QUANTIFYING THE IMPACT OF HIGHLY CORROSIVE ENVIRONMENTS ON FSRM BUDGETS AND INFRASTRUCTURE CONDITION AT AIR FORCE BASES

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ABSTRACT: The Department of Defense (DoD) faces significant challenges in maintaining mission-critical infrastructure in highly corrosive environments, leading to sustainment inefficiencies and increased costs. Maintaining resilient infrastructure at U.S. Air Force (AF) installations in the Pacific theater is essential for national defense operations, force projection, and rapid deployment. The Facility Sustainment Model (FSM) standardizes sustainment funding but does not fully capture the impact of environmental severity on infrastructure deterioration. This study examines the correlation between Environmental Severity Index (ESI) levels, Base Condition Index (BCI) trends, and Facility Sustainment, Restoration, and Modernization (FSRM) funding allocations. Statistical modeling and regression analysis reveal that bases in high-ESI environments require significantly greater investment per square foot to maintain comparable BCI levels, with maintenance costs increasing 30-50% compared to lower-ESI bases. Time-series analysis further demonstrates a delayed impact of sustainment investments on BCI, highlighting the need for proactive funding strategies. Findings confirm that sustainment costs and infrastructure conditions are strongly influenced by environmental severity. This study introduces Environmental Corrosion Factors (ECFs) to adjust funding allocation models, ensuring more accurate sustainment projections. The integration of ECFs into the FSM provides a data-driven approach to optimizing resource distribution, informing policy adjustments, and improving infrastructure resilience.

1. INTRODUCTION

1.1 Background

The 2022 National Defense Strategy (NDS) underscores the critical role of resilient military infrastructure in ensuring force readiness and global deterrence. As strategic competition intensifies in the Indo-Pacific, maintaining reliable infrastructure at U.S. Air Force bases is paramount to sustaining a forward-deployed posture and enabling rapid response capabilities. Corrosion-related degradation presents a significant challenge for U.S. Air Force installations, particularly those in highly corrosive coastal environments. Many of these installations fall within the Pacific Air Forces (PACAF) and Indo-Pacific Command (INDOPACOM) regions, which are vital for strategic defense operations. The ability to maintain infrastructure in these environments directly impacts force projection, regional deterrence, and rapid response capabilities in critical geopolitical regions. Bases in these environments experience accelerated deterioration due to exposure to humidity, salt-laden air, and extreme temperatures.

Despite the accelerated degradation, the present Facility Sustainment Model (FSM) does not adequately account for environmental severity conditions. The FSM compares sustainment requirements to Program Element Code (PEC) 78 funding, which includes programmed and appropriated resources. However, funding does not fully cover the calculated need, with sustainment levels reaching only 79% in FY25, short of the OSD's 85% goal. The FSM also aligns with the 2% Plant Replacement Value (PRV) resourcing goal, combining sustainment, repair, and recapitalization funding.

1.2 Literature Review

Corrosion significantly affects infrastructure longevity, particularly in high-humidity, salt-laden, and extreme-temperature environments (Melchers & Jeffrey, 2008). It accelerates material degradation, leading to increased maintenance costs and structural failures (Wasim et al., 2019). Military installations in these conditions require more frequent maintenance cycles and higher sustainment investments (Khan et al., 2023). The Environmental Severity Index (ESI) provides a standardized framework for quantifying material deterioration based on empirical corrosion data (Silver & Gaebel, 2017). Studies indicate that bases in high-ESI locations experience faster infrastructure degradation, necessitating greater sustainment funding (Frank et al., 2024). Installations in maritime climates, such as those in the Indo-Pacific region, are particularly susceptible to accelerated degradation due to salt exposure (Lamm et al., 2022).

To mitigate corrosion-related damage, the Department of Defense (DoD) has incorporated corrosion prevention guidelines into its Unified Facilities Criteria (UFC). These regulations require the use of corrosion-resistant materials in harsh environments and provide assessment methodologies for reducing degradation. However, despite these preventive measures, the FSM does not fully account for environmental severity when determining sustainment funding allocations (UFC 3-701-01, 2024). Researchers have proposed integrating Environmental Corrosion Factors (ECFs) into the FSM to improve funding accuracy and infrastructure resilience (Baten et al., 2019; Meiyan et al., 2021). Although prior DoD studies have acknowledged the funding gaps in high-ESI environments (Silver & Gaebel, 2017), no systematic funding adjustments have been implemented. Recent research suggests that predictive models and machine learning techniques could enhance sustainment funding allocation strategies (Melchers et al., 2024; Al-Khalidi, 2023). This study aims to bridge the research gap by incorporating ECFs into the FSM to reflect the impact of environmental severity on sustainment requirements.

