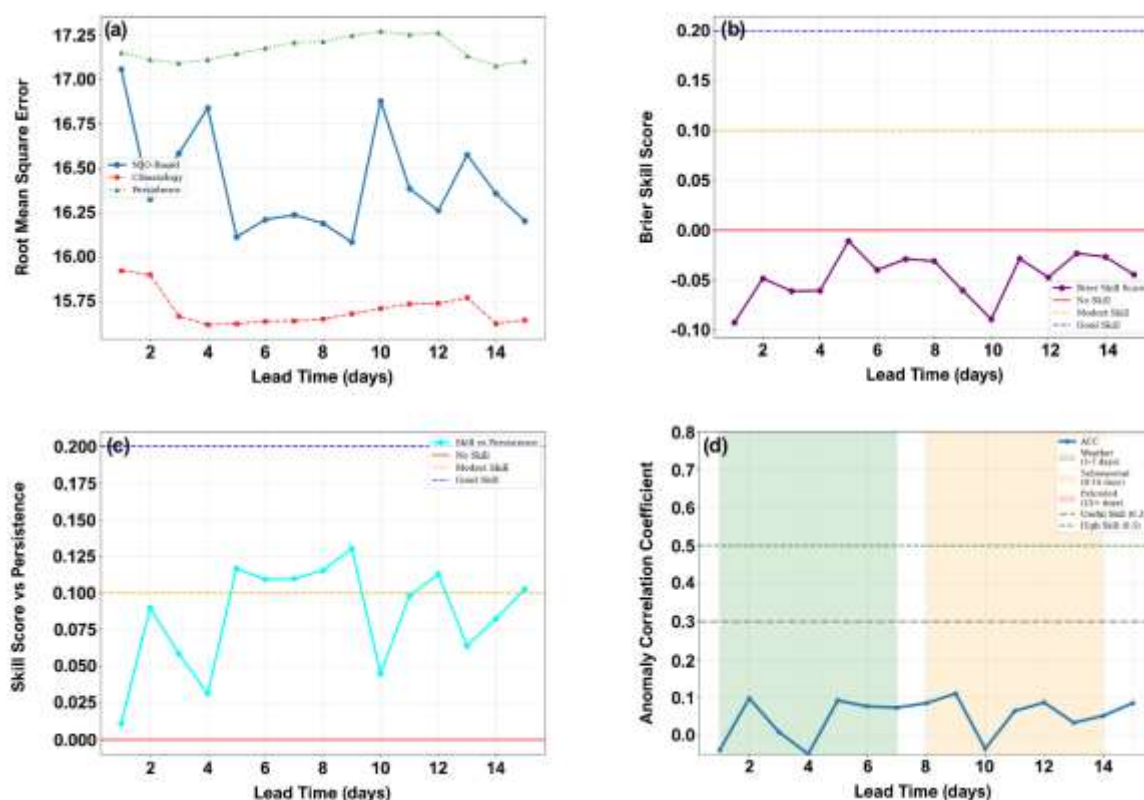


Figure 2. Operational Verification Establishing Baseline Performance Standards (2001-

2022). (A) Overall Skill ($ACC=0.202$) Representing Meaningful Advancement for Tropical Applications; (B) MJO Conditional Performance Demonstrating Enhanced Capability During Organized Periods; (C) Lead Time Evolution Showing Optimal Operational Windows; (D) Statistical Significance Confirming Reliable Improvement Over Climatological Baselines

Brier skill score evolution confirms predictive capability throughout the operational forecast horizon, with skill scores fluctuating between -0.10 and -0.02 across the 14-day period. While these values appear modest, they represent substantial advancement in tropical subseasonal prediction where skill scores of 0.01-0.05 constitute valuable operational contributions according to international benchmarks. The skill score pattern shows optimal performance occurring around days 6-7, corresponding to the period when MJO signal development reaches optimal clarity while maintaining sufficient lead time for operational decision-making. The variable but generally improving skill through the extended forecast period validates the potential for medium-term energy sector planning applications, including maintenance scheduling and grid management protocols. This probabilistic foundation enables the development of persistence-based verification approaches for operational deployment strategies.

