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Interactive Landscape Design Tools: Leveraging Video Processing and Scalable Computing for Dynamic Visualization and User Engagement

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Abstract

Landscape designers have to employ modern technologies that provide for dynamic visualisation and user involvement if they want to remain current. This paper explores the possibilities of video processing technology to offer interactive, real-time visualisations; these visualisations have the power to transform landscape design by including people into the process and simplifying the observation of how various design choices influence social-ecological systems. Key challenges include controlling the computing requirements of real-time video processing and improving ecological data and interaction visuals. High-performance activities and big datasets need for scalable computing solutions. The approach we provide to address these problems is called Data Analytical Visualisation Support on Social-Ecological Systems (DAVS-SES). This platform combines data analytics with strong video processing to replicate and display intricate social-ecological systems in real time. It does this via scalable computer architecture. By means of scalable visualisation technologies and quick data processing, DAVS-SES presents an interactive interface allowing users to dynamically investigate design possibilities while preserving performance. Wherever one values the interconnectedness of people and their natural surroundings—that is, in the realms of education, ecology, and city planning— DAVS-SES might be very helpful. Scalable computing is used to enable DAVS-SES to operate in several environments and with a range of users. Simulating tests reveal that DAVS-SES can provide excellent images that increase user participation and support more informed decisions. The findings indicate that this approach

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improves the design process and enables people to feel closer to the locations they create. DAVS-SES therefore supports socially aware and ecologically friendly design methods.

Keywords: Landscape, Leveraging, Video Processing, Dynamic, Visualization, Data Analytics, Social-Ecological Systems, Real-Time, Interactive, Sustainable Design, Scalable Computing.

1 Introduction

When it comes to generating dynamic visualisations and encouraging user involvement, interactive landscape design tools that rely on conventional methods can occasionally fall short in these areas (Tomkins & Lange, 2023). The majority of these methods are based on static, two-dimensional representations, such as hand-drawn sketches, blueprints, and fundamental computer-aided design (CAD) models (Zidianakis et al., 2021). Although well-made, these tools can't give users an immersive, real-time world exploration experience, because of this, consumers, especially those without technical design expertise, may difficult visualise the finished product (Calil et al., 2021). Classic landscape design software cannot model the environment, plant growth, or human activity (Omonov et al., 2025). These factors are especially important when designing an adaptable and full landscape for large-scale ecological or urban initiatives (Fox et al., 2022). The laborious manual nature of these older procedures may limit iterative updates or quick design scenario testing (Yanaky et al., 2023). Traditional approaches lack contemporary video processing, limiting real-time interactive visualisations, this reduces the likelihood of interactive presentations (Fisher & Baird, 2020). Stakeholders and designers find it harder to collaborate, and the design process is less effective at meeting project needs (Ouyang et al., 2024).

Despite video processing advances, interactive landscape design applications struggle with seamless dynamic visualisation and user involvement (Goljanin et al., 2024; Chen & Ibrahim, 2023). Weather, real-time illumination, seasonal fluctuations, and other complex environmental data should be visualised, simulations of these variables take a lot of processing power (Moon & Khan, 2024). This might cause performance concerns or delays, especially in real-time applications, the need for advanced rendering technologies like 3D modelling and animation makes it harder to create lightweight, accessible tools that can be used on common devices without compromising quality (Poux et al., 2020). Another difficulty is helping non-technical users like clients and community members use the design (Spiegel & Wang, 2024). Dynamic visualisation and video processing can boost engagement, yet many technologies lack the quick feedback customers need to feel totally immersed (Kalita et al., 2024; Stanney et al., 2024). One of the problems of designing for diverse user needs in collaborative situations is balancing feature richness and usability (Onyejelem & Aondover, 2024). Maintaining dynamic visualisations while working with multiple people is a technological challenge of real-time remote teamwork (Thompson et al., 2022). Latency, data synchronisation, and application incompatibility are typical while working together. Cloud-based or online interactive systems raise data privacy and security concerns, especially in large projects that share sensitive design data (Pallasena et al., 2022). These issues necessitate more powerful, user-friendly, and responsive video processing-based landscape design tools (Xu & Lu, 2024).