1.3 Problem Statement

The FSM provides a standardized calculation for installation sustainment funding is published in UFC 3-701-01 DoD Facilities Pricing Guide. Equation 1 represents the formula used to calculate the sustainment requirement:

[1] $SR = Q * SUC * SACF * I$

where,
SR = Sustainment requirement,
Q = Facility quantity,
SUC = Sustainment unit cost,
SACF = Sustainment area cost factor, and
I = Future-year escalation value(s) from Table 4-4 UFC 3-701-01

While the FSM effectively estimates general sustainment costs, it lacks specific adjustments for installations in highly corrosive environments, where deterioration rates are commonly accelerated. This model fails to account for the heightened maintenance demands these environments impose, leaving these bases to struggle with disproportionately high repair costs and diminished returns on investment in facility improvements. This research quantifies the additional costs required to maintain infrastructure at these bases and evaluates the efficiency of existing funding mechanisms. Additionally, this study proposes modifications to the FSM to better align funding allocation with environmental degradation rates.

1.4 Research Objectives

This study’s objective is to determine how the current FSM can more accurately reflect the maintenance needs of Air Force bases in highly corrosive environments. Addressing the limitations in the existing sustainment strategies, this research aims to:

1. Analyze trends between ESI and infrastructure condition at various Air Force bases.
2. Quantify sustainment funding gaps between bases in corrosive and non-corrosive environments and evaluate how these gaps impact infrastructure performance.
3. Propose modifications to the FSM to incorporate environmental severity

2. METHODOLOGY

This study employed a four-phased approach to analyze the impact of environmental severity on sustainment funding and infrastructure degradation.

2.1 Phase One: Selection of Study Installations

Ten Air Force installations, shown in Table 2, were selected to ensure a representative analysis across varying ESIs. Previous DoD studies classified ESIs more than a decade ago, requiring updates for accuracy. To achieve this, the ISO Corrosivity Category Estimation Tool (ICCET) was used to recalculate each installation’s ESI using historical NOAA data. This tool measured steel mass loss in μg/cm², allowing for precise reassessment of corrosion severity. The recalculated values were then compared to previous ESI classifications to ensure consistency with present-day environmental conditions.

Table 1: List of study installations’ estimated steel mass loss, original ESI zones, and updated ESI zones.

Study Installations	Estimated Steel Mass Loss μg/cm²	Original ESI Zone	Updated ESI Zone
Nellis AF Base, NV	8,301	1	3
Fairchild AF Base, WA	11,877	3	4
Dyess AF Base, TX	18,392	6	6
McConnell AF Base, KS	20,421	8	7
Little Rock AF Base, AR	27,940	7	9
Moody AF Base, GA	33,606	10	11
Eglin AF Base, FL	46,981	15	15
Lajes Field AB, Portugal	63,067	16	17
MacDill AFB, FL	75,106	15	18
Kadena AB, Japan	94,517	9	19

2.2 Phase Two: Data

2.2.1 Data Collection

Facility condition metrics and financial data for sustainment, repair, and modernization efforts were gathered from multiple sources covering 2020 to 2024. The BUILDER online inventory system provided infrastructure condition indices and total facility square footage for each installation. NexGenIT, an Air Force real-property management system, supplied detailed cost data on completed sustainment, repair, and maintenance work tasks. Additionally, the Air Force Installation and Mission Support Center (AFIMSC) provided aggregated investment data for FSRM capital projects, separated into centralized (cFSRM) and decentralized (dFSRM) funding categories.

To standardize the data, facility square footage values were extracted from BUILDER reports, ensuring consistency across installations. A three-step filtering process identified the primary complex at each base by:

- Filtering BUILDER reports to include only facilities with measured square footage,

- Validating complex relevance through NexGenIT to exclude non-real property assets, and
- Determining the most significant complex based on total square footage and Plant Replacement Value (PRV) using JMP software.

