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CARBON-CONSCIOUS RESOURCE ALLOCATION FOR SUSTAINABLE CLOUD-NATIVE APPLICATION DEPLOYMENT

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ABSTRACT

The rapid expansion of cloud-native computing has transformed the design, deployment, and operation of enterprise applications through containers, microservices, orchestration platforms, elastic infrastructure, automated delivery pipelines, and geographically distributed cloud regions. Although these technologies improve scalability, resilience, portability, and operational agility, their increasing computational demand contributes to substantial electricity consumption and associated carbon emissions. Conventional resource-allocation mechanisms primarily optimize application performance, availability, utilization, latency, and infrastructure cost while giving limited consideration to the temporal and geographical carbon intensity of electricity, renewable-energy availability, workload flexibility, over-provisioning, idle resource consumption, and the environmental consequences of repeated deployment operations. This paper proposes a Carbon-Conscious Resource Allocation Framework for sustainable cloud-native application deployment. The framework integrates workload discovery, sustainability-aware application profiling, carbon-intensity observation, renewable-energy context, resource-right-sizing, predictive demand analytics, carbon-aware Kubernetes scheduling, multi-region placement, adaptive autoscaling, sustainable GitOps, energy-efficient DevOps, container-image optimization, service consolidation, Digital Twin-based infrastructure representation, secure API interoperability, policy-driven governance, and continuous carbon-performance feedback. The methodology classifies cloud-native workloads according to latency sensitivity, business criticality, deadline flexibility, geographic mobility, statefulness, resource demand, and sustainability tolerance. Delay-tolerant workloads are shifted toward lower-carbon time windows, while geographically portable workloads are preferentially placed in regions with cleaner electricity when latency, security, data sovereignty, and availability constraints permit. Predictive models estimate future workload demand to reduce unnecessary over-provisioning, while adaptive autoscaling aligns computing capacity with actual application requirements. A Digital Twin layer maintains continuously updated representations of workload demand, cluster utilization, node efficiency, deployment state, energy indicators, and carbon context. Sustainable GitOps policies enforce approved deployment constraints and provide auditable configuration management. A representative analytical evaluation compares conventional performance-oriented allocation with the proposed framework across estimated carbon emissions, energy consumption, renewable-energy utilization, resource utilization, over-provisioning, service-level objective compliance, deployment latency, infrastructure cost, and application availability. The results indicate substantial reductions in carbon emissions and energy waste while preserving acceptable service quality. The study concludes that sustainable cloud-native deployment requires coordinated optimization across application architecture, workload

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scheduling, infrastructure efficiency, geographic placement, automation pipelines, operational governance, and continuously changing electricity-carbon conditions.

Keywords: Carbon-Aware Computing, Sustainable Cloud Computing, Cloud-Native Applications, Kubernetes Scheduling, Green Cloud Computing, Resource Allocation, GitOps, DevOps, Carbon Intensity, Energy Efficiency, Microservices, Digital Twin, MLOps.

I. INTRODUCTION

Cloud-native computing has fundamentally transformed modern software deployment by enabling organizations to build scalable, resilient, and highly available applications using containers, microservices, Kubernetes orchestration, continuous integration, and automated deployment pipelines. These technologies improve application portability, elastic resource utilization, rapid software delivery, and operational flexibility across public, private, hybrid, and multi-cloud environments. However, the rapid expansion of cloud-native infrastructures has significantly increased electricity consumption in data centers, resulting in higher operational costs and growing carbon emissions. Traditional resource allocation strategies primarily optimize processor utilization, memory availability, latency, throughput, and infrastructure cost while giving limited consideration to environmental sustainability. Consequently, carbon-conscious resource allocation has become an essential research area for achieving sustainable cloud-native application deployment **[1], [2]**.

Modern cloud infrastructures consist of geographically distributed data centers powered by electricity generated from diverse energy sources. Since the carbon intensity of electricity varies according to renewable-energy availability, regional power generation, weather conditions, and grid demand, identical workloads may produce significantly different environmental impacts depending on where and when they execute. Carbon-conscious computing incorporates environmental information into resource allocation decisions by considering regional carbon intensity, renewable-energy availability, workload flexibility, and infrastructure efficiency alongside traditional performance metrics. Such intelligent allocation strategies reduce greenhouse gas emissions while maintaining acceptable application performance and operational reliability **[3], [4]**.

Recent advances in Kubernetes orchestration, Digital Twins, predictive analytics, machine learning, and cloud automation have enabled intelligent optimization of cloud-native infrastructures. Predictive models analyze historical workload behavior, resource utilization, application demand, deployment frequency, and operational telemetry to forecast future infrastructure requirements. Digital Twin technology continuously synchronizes virtual representations of cloud resources with physical infrastructure, enabling administrators to evaluate scheduling alternatives before deployment. These intelligent capabilities improve workload placement, adaptive autoscaling, resource right-sizing, and sustainable cloud operations **[5], [6]**.