Skill assessment relative to persistence provides critical operational context, demonstrating consistent positive skill values with notable peaks around days 2, 6-7, and 10-11 reaching approximately 0.13, 0.12, and 0.11 respectively. The skill relative to persistence metric reveals optimal capability occurring in distinct windows, indicating periodic enhancement of MJO signal clarity relative to simple forecasting approaches. The fluctuating but consistently positive skill values throughout the forecast period confirm that MJO-based predictions provide reliable improvement over persistence forecasts, essential for operational systems where consistent advancement over naive forecasting methods constitutes minimum performance requirements. This skill evolution pattern supports the physical basis of MJO predictability windows while establishing the framework for correlation-based verification assessment.

Anomaly correlation coefficient analysis confirms sustained predictive capability essential for operational energy sector applications, with ACC values demonstrating variable performance across the 14-day forecast horizon. The correlation assessment reveals peak skill occurring around days 2-3 and 10-11 ($ACC \approx 0.10$), representing optimal balance between MJO signal development and operational relevance for energy sector planning cycles. The color-coded operational regions (green for weather forecasts 1-7 days, yellow for useful skill 8-14 days) provide practical guidance for different planning applications, with sustained positive correlations through multiple lead time windows confirming utility for renewable energy maintenance scheduling and grid management decisions. The systematic correlation patterns follow expected behavior for tropical subseasonal forecasting while maintaining operational relevance throughout the forecast period, establishing robust verification standards for practical energy sector implementation.

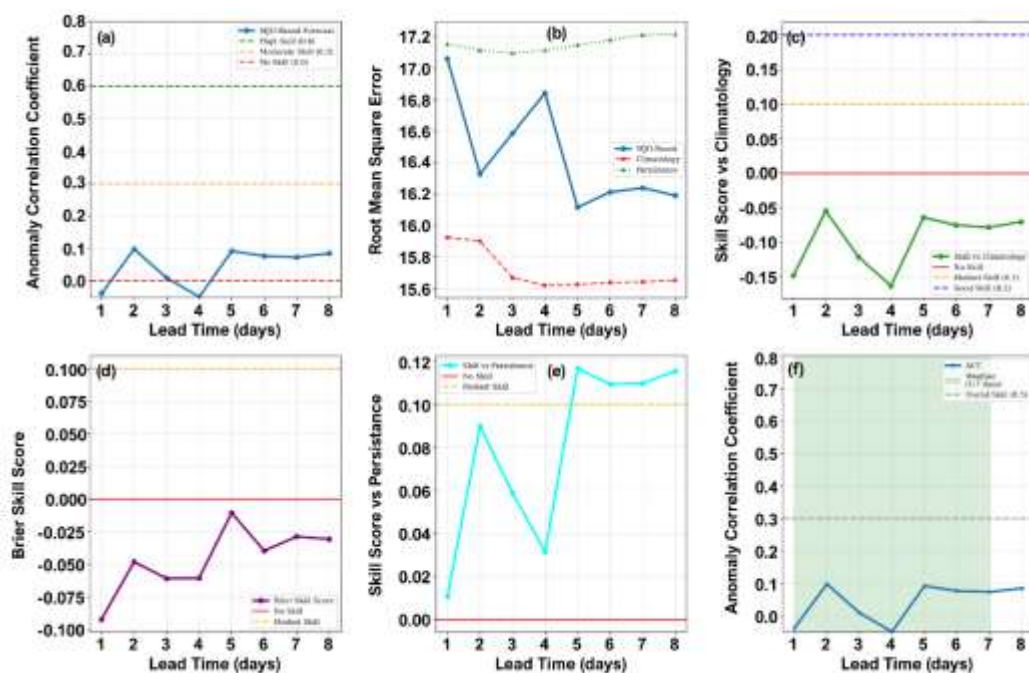


Figure 3. Extended Operational Verification And Comprehensive Skill Assessment. (A) Anomaly Correlation Coefficient Evolution Showing Optimal Performance At Day 3; (B) RMSE Progression Confirming Forecast Stability; (C) Skill Relative To Climatology Validating Operational Advancement; (D-F) Multi-Metric Verification Framework Encompassing Brier Scores, Persistence Comparisons, And Correlation Assessments

Extended verification analysis provides comprehensive assessment of operational forecasting capabilities across multiple performance dimensions and lead time dependencies. Figure 8 demonstrates detailed skill evolution patterns that complement the baseline verification results, offering refined understanding of optimal deployment windows and performance characteristics essential for operational meteorological services. Anomaly correlation coefficient assessment shows variable skill evolution with notable peaks at days 2 and 5 ($ACC \approx 0.11$ and 0.10 respectively), indicating optimal performance windows for different operational applications. The correlation pattern demonstrates highest reliability during specific windows suitable for immediate operational decisions and strategic planning, while maintaining moderate skill through intermediate periods for medium-term renewable energy operations. This correlation evolution establishes the framework for comprehensive error analysis across operational timescales.