Following this filtering process, the BUILDER “Condition Index Performance” report was generated for the selected complexes from 2020 to 2024, which provided a time-series dataset for infrastructure condition changes. The Complex Condition Index is defined as a rating (0-100) for the target complex, calculated by averaging the BCIs of each building within the complex, with each building’s BCI weighted by its replacement cost (BUILDER Inventory Guide 2022).

For sustainment, repair, and maintenance work task costs, the "AFCEC COOM WM-Rpt-001 Work Task General Purpose" report was run for each installation using the NextGenIT reporting tool. This report contained key details including the associated materials costs and labor hours to complete work. To account for larger capital project investments affecting installation conditions, AFIMSC funding data was incorporated. AFIMSC allocates FSRM funding through centralized (cFSRM) and decentralized (dFSRM) mechanisms. Centralized funds are managed at the enterprise level, while decentralized funds serve as local installation budgets. The analysis used total obligated amounts for 2020-2023 and issued amounts for 2024, as the fiscal year had not yet concluded at the time of the analysis.

2.2.2 Data Processing and Transformation

After all the NexGenIT data was collected, it was cleaned and standardized to ensure accuracy and consistency across sources using RStudio software. This included correcting errors in installation names, formatting columns uniformly, and addressing missing data by filling gaps with ‘NA’ values where necessary. Data from multiple reports were merged to create a comprehensive dataset for analysis that included all study installations.

To adjust for cost variations between installations, labor and material costs were normalized using the Area Cost Factors (ACFs) from UFC 3-701-01 Table 4-1. These adjustments, executed in JMP Pro, accounted for regional differences in expenses for material and labor costs. Finally, total labor and material costs were aggregated by fiscal year and installation, then divided by total facility square footage to calculate cost per SF. Future-year escalation rates from UFC 3-701-01 Table 4-2 were applied to convert all cost data to 2024 dollars, ensuring consistent comparisons across years and installations. Similarly, the same future-year escalation process was applied to the AFIMSC financial data

Subsequently, the escalated costs were then divided by the respective installations’ total facility square footage (calculations from the three-step filtering process) for each year. Last, dFSRM cost per SF, cFSRM cost per SF, and Work Task Total cost per SF were summed to acquire a Total dollars per SF.

2.3 Phase Three: Trends and Statistical Analysis

2.3.1 Development of Derived Variables

The initial step in analyzing how spending influenced BCI changes required creating two key variables: ΔBCI (Change in BCI) and Total $/SF per Incremental BCI Change (Three-Year Delay). The first variable measured year-over-year changes in BCI values at the study installations. The second variable accounted for the delayed effects of funding expenditures on infrastructure condition assessments, acknowledging that facility condition updates typically occur every 3-5 years. To address this lag, the variable was calculated by dividing the Total $/SF for a given year by the corresponding change in BCI observed three years later. The original variables and derived variables and their respective definitions are presented in Tables 2 and 3 below.

Table 2: Explanation of original variables used for visualization and statistical analysis

Original Variables	Variable Definition
Total $/SF	Total FSRM dollars spent for the respective FY and Installation

BCI	Complex condition metric for the respective FY and Installation
ESI	The Environmental Severity Index category assigned to each respective installation

Table 3: Explanation of derived variables used for visualization and statistical analysis

Created Variables	Variable Definition
ΔBCI	Change in BCI values between years (I.e. 2020 to 2021)
Total $/SF per Incremental BCI Change (Three-year delay)	Represents the cost-effectiveness of maintenance and sustainment expenditures over a three-year lag period. It is calculated by dividing the total $/SF by the corresponding incremental change in the Base Condition Index (ΔBCI) observed three years later.

2.3.2 Visualizations and Trends Analysis

A series of graphical visualizations were developed to explore relationships and trends in the dataset. Line graphs were generated to examine spending patterns across different funding sources (dFSRM, cFSRM, and Work Task costs) and their relationship with BCI over time. Temporal trends were further explored using line graphs showing BCI changes across ESI categories from 2020 to 2024, highlighting year-over-year shifts in infrastructure conditions. Another visualization depicted Total $/SF spending trends over time, clarifying how financial investments align with environmental severity levels. Additionally, a comparative graph was created to assess whether increased spending corresponds with improvements in BCI or if diminishing returns occur at higher ESI levels.