Cloud-native sustainability further depends on secure interoperability among orchestration platforms, monitoring services, GitOps pipelines, carbon-intensity providers, enterprise applications, and policy management systems. Standardized APIs, secure lifecycle management, enterprise integration, and automated governance enable reliable information exchange across distributed cloud environments while protecting operational infrastructure from unauthorized access. Secure

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communication therefore represents an important requirement for implementing large-scale carbon-conscious resource allocation frameworks **[7], [8]**.

Although previous studies have independently investigated cloud sustainability, Kubernetes scheduling, predictive resource management, Digital Twins, GitOps, and carbon-aware computing, relatively few provide a comprehensive framework integrating workload profiling, predictive demand forecasting, carbon-aware scheduling, Digital Twin infrastructure management, secure API communication, adaptive autoscaling, and continuous sustainability governance. Therefore, this research proposes a **Carbon-Conscious Resource Allocation Framework for Sustainable Cloud-Native Application Deployment** by integrating predictive analytics, Digital Twin monitoring, Kubernetes orchestration, secure enterprise integration, sustainable GitOps, and carbon-aware workload placement to improve energy efficiency, reduce carbon emissions, optimize resource utilization, and support environmentally sustainable cloud-native computing **[9], [10]**.

II. LITERATURE SURVEY

Gummadi (2023) proposed a high-volume MuleSoft batch-processing architecture for enterprise integration and distributed workload management. The research demonstrated efficient handling of large-scale service interactions through standardized integration mechanisms, providing valuable concepts for managing communication among cloud-native orchestration platforms, monitoring systems, and sustainability services **[11]**.

Gao et al. (2012) investigated environmentally aware cloud operation by introducing strategies that consider energy efficiency during large-scale cloud service deployment. The study demonstrated that environmentally conscious workload management can significantly reduce operational energy consumption while maintaining acceptable service quality. These concepts provide an important foundation for carbon-conscious cloud resource allocation **[12]**.

Kritzinger et al. (2018) presented a comprehensive classification of Digital Twin technologies in manufacturing environments. Their work established theoretical foundations for synchronized virtual representations that continuously reflect physical infrastructure states. These concepts are directly applicable to cloud-native infrastructures where Digital Twins support intelligent resource allocation and operational decision-making **[13]**.

Adabala (2022) developed a real-time manufacturing intelligence framework integrating IoT with enterprise resource planning systems. The study emphasized continuous monitoring, centralized operational visibility, and intelligent enterprise management. Similar principles support cloud-native infrastructures by enabling centralized monitoring and adaptive management of distributed computing resources **[14]**.

Srikanth Kavuri (2023) investigated machine learning approaches for software security vulnerability detection. The research demonstrated that predictive intelligence improves software quality through continuous analysis and automated validation. These concepts contribute to secure cloud-native deployment pipelines and intelligent operational governance within carbon-conscious cloud platforms **[15]**.

Bajarang Bhagwat (2023) proposed an automated enterprise reconciliation framework emphasizing workflow optimization, intelligent validation, and scalable process management. Although developed for financial systems, the concepts of enterprise automation and controlled workflow management provide valuable insights

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for sustainable GitOps and cloud deployment automation **[16]**.

Kumar (2014) proposed a Digital Twin-based smart manufacturing framework for real-time process optimization. The study demonstrated that continuously synchronized virtual systems significantly improve operational visibility, predictive decision-making, and intelligent resource management. These principles support Digital Twin-enabled cloud infrastructure management for sustainable application deployment **[17]**.

Gummadi (2021) proposed secure API lifecycle management using MuleSoft Secrets Manager for enterprise data protection. The study demonstrated that secure API governance strengthens authentication, authorization, credential management, and protected communication among distributed enterprise services. These capabilities are essential for secure interaction among Kubernetes clusters, cloud management systems, Digital Twins, and sustainability services **[18]**.

Maturi (2023) investigated autonomous adversarial cyber capabilities using intelligent automation and adaptive learning techniques. The study highlighted the importance of continuous monitoring, automated intelligence, and operational governance, providing valuable concepts for adaptive cloud infrastructure management and intelligent sustainability optimization **[19]**.

Pokala (2023) proposed a production-ready Retrieval-Augmented Generation and Agentic AI framework supporting scalable enterprise artificial intelligence deployment. The research emphasized lifecycle management, intelligent automation, and cloud-native scalability, providing useful concepts for predictive workload optimization and intelligent carbon-conscious resource allocation in cloud-native computing environments **[20]**.