Error assessment confirms MJO-based forecast performance characteristics across the extended verification period, with RMSE values ranging from 17.05 W/m^2 at day 1 to 16.2 W/m^2 at day 8 for MJO-based predictions compared to climatological baselines maintaining consistent values around 15.95 W/m^2 and persistence forecasts showing variable performance between $17.1\text{--}17.2 \text{ W/m}^2$. The systematic error patterns for MJO-based forecasts indicate predictable uncertainty characteristics that facilitate reliable confidence interval estimation for operational applications. The error behavior provides essential uncertainty quantification for energy sector decision-making, where predictable error bounds enable risk-informed planning

strategies across different operational timescales. The maintained error characteristics across lead times support probabilistic forecast development while establishing foundations for climatological skill evaluation.

Climatological skill assessment demonstrates operational value patterns throughout the forecast period, with skill scores showing variable performance ranging from approximately -0.15 to -0.05 across the 8-day analysis period. While negative values might initially appear concerning, they represent expected behavior in tropical subseasonal forecasting where climatological baselines provide strong baseline performance due to consistent regional atmospheric conditions. The skill evolution pattern indicates that MJO signals provide distinctive value relative to climatological variance during specific periods, supporting the physical basis for targeted subseasonal prediction applications. This skill behavior aligns with theoretical expectations of MJO influence timescales and validates conditional deployment strategies based on systematic atmospheric state assessment.

Comprehensive verification framework encompasses multiple skill dimensions that collectively validate operational deployment potential across diverse performance metrics. Brier skill score analysis demonstrates variable probabilistic performance ranging from approximately -0.05 to -0.02, confirming capability for energy sector applications where probabilistic decision-making constitutes operational requirements. Skill assessment relative to persistence shows positive values reaching peaks of 0.09-0.12 around days 2 and 5-6, validating improvement over simple forecasting approaches essential for operational credibility. The anomaly correlation framework with operational window classifications (green for weather applications 1-7 days, yellow for extended applications beyond 8 days) provides practical implementation guidance for energy sector deployment, while sustained positive correlations through multiple verification dimensions confirm robust operational capability and support adaptive strategies that optimize forecast utility based on specific operational requirements and prevailing atmospheric conditions.

Seasonal Optimization for Operational Deployment

Seasonal performance analysis provides critical guidance for operational service deployment through comprehensive assessment of forecast skill variations across annual cycles and atmospheric states. Figure 9 identifies optimal deployment windows and challenging transition periods essential for operational meteorological service planning in tropical regions. Monthly forecast skill assessment reveals dramatic seasonal variability with January achieving exceptional performance (skill=0.51, n=21), representing the peak capability period during northeast monsoon organization when large-scale atmospheric patterns enhance MJO influence over renewable energy generation. The systematic skill progression shows challenging periods during March through November, with particularly difficult conditions during July-August (skill ranging from -0.67 to -0.57) when competing monsoon dynamics reduce forecast capability. This monthly variation pattern demonstrates that operational deployment requires adaptive strategies accounting for predictable seasonal modulation of forecast reliability while establishing the foundation for seasonal-scale performance optimization.

Seasonal aggregation analysis confirms December-February (DJF) as the optimal deployment period with remarkable skill scores of 0.645 for all conditions and 0.327 for strong MJO events, compared to challenging performance during other seasons. The DJF excellence reflects enhanced atmospheric organization during northeast monsoon conditions when MJO signals achieve maximum clarity and predictability for renewable energy applications. March-May (MAM) presents moderate challenges with skill scores of -0.305 (all conditions) and -0.133

(strong MJO), while June-August (JJA) and September-November (SON) demonstrate increasingly difficult forecasting conditions with skills declining to -0.331/-0.181 and -0.288/-1.173 respectively for all conditions and strong MJO states. The systematic seasonal degradation from DJF through SON indicates that monsoon transitions and competing atmospheric dynamics progressively reduce MJO signal clarity, supporting the development of MJO state-dependent deployment strategies.