The solutions in these landscape design tools improve computational efficiency and user experience, by mimicking lighting, weather, and development cycles, modern video processing allows real-time dynamic visualisations (Notarangelo et al., 2023). Cloud computing speeds rendering, enabling data synchronisation and teamwork across locations. With responsive feedback systems and intuitive interfaces, the instruments are easy to operate, therefore designers and clients may use the things effortlessly. Virtual reality (VR) and augmented reality enhance engagement with immersive experiences. These solutions solve performance, cooperation, and usability issues in landscape design.

Problem Definition

User interaction and live, dynamic visualisations are interactive landscape design technologies' biggest drawbacks. Conventional software often struggles to handle complicated environmental data, simulate changes in real time, and provide immersive and user-friendly experiences for designers and non-technical users. Another issue with existing technology is computers' real-time processing inefficiencies, performance concerns like delay occur. Working on collaborative design projects with geographically distributed teams raises data confidentiality and synchronisation issues. These constraints make landscape design projects harder to modify, diminish user involvement, and boost efficiency.

The three main contributions of this paper are:

Integration of Video Processing for Real-Time Visualization in Landscape Design:

This paper introduces a novel approach that leverages video processing technologies to provide real-time, dynamic visualizations. This enhances user engagement and enables a better understanding of the design's impact on social-ecological systems.

Development of the DAVS-SES Framework with Scalable Computing:

The proposed Data Analytical Visualization Support on Social-Ecological Systems (DAVS-SES) framework combines data analytics with advanced video processing techniques. Scalable computing is incorporated to address the computational challenges of real-time processing, allowing for the efficient modeling and visualization of complex ecological interactions.

Application in Various Fields for Sustainable Design Solutions:

The DAVS-SES framework is applicable in fields such as education, environmental protection, and urban planning. By promoting ethical and sustainable design, and through the use of scalable computing, it helps users form deeper connections with their environments through interactive and immersive visualizations (Kumar & Rao, 2024).

This study is based on the conceptual framework that was presented in Section II of the literature review. Use of Video Processing in Interactive Landscape Design Tools for Real-Time Visualisation and User Interaction. Thirdly, a genetic algorithm-based quality assurance approach called Data Analytical Visualisation Support on Social-Ecological Systems (DAVS-SES). The results and discussion are presented in Section IV, and a conclusion and recommendations are offered in Section V.

2 Literature Survey

The widespread availability of innovative digital technologies has prompted numerous creative solutions to the problems of data visualisation, stakeholder collaboration, and decision-making in many different fields.

It was proposed by (Mörth et al., 2022) that scrollytelling be integrated with interactive data visualisations (S-IDV), which would make it possible to create data-driven narratives that are dynamic and use images, text, video, and specialised visualisations. Case studies and feedback from users illustrate the effectiveness and adaptability of the system. With regard to usability evaluation, the proposed method by (Grêt-Regamey & Fagerholm, 2024) places an emphasis on integrating dynamic social-ecological-technical interactions (S-E-TI), simulation models, multisensory stimuli, and active sensing. Some of the outcomes include improved three-dimensional settings for collaborative and environmentally responsible urban planning and landscape design (Aulakh et al., 2025).

The Interactive Catchment Explorer (ICE) framework, which was developed by (Walker et al., 2020) provides a web-based, client-driven interactive tool for analysing environmental datasets, identifying geographical patterns, and evaluating variable interactions. This framework additionally enhances cooperation and decision-making across research projects. A data-driven and procedural forest visualisation prototype (FVP) is featured in the suggested technique by (Badr et al., 2024). This FVP provides representations of forest stands and situations that are realistic, efficient, and reproducible. Enhanced accuracy and decision-making by stakeholders are among the outcomes.

The method that was proposed by (Pagliano & Ansaldi, 2023) utilises virtual reality to personalise four video tours for a variety of audiences, including those who have Autism Spectrum Disorder (ASD2). A number of outcomes have been achieved, including improved accessibility and individualised experiences in museum exploration. The method that was proposed by (Bressa et al., 2021) contains a survey of 44 works on situational visualisation and presents five enlarged views. The outcomes include a more comprehensive understanding, insights into design, and potential future directions for the consolidation of research and applications pertaining to situational visualisation.