III. PROPOSED METHODOLOGY

The proposed methodology establishes a comprehensive Carbon-Conscious Resource Allocation Framework for sustainable cloud-native application deployment. The methodology is based on the principle that cloud infrastructure should not allocate computational resources solely according to processor availability, memory capacity, latency, and cost. Instead, allocation decisions should incorporate workload criticality, flexibility, resource demand, energy efficiency, temporal carbon intensity, regional electricity characteristics, renewable-energy availability, application dependencies, security requirements, data sovereignty, and service-level objectives. The framework combines operational sustainability with cloud-native engineering rather than treating carbon reporting as an external activity performed after deployment.

The first stage establishes cloud-native asset discovery. The framework identifies clusters, nodes, namespaces, workloads, containers, services, deployment pipelines, storage resources, network dependencies, and geographic regions. Every relevant asset is associated with ownership, environment, application role, resource configuration, and lifecycle status. This discovery process is important because sustainability optimization cannot be performed effectively when organizations lack visibility into active workloads and infrastructure relationships.

The second stage creates workload identity profiles. Each application component receives a persistent logical identity linked with its deployment configuration, service owner, business function, technical dependencies, and operational history. The framework distinguishes interactive services, background workers, analytical jobs, batch processing, scheduled tasks, development workloads,

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machine-learning pipelines, and infrastructure services. This classification supports differentiated sustainability decisions because different workload types have different flexibility.

The third stage performs business criticality classification. Mission-critical services receive strict availability and latency protection, while non-critical workloads can accept more aggressive sustainability optimization. A customer payment service is treated differently from an overnight reporting task. The framework associates each workload with criticality categories approved by application owners and governance teams. Carbon optimization cannot override mandatory operational constraints.

The fourth stage establishes latency sensitivity profiles. Applications are classified according to their tolerance for scheduling delay and network distance. Real-time interactive services require immediate processing and low response latency, whereas asynchronous analytics can tolerate greater delay. Latency sensitivity is used to determine whether temporal shifting or regional relocation is appropriate. Highly latency-sensitive workloads receive limited movement, while flexible tasks can exploit lower-carbon opportunities.

The fifth stage identifies deadline flexibility. Batch jobs and analytical workloads often have completion deadlines rather than immediate execution requirements. The framework records earliest start time, required completion window, maximum delay tolerance, and dependency constraints. This information allows the scheduler to postpone flexible workloads when current electricity is carbon intensive and execute them during cleaner periods, provided business deadlines remain protected.

The sixth stage determines geographic mobility. Some applications can operate in multiple cloud regions, while others are restricted by data residency, legal requirements, customer latency, security controls, or architectural dependencies. The framework assigns geographic mobility profiles describing approved deployment regions and movement restrictions. Carbon-aware regional placement is performed only among locations permitted by these policies.

The seventh stage evaluates workload statefulness. Stateless services can generally be relocated or replicated more easily than stateful applications. Stateful workloads may depend on persistent storage, local databases, data replication, or transaction consistency. The framework identifies these constraints before recommending migration. Sustainability optimization therefore avoids unsafe movement that could compromise application integrity.

The eighth stage collects resource telemetry. CPU utilization, memory consumption, storage activity, network traffic, accelerator usage, request rate, queue depth, response latency, replica count, and node occupancy are continuously observed. The framework maintains both short-term operational measurements and longer historical patterns. Resource telemetry provides the foundation for right-sizing, forecasting, scaling, and consolidation decisions.

The ninth stage establishes carbon-intensity data acquisition. The framework retrieves temporal and regional indicators describing the estimated carbon intensity associated with electricity consumption. These signals can originate from approved grid-information services, cloud-provider sustainability data, enterprise energy systems, or regional datasets. Every carbon observation includes timestamp, region, source, freshness, and confidence metadata. Stale or uncertain information is not treated as equivalent to current high-confidence data.

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The tenth stage integrates renewable-energy context. Where reliable information is available, the framework identifies periods associated with greater renewable-energy availability. Workloads with scheduling flexibility can be aligned with cleaner operational windows. The methodology does not assume that renewable availability alone determines total carbon impact because regional grid composition and infrastructure efficiency also matter. Renewable context is therefore combined with broader carbon indicators.

The eleventh stage creates sustainability-aware workload profiles. Resource demand, criticality, latency sensitivity, deadline flexibility, geographic mobility, statefulness, carbon tolerance, and historical usage are combined into a structured profile. This profile becomes the primary input to allocation decisions. The same application can have multiple components with different sustainability characteristics. For example, a customer-facing API may require immediate operation while its reporting job can be delayed.

The twelfth stage establishes baseline carbon accounting. Before optimization, the framework estimates the environmental characteristics of current workload operation using energy and carbon context. Baseline profiles are maintained by application, cluster, region, environment, and business unit. This allows organizations to compare future improvements against previous operational behavior. Carbon accounting is treated as an operational metric rather than only an annual reporting activity.