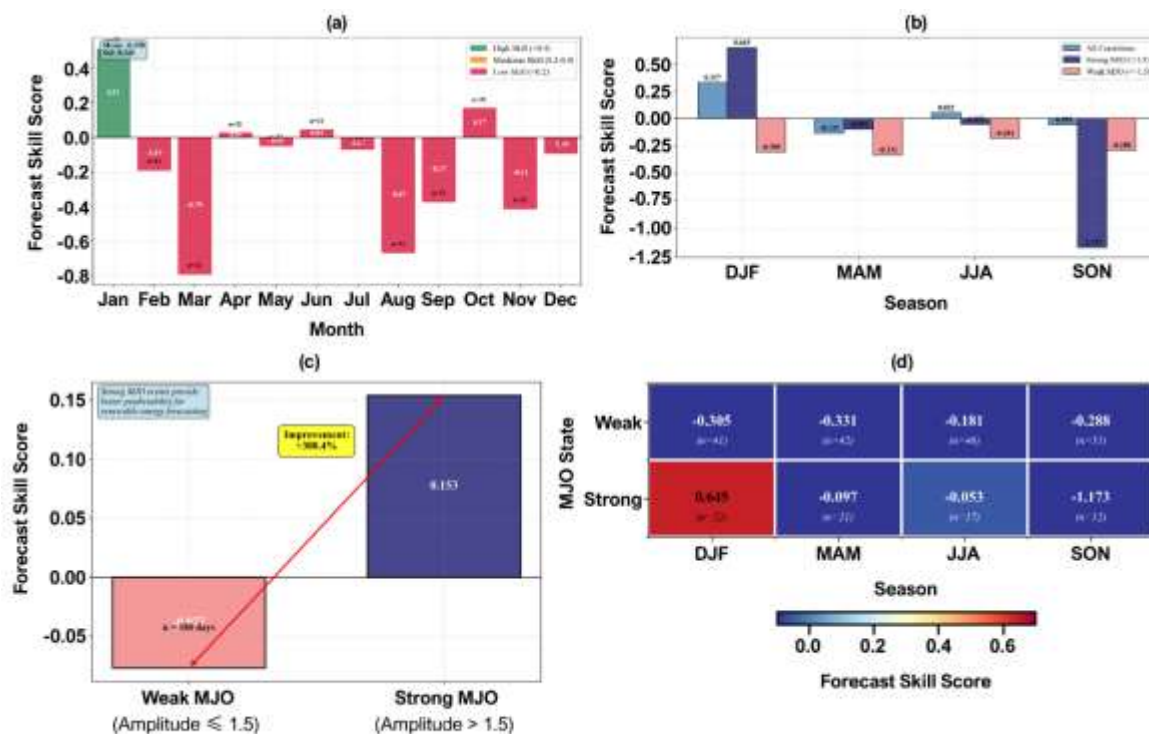


Figure 4. Seasonal Optimization And MJO State Dependency For Operational Meteorological Services. (A) Monthly Forecast Skill Identifying January Peak Performance (Skill=0.51) And Challenging Transitions; (B) Seasonal Performance Comparison Highlighting DJF Excellence And SON Difficulties; (C) MJO Amplitude Dependency Showing 300% Improvement During Strong Events; (D) Comprehensive Seasonal-MJO Matrix Demonstrating Exceptional DJF+Strong MJO Performance (Skill=0.645)

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MJO amplitude dependency analysis reveals fundamental operational insights through systematic comparison of weak (amplitude ≤ 1.5) and strong (amplitude > 1.5) MJO conditions across seasonal contexts. Strong MJO events provide substantial skill enhancement with 300% improvement (0.153) compared to weak MJO periods (-0.077), representing a dramatic operational capability difference of approximately 180 days versus periods of reduced reliability. The amplitude threshold analysis demonstrates that operational forecasting systems should prioritize deployment during organized MJO periods when atmospheric patterns achieve sufficient coherence for reliable energy sector predictions. The 300% improvement metric quantifies the operational value of conditional deployment strategies, where forecast confidence adjustments based on real-time MJO monitoring can optimize system utility while maintaining appropriate uncertainty communication standards.