2.3.3 Statistical Analysis

To validate observed trends, multiple one-way ANOVA tests were conducted to evaluate the impact of ESI on Total $/SF, BCI, ΔBCI (Three-Year Delay), and Total $/SF per Incremental BCI Change. These tests assessed whether mean differences across ESIs were statistically significant, using a significance level of $\alpha=0.05$. The ANOVA tests included:

1. ANOVA for Total $/SF by ESI: Examining whether spending per square foot differs significantly across ESI categories.
2. ANOVA for BCI by ESI: Assessing whether BCI varies across different levels of environmental severity.
3. ANOVA for ΔBCI (Three-Year Lag) by ESI: Determining whether the delayed change in BCI is influenced by environmental severity.
4. Regression ANOVA for Total $/SF per Incremental BCI (Three-Year Delay) by ESI: Evaluating whether ESI serves as a significant predictor of sustainment costs per incremental BCI improvement.

Following the regression ANOVA, three out of four key assumptions were checked to validate the statistical model which included: normality of residuals, homogeneity of variances, and homoscedasticity. Independence could not be completed due to data limitations.

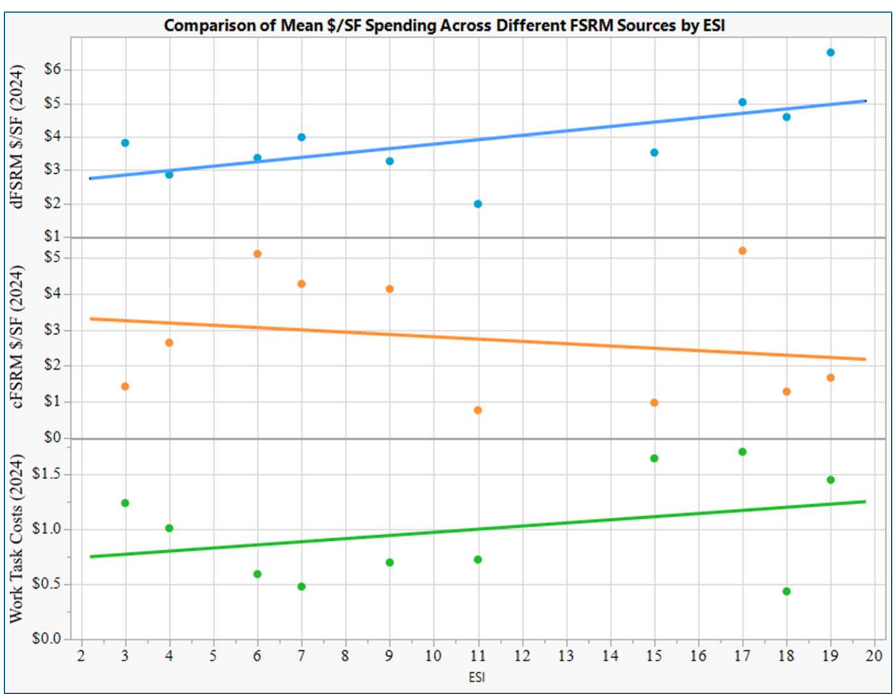
2.4 Phase Four: Development and Implementation of ECFs

This methodological process integrates outputs from the regression model to develop ECFs that adjust sustainment funding based on environmental severity. The structured approach for developing the ECFs are summarized in Table 4 below. It should be noted that in Step 3, the constant C was selected to be 0.13. This is justified by the observation that the differences between the initial multipliers across each ESI are approximately consistent with 0.13.