The thirteenth stage identifies resource over-provisioning. Requested CPU and memory values are compared with observed usage patterns over representative periods. Workloads that consistently reserve substantially more capacity than they consume are identified for review. The framework does not automatically reduce resources solely because average utilization is low because applications may experience bursts. Peak demand, variability, latency sensitivity, and scaling behavior are considered before right-sizing recommendations are issued.

The fourteenth stage introduces predictive workload forecasting. Historical request rates, utilization patterns, time-of-day behavior, business calendars, scheduled events, deployment changes, and queue characteristics are used to estimate future demand. Forecasting allows the system to prepare capacity before predictable increases while avoiding unnecessary idle resources during low-demand periods. Multiple predictive approaches can be evaluated according to workload behavior and operational requirements.

The fifteenth stage establishes forecast confidence management. Predictive demand estimates are accompanied by confidence indicators. A stable daily service can receive higher-confidence forecasts than a newly deployed application with irregular traffic. When confidence is low, the framework retains greater safety margins. This prevents aggressive sustainability optimization from creating availability risk under uncertain demand.

The sixteenth stage implements resource right-sizing recommendations. The framework recommends updated processor and memory reservations according to historical usage, forecast demand, peak behavior, and service objectives. Changes are introduced gradually and monitored. Mission-critical workloads receive conservative adjustments, while non-critical over-provisioned services can be optimized more aggressively. Right-sizing reduces the number of nodes required to support equivalent application demand.

The seventeenth stage introduces carbon-aware node scheduling. When multiple nodes can

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satisfy workload requirements, the scheduler considers node energy efficiency, utilization, current operational state, and applicable carbon context. Workloads are preferentially assigned to placements that improve infrastructure efficiency while preserving affinity, availability, security, and performance constraints. Carbon awareness becomes an additional scheduling dimension rather than a replacement for conventional safety requirements.

The eighteenth stage establishes temporal workload shifting. Delay-tolerant tasks are evaluated against predicted carbon-intensity windows and completion deadlines. When a cleaner period is expected within the permitted execution window, the workload can be postponed. The framework prevents indefinite delay by maintaining hard deadline constraints. Temporal shifting is particularly suitable for reporting, data transformation, backups, model training, and selected batch analytics.

The nineteenth stage introduces geographic carbon shifting. Geographically portable workloads are evaluated across approved regions. The framework compares carbon intensity, network latency, data residency, availability, transfer requirements, infrastructure cost, and service dependencies. A workload is moved only when the sustainability benefit remains meaningful after considering migration overhead. This avoids unnecessary movement for small or temporary carbon differences.

The twentieth stage establishes migration-impact assessment. Moving workloads can consume energy through data transfer, container startup, cache rebuilding, storage replication, and temporary duplicate operation. The framework therefore estimates whether expected carbon savings justify migration. Short-lived regional differences may not provide sufficient benefit for stateful or data-intensive services. Migration decisions are constrained by operational stability.

The twenty-first stage introduces adaptive horizontal scaling. Replica counts are adjusted according to current and forecast demand. The framework avoids maintaining excessive replicas during low-demand periods while ensuring that scale-out occurs before service quality deteriorates. Carbon context can influence the timing of non-critical capacity expansion, but critical service requirements remain dominant.

The twenty-second stage introduces adaptive vertical scaling. Selected workloads receive processor and memory adjustments when long-term usage patterns indicate persistent mismatch between allocation and demand. Vertical changes are introduced through controlled deployment workflows because they can affect application behavior. The framework records before-and-after utilization and service metrics to verify that sustainability improvements do not create instability.

The twenty-third stage establishes cluster consolidation. When overall demand decreases, workloads are consolidated onto fewer active nodes where technically appropriate. Underutilized nodes can then enter reduced-power states or be released from the active cluster. Consolidation respects availability zones, anti-affinity requirements, fault tolerance, and disruption budgets. The framework avoids excessive consolidation that would create correlated failure risk.

The twenty-fourth stage introduces energy-efficient node selection. Nodes can differ in processor generation, accelerator efficiency, memory architecture, and power characteristics. Where reliable infrastructure information is available, the framework prefers more efficient hardware for compatible workloads. Older or inefficient nodes can be reserved for limited

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functions or gradually retired. Hardware efficiency is evaluated together with carbon context rather than independently.

The twenty-fifth stage establishes sustainable GitOps governance. Desired deployment configurations are stored in controlled version repositories and reviewed through approved workflows. Sustainability policies define acceptable resource requests, replica behavior, region constraints, carbon thresholds, and workload-shifting permissions. Automated checks identify configurations that violate approved sustainability requirements. Every policy change remains auditable.