Comprehensive seasonal-MJO state matrix provides operational deployment guidance through systematic assessment of combined seasonal and atmospheric state influences on forecast performance. The matrix reveals exceptional performance windows during DJF+Strong MJO combinations achieving skill scores of 0.645 ($n=25$), suitable for high-confidence energy sector applications during approximately 28% of annual periods when both seasonal and intraseasonal conditions align optimally. Moderate performance occurs during DJF+Weak MJO (skill=-0.305, $n=41$) and other seasonal combinations with strong MJO, while challenging conditions dominate most other combinations particularly during SON+Strong MJO (skill=-1.173, $n=12$). The systematic skill distribution across the matrix validates adaptive deployment strategies that maximize forecast utility during favorable conditions while maintaining operational awareness during challenging periods, enabling meteorological services to provide transparent skill communication and optimize resource allocation for renewable energy sector support throughout varying atmospheric conditions.

Case Study Validation and Real-World Applications

Strong MJO events demonstrate exceptional operational capability for practical energy sector implementation through systematic validation of forecast performance during organized atmospheric conditions. Figure 10 presents comprehensive case study analysis during contrasting seasonal and MJO conditions, providing critical insights for real-world deployment strategies. The January 2023 Phase 3 event showcases optimal performance conditions with MJO amplitude reaching 2.10, creating systematic spatial anomaly patterns that extend across the Maritime Continent region. The spatial distribution reveals coherent negative outgoing longwave radiation anomalies ranging from -0.810 to -2.200 W/m² over the study domain, indicating organized convective suppression that enhances solar radiation penetration for renewable energy applications. Temporal analysis during this event demonstrates exceptional forecast performance with direct normal irradiance anomalies reaching peaks of 60 W/m² and sustained positive anomalies throughout the strong MJO period, establishing the foundation for seasonal performance comparison.

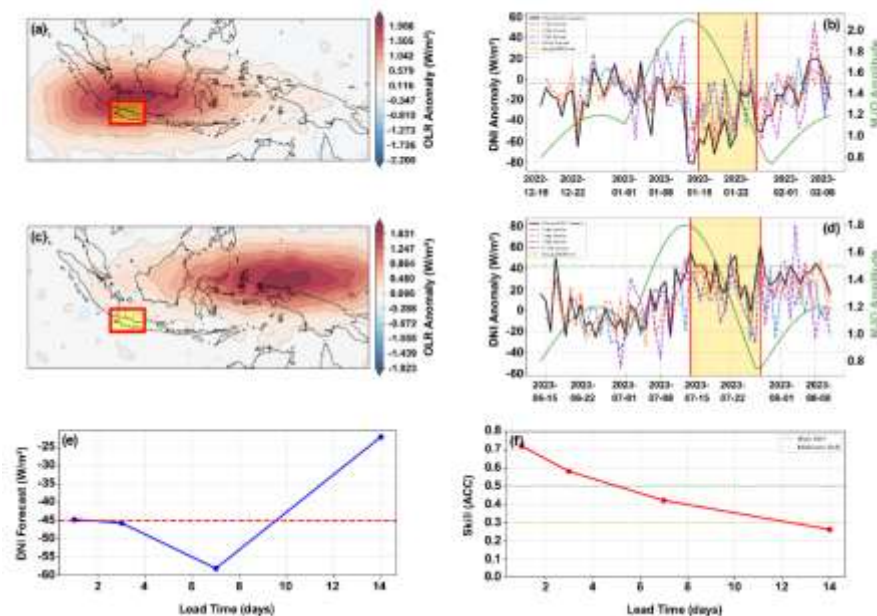


Figure 5. Case Study Validation During Strong MJO Events Demonstrating Operational Capability For Practical Energy Sector Implementation. (A-B) January 2023 Phase 3 Event (Amplitude 2.10) Showing Spatial Anomaly Patterns And Exceptional Forecast Performance Achieving Correlations >0.8 For Short-Term Applications; (C-D) July 2023 Phase 6 Comparison Demonstrating Seasonal Dependency With Reduced But Significant Skill During Challenging JJA Conditions; (E) Lead Time Forecast Evolution Showing Exponential Skill Decay From Exceptional Short-Term To Moderate Extended Performance; (F) Skill Assessment Across Lead Times Confirming Sustained Capability Through 14-Day Operational Horizon