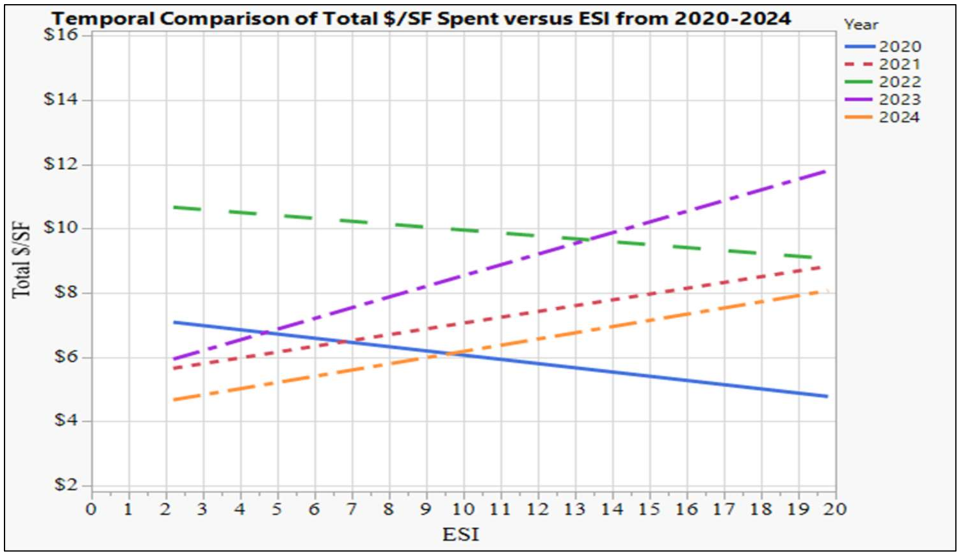
Table 4: ECF development approach using output from regression model

Step	Description	Equation
Step 1: Calculating Predicted Residuals	Quantifies deviations between observed and expected sustainment costs based on ESI values, by output from ANOVA.	$\text{Predicted}_{\text{Residuals}}$ = Intercept+(Coefficient*ESI)
Step 2: Initial Multiplier Determination	Establishes an initial multiplier using predicted residuals, ensuring meaningful comparisons across ESI levels.	Initial Multiplier = 1+(($\text{Predicted}_{\text{Residuals}}$) / (Scaling Factor))
Step 3: Shifting the Multiplier	Ensures positive and usable values by adding a constant (C), preventing negative values.	Shifted Multiplier = |(Initial Multiplier)|+C
Step 4: Final Multiplier Derivation (ECF)	Normalizes the shifted multiplier, setting ESI 12 as the reference point for intuitive scaling. Yielding the ECF for each ESI.	Final Multiplier = (Shifted Multiplier) / ($\text{Shifted Multiplier}_{\text{Max}}$)
Step 5: Application of the ECF	Adjusts each installation's Sustainment ACF, integrating environmental severity into funding calculations.	Sustainment $\text{ACF}_{\text{Adjusted}}$ = Final Multiplier*Sustainment $\text{ACF}_{\text{Current}}$

3. RESULTS



(a)



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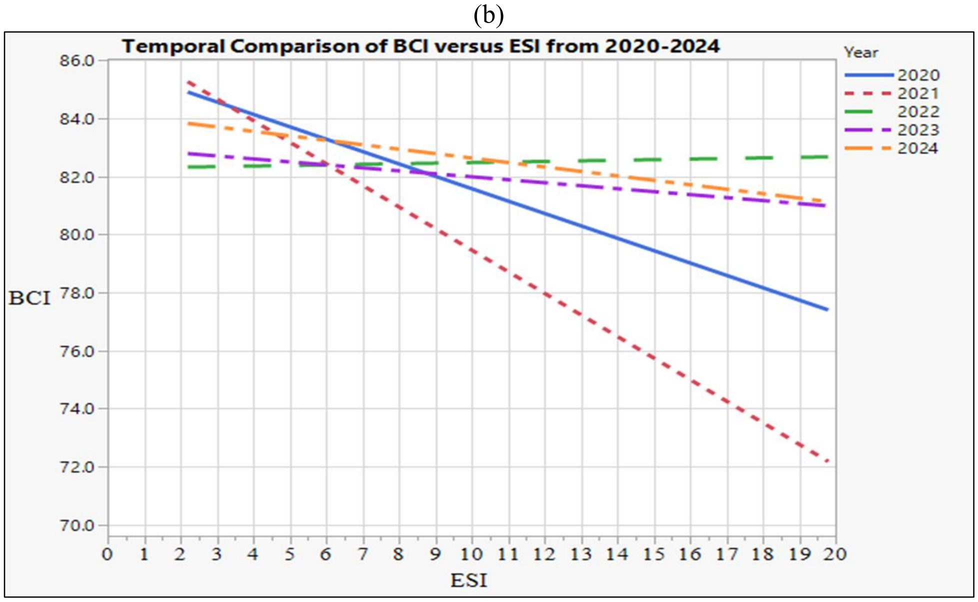