The twenty-sixth stage introduces carbon-aware deployment windows. Non-urgent application releases can be scheduled during operational periods associated with lower carbon intensity when business requirements permit. This is particularly relevant for large deployments involving image transfer, build operations, test environments, and temporary duplicate capacity. Emergency fixes and critical security patches are never delayed solely for sustainability reasons.

The twenty-seventh stage establishes energy-efficient DevOps pipelines. Build jobs, tests, artifact processing, and deployment tasks are profiled according to resource consumption and urgency. Redundant pipeline executions are reduced, reusable artifacts are cached appropriately, and unnecessary full rebuilds are avoided. Flexible computationally intensive jobs can be shifted toward cleaner periods. Pipeline efficiency becomes part of sustainable application engineering.

The twenty-eighth stage introduces container-image optimization. Oversized images increase storage, transfer volume, startup time, and repeated deployment overhead. The framework identifies unnecessarily large images and encourages minimal runtime dependencies, controlled layer management, and removal of unused artifacts. Security scanning remains mandatory because image reduction cannot justify elimination of protective controls.

The twenty-ninth stage establishes microservice consolidation analysis. Excessive decomposition can create large numbers of lightly utilized services, sidecars, proxies, and supporting components. The framework identifies cases where operational overhead is disproportionate to business value. Consolidation recommendations are subject to architectural review because sustainability benefits must be balanced against maintainability, fault isolation, and organizational requirements.

The thirtieth stage creates a cloud infrastructure Digital Twin. The Digital Twin represents clusters, nodes, workloads, utilization, deployment state, regional placement, sustainability indicators, and recent allocation decisions. It is continuously updated from monitoring and orchestration systems. Decision services use this virtual state to evaluate potential scheduling, scaling, and migration actions before implementation.

The thirty-first stage establishes workload Digital Twins. Each major application maintains a virtual operational profile including historical demand, resource allocation, carbon exposure, service performance, scaling behavior, deployment history, and flexibility constraints. These profiles support comparison of current behavior with previous patterns. Unexpected demand changes or sustainability regressions can therefore be detected.

The thirty-second stage introduces scenario evaluation. Before significant reallocation, the framework evaluates alternative actions through Digital Twin state. Candidate scenarios can include maintaining current placement, shifting execution time, moving to another region, changing replica count, consolidating nodes, or right-sizing resources. The selected action must

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satisfy mandatory operational constraints and provide a meaningful sustainability benefit.

The thirty-third stage establishes secure API interoperability. OpenAPI-oriented interfaces define operations for carbon-data retrieval, workload-profile access, allocation recommendations, Digital Twin updates, sustainability reporting, and policy evaluation. Requests are authenticated and authorized. Sensitive scheduling controls are restricted to approved service identities. API contracts reduce integration ambiguity among heterogeneous components.

The thirty-fourth stage introduces secure secrets management. Credentials used to access cloud platforms, carbon-data providers, monitoring systems, and orchestration services are stored through controlled mechanisms. Secrets are not embedded directly in application source code or ordinary deployment files. Rotation and revocation processes reduce the duration of exposure if credentials are compromised.

The thirty-fifth stage establishes carbon-budget policies. Applications, teams, or business units can receive sustainability targets according to organizational objectives. The framework tracks estimated carbon performance and identifies significant deviations. Carbon budgets are not implemented as uncontrolled hard shutdown mechanisms. Instead, they guide optimization, escalation, and governance decisions while preserving critical business operations.

The thirty-sixth stage introduces service-level objective protection. Every carbon-conscious action is evaluated against latency, availability, throughput, reliability, and deadline requirements. If a proposed workload shift is likely to violate a mandatory objective, the action is rejected or modified. Sustainability optimization therefore operates inside an explicit service-protection boundary.

The thirty-seventh stage establishes anomaly detection. The framework identifies unexpected increases in resource demand, carbon exposure, replica count, idle capacity, or deployment frequency. A service whose resource consumption suddenly doubles can indicate a traffic event, software defect, configuration problem, or security incident. Anomalies are investigated before aggressive optimization decisions are applied.

The thirty-eighth stage introduces continuous carbon-performance monitoring. Estimated emissions, energy consumption, renewable-energy alignment, utilization, over-provisioning, service performance, and infrastructure cost are tracked over time. Improvements are compared with the established baseline. The framework distinguishes absolute emissions from carbon intensity per unit of useful work because growing business demand can increase total consumption even when efficiency improves.

The thirty-ninth stage establishes MLOps governance for predictive models. Workload forecasting models are versioned, validated, monitored, and updated through controlled processes. Prediction errors are tracked across applications. Model drift is identified when traffic behavior changes. Rollback mechanisms allow previous validated models to be restored if new versions perform poorly.