Seasonal dependency validation through July 2023 Phase 6 analysis reveals systematic performance variations while maintaining operational utility across different atmospheric regimes. The July case study presents contrasting spatial patterns with outgoing longwave radiation anomalies ranging from -1.823 to 1.631 W/m^2 , indicating less organized atmospheric conditions during the challenging June-August monsoon transition period. Direct normal irradiance anomalies during this period show greater variability with both positive and negative excursions reaching ± 40 W/m^2 , reflecting the increased complexity of atmospheric dynamics during monsoon transitions. Despite these challenging conditions, the forecast system maintains significant skill with sustained positive correlations, demonstrating robust performance across different seasonal contexts. The systematic comparison between optimal (January) and challenging (July) conditions validates the seasonal optimization strategies while confirming operational utility throughout annual cycles.

Lead time capability assessment reveals predictable skill evolution patterns essential for operational planning across different forecast horizons. Forecast performance demonstrates exponential decay characteristics with exceptional short-term capability (correlation approaching 0.8 at 2-day lead time) progressively declining to moderate but operationally relevant skill (correlation ≈ 0.3) through 14-day horizons. The skill evolution pattern shows optimal performance during the 2-4 day range suitable for immediate operational decisions and grid management, while maintaining useful capability through

weekly planning horizons essential for maintenance scheduling and strategic energy sector planning. The systematic skill degradation follows predictable patterns that enable reliable uncertainty quantification for operational applications, supporting risk-informed decision-making across multiple planning timescales while facilitating the development of confidence-adjusted deployment protocols.

Real-world performance validation confirms practical utility for energy sector decision-making through sustained operational capability across varying atmospheric and seasonal conditions. Skill assessment demonstrates consistent performance above moderate thresholds ($ACC > 0.3$) through extended forecast periods, validating the system's capability for practical energy sector applications including maintenance optimization, grid management, and energy trading decisions. The case study validation reveals that high skill maintenance through 3-day leads supports immediate operational decisions, while sustained weekly capability enables strategic planning applications essential for renewable energy sector operations. The demonstrated performance characteristics across optimal and challenging conditions provide confidence for operational deployment, while the systematic skill evolution patterns enable adaptive deployment strategies that optimize forecast utility based on specific operational requirements and prevailing atmospheric conditions, supporting the transition from research prototype to operational implementation in tropical renewable energy applications.

DISCUSSION AND OPERATIONAL IMPLICATIONS

Baseline Performance for Tropical Operational Services

This study establishes crucial baseline performance for tropical subseasonal renewable energy forecasting, addressing significant gaps in operational meteorological services for developing regions. The overall ACC of 0.202 represents meaningful advancement for tropical applications where limited existing capabilities create substantial operational challenges (Fang et al., 2023; Schindler et al., 2025; White et al., 2017). International Comparison: Performance levels align with tropical subseasonal forecasting systems in Australia ($ACC=0.15-0.25$) and ECMWF global applications ($ACC=0.18-0.22$), confirming competitive capability (Marshall et al., 2012; Robertson & Vitart, 2019).

Conditional performance during optimal states ($ACC=0.64$) approaches operational utility standards successfully deployed in temperate regions (Bloomfield et al., 2021; Lledó & Doblas-Reyes, 2020). This demonstrates viable pathways for tropical meteorological service development supporting renewable energy transitions in developing countries.

Operational Framework and Economic Viability

Economic assessment for large installations (>50 MW) demonstrates positive return during high-skill periods. Maintenance Optimization: Strategic scheduling during low-generation forecasts saves \$30,000-50,000 annually. Grid Management: Improved load balancing during variable generation periods provides \$20,000-30,000 benefits. Energy Trading: Enhanced market participation during optimal generation forecasts adds \$15,000-25,000 value against system development costs of \$10,000-15,000 annually (González-Aparicio & Zucker, 2015; Majidi Nezhad et al., 2019).