(c)

Figure 1a-c: Visual correlations between ESI levels, spending patterns, and BCI metrics, across varying environmental severities and timeframes

Figure 1a-c highlights key spending and condition trends across ESI levels. Figure 1a shows a positive correlation between dFSRM spending and ESI, reflecting increased reliance on decentralized funds in harsher environments. However, cFSRM spending in Figure 1b exhibits a negative correlation, suggesting fewer large-scale projects are allocated to high-ESI installations. Figure 1c reveals a slight upward trend in Work Task Costs with ESI, indicating higher day-to-day sustainment expenses in corrosive environments. Together, these figures illustrate a shift toward reactive, localized maintenance as ESI increases, potentially leaving high-ESI installations underfunded for larger, proactive investments.

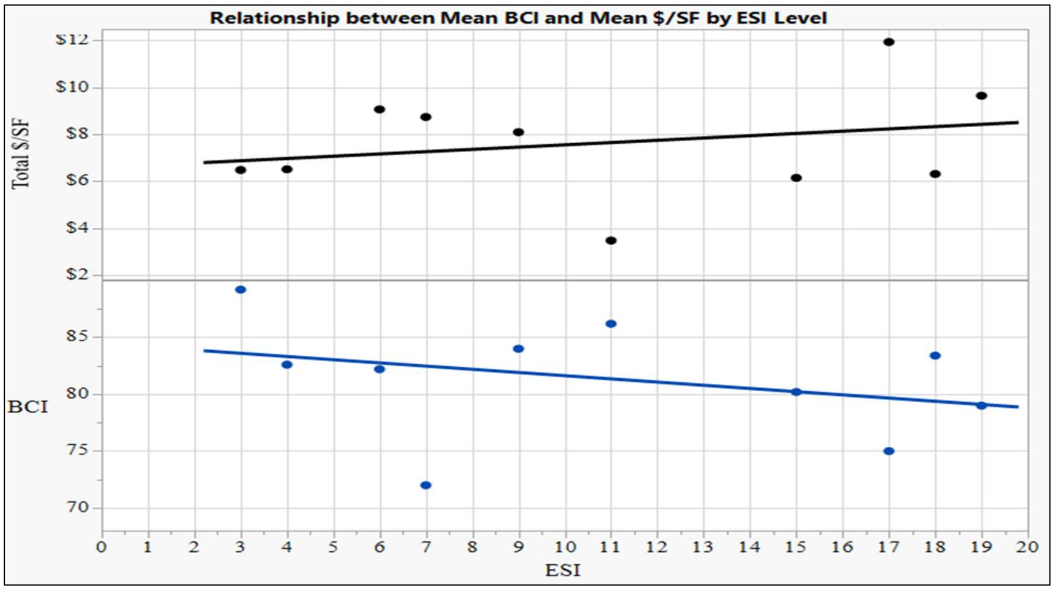

Figure 2: Relationship between ESI, BCI, and Total $/SF across different ESIs.

Figure 2 shows that as ESI increases, the total $/SF spent increases. This observation validates the higher financial demands of maintaining infrastructure in more corrosive environments. However, this increased spending is accompanied by a general decrease in BCI, indicating that infrastructure conditions worsen in these severe environments despite higher investments. This trend underscores a diminishing return on investment, as greater expenditures in high-ESI areas are insufficient to fully mitigate the accelerated degradation driven by environmental severity.

Table 5: Means ANOVA Results for Variables: Total $/SF, BCI, and ΔBCI (3-Year Delay)

Summary of means ANOVA Results			
Independent Variable	Key Variables	p-value	Reject Ho
ESI vs.	Total $/SF	0.0216	Yes
	BCI	0.0034	Yes
	ΔBCI (3-Year Delay)	0.0008	Yes

Table 6: Regression ANOVA results for Total $/SF per Incremental BCI (3-Year Delay

Summary of Regression ANOVA Results			
Predictor Variable	Response Variable	p-value	Reject Ho
ESI	Total $/SF per Incremental BCI (3-Year Delay)	0.03	Yes

The results from the ANOVA analyses shown in Tables 5 and 6 confirmed that ESI significantly influences key variables related to infrastructure costs and conditions. Total $/SF showed a significant relationship with ESI (p=0.0216), indicating that installations in higher ESI environments incur greater costs per square foot. Similarly, BCI (p=0.0034) and ΔBCI with a three-year delay (p=0.0008) were also significantly impacted by ESI, highlighting that infrastructure conditions deteriorate more severely in these environments. Additionally, the regression ANOVA demonstrated that ESI is a significant predictor of Total $/SF per Incremental BCI improvement (p=0.0300), revealing that higher ESI levels result in greater financial burdens to achieve incremental condition improvements.