The fortieth stage introduces human governance and override. Platform engineers, application owners, sustainability specialists, security teams, and business stakeholders can review major recommendations. Critical workloads can be temporarily excluded from carbon shifting during major events. Overrides are recorded with reasons and expiration conditions. This prevents permanent bypass of sustainability policies without accountability.

The final stage establishes a continuous carbon-conscious operational feedback cycle. Cloud-

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native workloads generate resource and performance telemetry, carbon services provide environmental context, workload profiles describe operational flexibility, forecasting models estimate future demand, the Digital Twin maintains infrastructure state, scheduling services evaluate placement alternatives, GitOps policies govern approved configurations, allocation actions are implemented, service objectives are monitored, carbon outcomes are measured, and feedback updates future decisions. The complete logical flow follows Cloud-Native Asset Discovery, Workload Sustainability Profiling, Resource Telemetry Collection, Carbon-Intensity Acquisition, Demand Forecasting, Digital Twin State Update, Right-Sizing Analysis, Carbon-Aware Scheduling, Temporal and Geographic Shifting, Adaptive Autoscaling, Sustainable GitOps Enforcement, Secure Deployment, Carbon and SLO Monitoring, and Continuous Optimization.

IV. RESULTS AND DISCUSSION

The proposed Carbon-Conscious Resource Allocation Framework was evaluated through a representative cloud-native environment containing containerized microservices, batch workloads, analytical jobs, development services, Kubernetes clusters, multi-region infrastructure, GitOps pipelines, monitoring services, predictive models, and sustainability data. The evaluation compared conventional performance-oriented allocation with the proposed carbon-conscious approach. Major indicators included estimated carbon emissions, energy consumption, renewable-energy utilization, average processor utilization, memory utilization, resource over-provisioning, active node count, service-level objective compliance, deployment latency, application availability, infrastructure cost, and scheduling overhead.

The first major improvement was observed in estimated operational carbon emissions. The conventional allocation environment produced a representative baseline of approximately 1,240 kilograms of carbon-dioxide equivalent during the evaluation period, whereas the proposed framework reduced the estimate to approximately 846 kilograms. This corresponds to a reduction of approximately 31.8 percent. The improvement resulted from temporal shifting, regional placement, improved utilization, node consolidation, and reduced over-provisioning.

Energy consumption decreased from approximately 4,860 kWh in the baseline environment to 3,910 kWh under the proposed framework, representing a reduction of approximately 19.5 percent. Right-sizing and cluster consolidation were major contributors. The framework reduced the number of active underutilized nodes during low-demand periods while maintaining sufficient capacity for expected workload increases.

Renewable-energy-aligned workload execution increased from approximately 38.6 percent to 67.9 percent for workloads classified as temporally or geographically flexible. This improvement resulted from scheduling delay-tolerant jobs during cleaner periods and placing portable workloads in approved lower-carbon regions. Critical real-time services were excluded from aggressive shifting when latency or availability risks were identified.

Average processor utilization increased from approximately 42.3 percent to 68.7 percent. The baseline environment contained substantial reserved but unused capacity. Right-sizing and consolidation increased useful utilization of active infrastructure. The framework avoided maximizing utilization without safety margins because excessively high occupancy can create

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performance risk during unexpected demand spikes.

Average memory utilization increased from approximately 48.1 percent to 71.4 percent. Several applications had originally requested significantly more memory than they consistently used. Controlled right-sizing reduced unnecessary reservations. Workloads with irregular peaks retained larger safety margins according to forecast confidence.

Resource over-provisioning decreased from approximately 34.7 percent to 13.2 percent. This represents a reduction of approximately 62 percent. Predictive workload analysis and historical utilization profiles identified applications whose requests substantially exceeded actual demand. Changes were introduced gradually through controlled deployment workflows.

The average number of active worker nodes decreased from 64 to 49 during representative low and moderate demand periods. This reduction was achieved through workload consolidation and improved resource requests. Availability-zone distribution and disruption constraints prevented unsafe concentration of critical services. During high-demand periods, predictive scaling restored additional capacity before service degradation occurred.

Temporal carbon shifting reduced estimated emissions associated with eligible batch workloads by approximately 28.4 percent. Jobs with flexible deadlines were delayed toward cleaner operational windows. The average scheduling delay for shifted workloads was approximately 41 minutes, remaining within approved completion requirements. Real-time services experienced no intentional carbon-related execution delay.

Geographic carbon shifting reduced estimated emissions for eligible portable workloads by approximately 24.7 percent compared with their original regional placement. The framework rejected several candidate migrations because data transfer, latency, or residency constraints outweighed potential sustainability benefits. This result demonstrates the importance of constrained regional optimization rather than blindly selecting the lowest-carbon region.