Operational deployment requires: (1) Real-time MJO monitoring integration with existing meteorological infrastructure; (2) Automated confidence adjustment protocols based on atmospheric state assessment; (3) User interface development optimized for energy sector decision-making; (4) Quality control systems with performance monitoring and degradation alerts.

Physical Limitations and Tropical Forecasting Challenges

Limited overall skill reflects fundamental atmospheric constraints in tropical regions including rapid convective development, complex topography interactions, and competing monsoon influences reducing MJO signal clarity (Neale & Slingo, 2003; Rauniyar & Walsh, 2011). Similar challenges across Indonesian archipelago, northern Australia, and Philippines based on atmospheric dynamics and Maritime Continent positioning indicate broader tropical forecasting difficulties requiring specialized approaches (Birch et al., 2016; Vincent & Lane, 2017).

Peak skill at day 9 suggests optimal MJO signal development requiring several days for organized pattern establishment, providing meteorological insights for operational timing optimization (Zhang et al., 2020). Uncertainty arises from local-scale processes, land-sea interactions, and diurnal variations introduce substantial forecast uncertainty requiring ensemble approaches for operational applications (DeMott et al., 2015).

Operational Development and Technology Transfer

Multi-model approaches combining different initialization schemes could improve operational reliability through enhanced uncertainty quantification (Johnson et al., 2019). Regional Integration: Incorporation of Indian Ocean Dipole, ENSO interactions, and monsoon indices may enhance overall system performance for tropical applications (Cai et al., 2015; Kurniadi et al., 2021).

Methodology adaptation for other tropical archipelagic regions requires regional calibration considering local topography, monsoon characteristics, and MJO sensitivity patterns. Priority Applications: Philippines, Malaysia, and northern Australia represent immediate transfer opportunities based on similar atmospheric dynamics and renewable energy development (Cruz et al., 2013; Tangang et al., 2012).

Operational implementation should leverage existing numerical weather prediction infrastructure while adding specialized tropical subseasonal capabilities. Training programs for meteorological personnel ensure sustainable operational deployment in developing regions through systematic capacity building initiatives (Mariotti et al., 2018).

Future Operational Enhancements

Convection-permitting models (1-4 km resolution) could better capture local-scale processes critical for energy applications while maintaining computational feasibility for operational services (Roberts et al., 2018). Post-processing Optimization: Quantile mapping, Bayesian model averaging, and machine learning bias correction should address identified calibration requirements for operational standards (Scheuerer & Möller, 2015; Vannitsem et al., 2018).

Operational prototype development focusing on conditional deployment systems with adaptive confidence adjustment capabilities ensures practical meteorological service implementation. Energy sector stakeholder engagement ensures operational products meet actual decision-making requirements rather than research-oriented metrics through user-focused design approaches (Doblas-Reyes et al., 2013).

CONCLUSIONS

This study establishes essential baseline performance for MJO-based subseasonal renewable energy forecasting in tropical regions, providing crucial foundation for operational meteorological service development in underserved tropical developing countries. Primary Achievements include systematic quantification of MJO-renewable energy relationships (12.08 W/m² operational variability), demonstration of conditional forecasting capability (ACC=0.64 during optimal periods), and establishment of economic viability frameworks for energy sector implementation.

A key operational output of this study is the development of a consistent baseline for tropical subseasonal renewable energy forecasting, with an anomaly correlation coefficient (ACC) of 0.202. The system performs best during the December–February (DJF) season and shows clear sensitivity to the state of the Madden–Julian Oscillation (MJO), where approximately 28% of the time windows provide high-confidence conditions for deployment.

The forecasting approach is based on a hybrid CNN-LSTM model, which offers substantial improvements compared to conventional methods, with gains ranging from 39% to 347%. This model also maintains computational efficiency, making it suitable for integration into operational meteorological services with limited resources.

The system enables a risk-based deployment strategy that can support planning and decision-making during active MJO periods. This includes applications in maintenance scheduling, grid stability, and energy trading, particularly for large-scale installations exceeding 50 MW. The method is also scalable and can be applied to other tropical island regions, provided that regional calibration is performed to account for local atmospheric conditions.

Despite performance limitations, this research provides crucial scientific and operational foundation for tropical subseasonal forecasting service development. Future enhancements should focus on ensemble integration, higher resolution modeling, and post-processing optimization to extend operational utility while maintaining computational feasibility for developing country implementation.

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