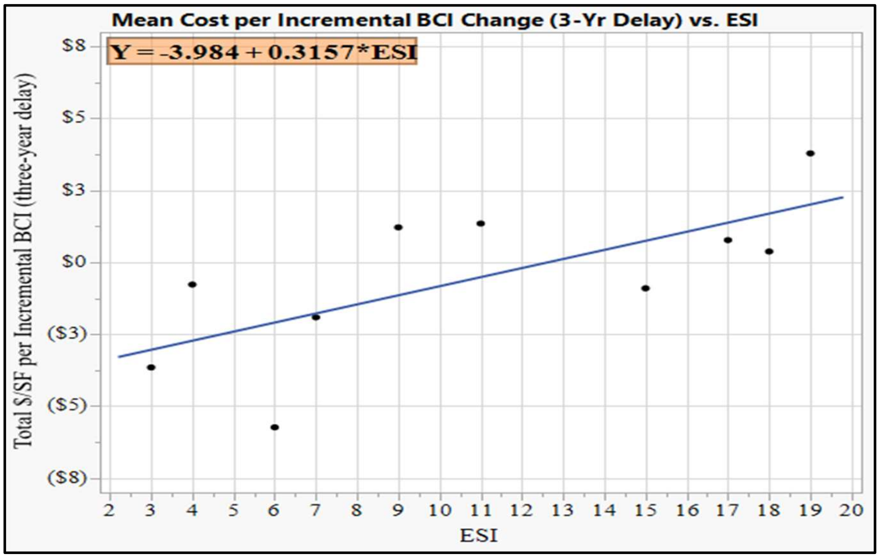

Figure 3: Line graph illustrating relationship between mean Cost per Incremental BCI change versus ESI

Figure 3 demonstrates the relationship between ESI and the mean cost per incremental BCI change over a three-year delay, derived from the regression model's parameter estimates. The positive trendline confirms that costs consistently rise as environmental severity increases. Negative values on the y-axis occur when the ΔBCI value for a given year is negative, resulting in a negative cost per incremental BCI change, but these do not alter the overall positive trend. While some data points, such as ESI 9, 11, and 19, exceed the trendline—indicating potentially proactive or inefficient spending—others, like ESIs 15, 17, and 18, fall below, suggesting insufficient resource allocation or competing funding priorities.
The regression model's underlying assumptions were thoroughly evaluated, and all were met, including normality of residuals, homogeneity of variances, and homoscedasticity, ensuring the model's accuracy and reliability.

Table 7: Application of ECFs on study installations and determining Adjusted SACFs

Study Installations	**ESI Zone**	**Environmental Corrosion Factor**	**Current Sustainment ACF**	**Adjusted Sustainment ACF**
Nellis AF Base	3	0.25	1.18	0.29
Fairchild AF Base	4	0.33	1.1	0.37
Dyess AF Base	6	0.50	0.8	0.40
McConnell AF Base	7	0.58	0.89	0.52
Little Rock AF Base	9	0.75	0.82	0.61
Moody AF Base	11	0.92	0.92	0.84
Eglin AF Base	15	1.25	0.93	1.16
Lajes Field AB	17	1.42	0.99	1.40
MacDill AFB	18	1.50	1.86	2.79
Kadena AB	19	1.58	0.89	1.41

The results of the ECF application in Table 7 show a significant redistribution of SACFs that better aligns funding with the sustainment needs of each installation. Bases in low-ESI zones, such as Nellis AFB and Fairchild AFB, experience notable reductions in their SACFs due to lower environmental severity. In contrast, high-ESI installations like MacDill AFB and Kadena AB see substantial increases in their adjusted SACFs, ensuring they have the resources to address accelerated infrastructure degradation. This straightforward method enhances the FSM's ability to reflect environmental conditions and equips Base Civil Engineers with an effective tool for making data-driven funding decisions.