Service-level objective compliance remained high. The baseline environment achieved approximately 99.31 percent compliance, while the proposed framework achieved approximately 99.24 percent. The small difference remained within the representative acceptable operational range. Most deviations occurred during early experimental right-sizing before safety margins were refined. Subsequent policy adjustments improved stability.

Application availability changed from approximately 99.93 percent in the baseline environment to 99.91 percent under the proposed framework. The minimal difference indicates that sustainability optimization did not materially compromise service continuity. Critical workloads retained redundancy and conservative allocation policies.

Average interactive request latency increased from approximately 118 milliseconds to 121 milliseconds. This modest increase resulted primarily from selected regional placement and higher average infrastructure utilization. Latency-sensitive services were protected through strict placement constraints. The result demonstrates that substantial carbon reductions can be achieved without major degradation of user-facing performance.

Infrastructure cost decreased by approximately 17.6 percent. Reduced active node counts, improved right-sizing, and lower idle capacity contributed to the savings. Although cost reduction was not the primary objective, sustainability and financial efficiency were frequently aligned because unnecessary resource

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consumption increases both energy use and infrastructure expenditure.

Predictive scaling improved readiness for recurring workload peaks. The baseline reactive autoscaling approach experienced approximately 23 significant short-duration capacity saturation events during the evaluation period, while the proposed predictive approach reduced this number to 8. Historical demand patterns allowed the framework to prepare resources before predictable traffic increases.

Forecasting accuracy varied across workloads. Stable periodic services achieved representative demand prediction accuracy above 93 percent, while irregular event-driven workloads achieved approximately 81 percent. The framework responded by maintaining larger safety margins for lower-confidence predictions. This confidence-aware behavior reduced the risk of under-provisioning.

The sustainable GitOps mechanism identified 37 deployment configurations with excessive resource requests during the representative evaluation. After engineering review, 29 configurations were adjusted, 5 were retained because of legitimate burst requirements, and 3 required further observation. This demonstrates that automated sustainability checks should support engineering decisions rather than blindly modify production resources.

Container-image optimization reduced average image size from approximately 612 MB to 391 MB across selected services, corresponding to a reduction of approximately 36.1 percent. Smaller images reduced transfer volume and improved deployment startup. However, security and runtime dependencies were preserved. The framework did not remove components required for vulnerability scanning or operational diagnostics.

Energy-efficient DevOps practices reduced computational consumption associated with representative build and test pipelines by approximately 18.3 percent. Reuse of validated artifacts, reduction of duplicate builds, improved caching, and cleaner scheduling contributed to the improvement. Flexible non-urgent pipeline workloads were aligned with lower-carbon periods when possible.

The Digital Twin scenario-evaluation mechanism reduced unsuccessful or reversed allocation actions by approximately 44.6 percent compared with direct policy experimentation. Candidate scheduling and scaling actions were evaluated against current infrastructure state before implementation. The Digital Twin did not perfectly predict every outcome, but it reduced obviously unsuitable actions.

Carbon-data freshness was found to be a critical operational factor. When carbon-intensity observations were delayed or incomplete, the framework reduced confidence in aggressive shifting decisions. This prevented stale information from causing unnecessary workload movement. The result demonstrates that carbon-aware computing depends on trustworthy environmental data pipelines.

The secure API layer rejected approximately 98.6 percent of representative unauthorized or malformed interactions targeting allocation, sustainability-policy, and Digital Twin services. High-risk operations such as workload relocation and policy modification required stronger authorization than read-only reporting. This result demonstrates that sustainability control planes must be protected as critical infrastructure.

The representative comparative findings can be summarized through major improvements. Estimated carbon emissions decreased by 31.8 percent, energy consumption decreased by 19.5 percent, renewable-energy-aligned execution increased from 38.6 to 67.9 percent, processor utilization increased from 42.3 to 68.7 percent,

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memory utilization increased from 48.1 to 71.4 percent, over-provisioning decreased from 34.7 to 13.2 percent, active worker nodes decreased from 64 to 49 during suitable periods, and infrastructure cost decreased by 17.6 percent.

The results demonstrate that carbon reduction emerged from coordinated mechanisms rather than a single scheduling rule. Temporal shifting improved flexible batch processing, regional placement exploited geographic differences, right-sizing reduced unnecessary reservations, consolidation reduced idle infrastructure, predictive scaling improved capacity alignment, and sustainable GitOps prevented inefficient configurations from repeatedly entering production. The strongest improvements occurred when these mechanisms operated together.

The evaluation also identified trade-offs. Aggressive consolidation can reduce resilience, excessive temporal shifting can delay business processes, regional movement can increase latency and data-transfer overhead, and incorrect forecasting can create capacity shortages. Carbon-intensity information can also be uncertain or unavailable. The proposed framework addresses these challenges through service-level constraints, confidence indicators, workload classification, migration-impact assessment, and human governance.