4. CONCLUSIONS

The findings of this research confirm that installations in high-ESI zones require significantly greater investments to maintain infrastructure conditions similar to those in less corrosive environments. Costs per incremental improvement in BCI increase substantially at higher ESI levels. Installations such as Moody AFB and Kadena AB face nearly double the cost per improvement compared to bases in lower ESI categories. A three-year delay exists between FSRM investments and observable improvements in infrastructure conditions, highlighting the importance of consistent and proactive funding. The analysis also identifies ESI 12 as a key threshold where sustainment costs begin to rise sharply, illustrating the disproportionate financial burden on bases in harsher environments. The introduction of ECFs offers an equitable adjustment tool to align funding allocations with environmental challenges.

This research addresses the critical issue of infrastructure degradation in corrosive environments, which poses significant risks to mission readiness and national security. Strategic bases in regions like the Indo-Pacific face accelerated deterioration due to extreme environmental conditions, making this work essential for sustaining operational capabilities. By assessing the impact of ESI on FSRM budgets and infrastructure performance, this study provides actionable recommendations to improve the fairness and efficiency of resource distribution in the FSM.

While the findings are impactful, they are constrained by the five-year temporal scope and sole reliance on ESI as a severity metric. Future research should expand data coverage, include additional environmental variables, and explore advanced predictive models to refine funding strategies. Without continued attention to these challenges, the DoD risks jeopardizing critical infrastructure and its operational effectiveness in these pivotal corrosive environments.

REFERENCES

Al-Khalidi, A. A. (2023). "Deep learning approaches for predicting corrosion rates in infrastructure." Journal of Infrastructure Systems, 29(4), 04023027. https://doi.org/10.1061/(ASCE)IS.1943-555X.0000672.

Baten, B., Torsha, T., Khan, M.F.A., Hasan, M.J., and Manzur, T. 2019. A Probabilistic Approach to Determine Adequate Concrete Cover for Desired Service Life of RC Infrastructure in Corrosion Prone Environment. *International Conference on Sustainable Infrastructure 2019*, ASCE, Los Angeles, CA, USA, 163–174.

Frank, T., Aldred, J., White, J., Catchpole, M., Cabonce, M., and Boulware, S. 2024. Exploring Environmental Impacts on HVAC Infrastructure Degradation Rate. *Sustainability*, 16(5): 1723. https://doi.org/10.3390/su16051723.

Khan, M., Deng, X., and Wang, Y. 2023. Service Life Prediction Model for Chloride-Induced Corrosion of Concrete-Steel Tubular Columns. *Journal of Building Engineering*, 74: 106761. https://doi.org/10.1016/j.jobe.2023.106761.

Lamm, K.R., Delorit, J.D., Grussing, M.N., and Schuldt, S.J. 2022. Improving Data-Driven Infrastructure Degradation Forecast Skill with Stepwise Asset Condition Prediction Models. *Buildings*, 12(8): 1288. https://doi.org/10.3390/buildings12081288.

Meiyan, Z., Jin, G., and Wang, M. (2021). "Effect of corrosion-inhibiting admixtures on the durability of reinforced concrete." Materials, 14(4), 812. https://doi.org/10.3390/ma14040812.

Melchers, R.E., Jeffrey, R., Chaves, I.A., and Petersen, R.B. 2024. Predicting Corrosion for Life Estimation of Ocean and Coastal Steel Infrastructure. *Materials & Corrosion*, maco.202314201. https://doi.org/10.1002/maco.202314201.

Silver, N. and Gaebel, R. 2017. Environmental Severity Index and Steel Corrosion: A Study of Long-Term Metal Loss Rates. *Journal of Materials Performance*, 26(4): 55-68.

Silver, N. A., and Gaebel, W. (2017). Facilities environmental severity classification study: Final report. Leidos, February 16.

Unified Facilities Criteria (UFC) 3-701-01. 2024. *DoD Facilities Pricing Guide*, U.S. Department of Defense.

Wasim, M., Li, C-Q., Mahmoodian, M., and Robert, D. 2019. Mechanical and Microstructural Evaluation of Corrosion and Hydrogen-Induced Degradation of Steel. *Journal of Materials in Civil Engineering*, 31(1): 04018349. https://doi.org/10.1061/(ASCE)MT.1943-5533.0002560.