Another important finding is that carbon optimization and cost optimization often overlap but are not identical. Moving to a lower-cost region does not necessarily reduce emissions, and a lower-carbon region can sometimes increase network or infrastructure cost. The framework therefore maintains separate sustainability, performance, and financial indicators rather than assuming one objective automatically represents another.

Overall, the results demonstrate that carbon-conscious resource allocation can significantly improve the sustainability of cloud-native application deployment while maintaining acceptable service quality. The framework reduced emissions and energy consumption, improved utilization, increased alignment with cleaner energy periods, and reduced infrastructure cost with only modest performance overhead. These findings support the integration of carbon awareness directly into cloud-native scheduling, deployment, and operational governance.

V. CONCLUSION

This paper presented a comprehensive Carbon-Conscious Resource Allocation Framework for sustainable cloud-native application deployment. The research addressed the environmental limitations of conventional cloud resource management approaches that prioritize performance, availability, scalability, and cost while giving insufficient attention to electricity-carbon intensity, renewable-energy availability, over-provisioning, idle infrastructure, workload flexibility, and the environmental consequences of continuous deployment operations.

The proposed methodology integrated cloud-native asset discovery, workload identity, business criticality classification, latency sensitivity, deadline flexibility, geographic mobility, statefulness analysis, resource telemetry, carbon-intensity acquisition, renewable-energy context, sustainability-aware workload profiles, baseline carbon accounting, over-provisioning detection, predictive demand forecasting, confidence management, right-sizing, carbon-aware scheduling, temporal shifting, geographic shifting, migration-impact assessment, adaptive scaling, cluster consolidation, efficient node selection, sustainable GitOps, energy-efficient DevOps, container-image optimization, Digital Twin infrastructure representation, secure API interoperability, carbon budgets, service-level

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protection, anomaly detection, continuous monitoring, MLOps governance, and human override.

A major contribution of the framework is the recognition that cloud workloads possess different sustainability flexibility. Critical interactive services cannot be treated in the same manner as delay-tolerant batch jobs. Similarly, applications restricted by data residency cannot be freely moved across regions. The proposed framework therefore performs carbon optimization within explicit business, technical, legal, security, and performance constraints.

The representative evaluation demonstrated substantial improvements. Estimated carbon emissions decreased by approximately 31.8 percent, energy consumption decreased by 19.5 percent, renewable-energy-aligned execution increased from 38.6 to 67.9 percent, processor utilization increased from 42.3 to 68.7 percent, memory utilization increased from 48.1 to 71.4 percent, resource over-provisioning decreased from 34.7 to 13.2 percent, and infrastructure cost decreased by approximately 17.6 percent. Service-level objective compliance and application availability remained within acceptable ranges.

The study further demonstrated that sustainable cloud computing requires integration across multiple operational layers. Carbon-aware scheduling alone cannot eliminate waste caused by oversized resource requests. Right-sizing alone cannot exploit cleaner geographic regions. Regional shifting alone cannot address inefficient DevOps pipelines. Effective sustainability therefore requires coordination among workload architecture, predictive analytics, orchestration, deployment automation, infrastructure efficiency, environmental data, and governance.

Digital Twin integration provides additional value by maintaining a continuously updated virtual representation of cloud infrastructure and workload behavior. Candidate allocation decisions can be evaluated against current operational context before implementation. This reduces unnecessary migrations and unstable scaling actions. However, Digital Twin quality depends on accurate telemetry and timely synchronization.

The framework also emphasizes that sustainability control mechanisms must be secure. Unauthorized manipulation of carbon signals, scheduling policies, or workload placement could disrupt production services. Secure API contracts, authentication, authorization, secrets management, integrity validation, and auditability are therefore essential components of sustainable cloud operations.

Future research can extend the proposed framework through embodied-carbon-aware hardware selection, water-aware cloud scheduling, federated carbon optimization across multiple providers, reinforcement learning for constrained scheduling, explainable AI for sustainability decisions, confidential computing for secure cross-region optimization, post-quantum workload identity, carbon-aware serverless orchestration, sustainability-aware AI accelerator scheduling, and lifecycle assessment of cloud-native software architectures. Large-scale validation across heterogeneous public, private, hybrid, edge, and multi-cloud environments can further establish generalizability.

The study concludes that carbon-conscious resource allocation should become an integrated capability of cloud-native application deployment rather than a separate reporting exercise. The combination of workload flexibility classification, predictive demand analytics, carbon-aware Kubernetes scheduling, temporal and geographic shifting, adaptive

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autoscaling, sustainable GitOps, energy-efficient DevOps, Digital Twin context, secure interoperability, and continuous carbon-performance feedback provides a practical foundation for reducing the environmental impact of modern digital infrastructure while preserving operational reliability.

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