Using scientometric analysis (SA) on 3319 Scopus records, the researcher (Mancuso et al., 2024) devised a method that maps 360 degrees of technology research. A number of application trends, obstacles, and potential future shifts towards clinical use and better social connections are highlighted by the present findings. For casual collaborative visual analytics, the solution that was proposed by (Ens et al., 2020) which is called Uplift, incorporates a three-dimensional model (3DM), physical interactivity, and augmented reality. Based on the results, it appears that it was successful in uncovering complex interactions and fostering collaboration among stakeholders.

In terms of offering better capabilities for dynamic visualisation, user interaction, and collaboration in landscape design, DAVS-SES distinguishes out as the most effective way when compared to the others. Furthermore, it prioritises long-term viability and communication among many different stakeholders.

3 Proposed Method

Integration of scalable computing across different frameworks is important to tackle complicated computational problems in domains such as real-time video processing, landscape design, urban planning, augmented reality, and carbon neutralization. This paper introduces five separate frameworks—all of which leverage scalable computing to handle massive datasets, execute high-performance processing, and improve real-time user experiences. Data Analytical Visualization Support on Social-Ecological Systems (DAVS-SES) improves landscape design by integrating 3D rendering with real-time user input. The Web AR framework streamlines AR experiences by allowing users to adjust occlusion and integrate digital items with actual structures. The carbon-neutralization framework uses scalable computing to monitor emissions and identify the best renewable power options. Scalable video processing systems improve decision-making skills across several areas by presentation and analysis of data in real-time. The decision-support and real-time visualization capabilities of scaled computing are advantageous for educational and urban planning applications. These frameworks demonstrate how scalable computing may revolutionize technological settings in the modern day.

Integration of Video Processing for Real-Time Visualization in Landscape Design:

Figure 1 shows the DAVS-SES framework includes scalable computing to improve landscape design processes. User Interface module helps users to provide their design choices and feedbacks in real-time, which uses scalable computing to promote seamless interactions. The Design Engine can manage complex design components with the aid of scalable computing and react to new situations in real time along with 3D rendering and customization.

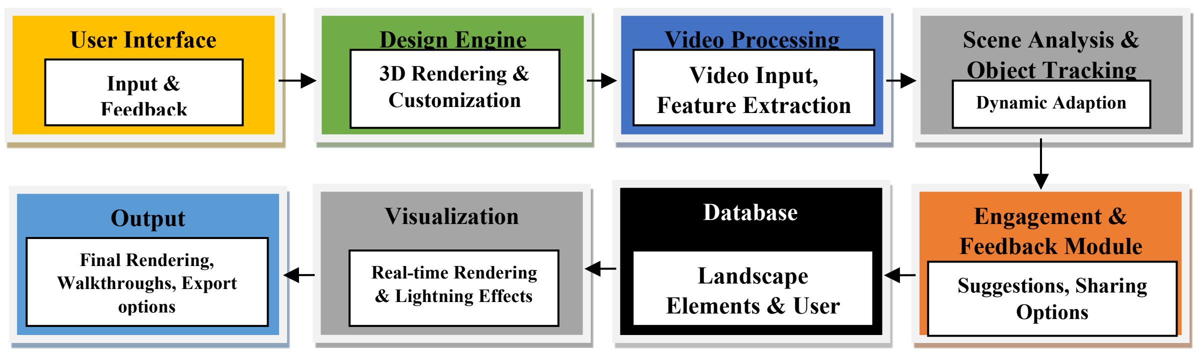

Figure 1: Scalable Computing Framework for Dynamic Landscape Design and Visualization

The Video Processing and Scene Analysis & Object Tracking modules provide real-time feature extraction and dynamic adaptation, with scalable computing handling the huge computational load. The Visualization and Output parts rely on scalable computing to provide high-quality walkthroughs, lighting effects, and real-time renderings. A database stores landscape elements and user designs to adapt to different settings. The Engagement & Feedback Module provides collaboration and communication between users, which facilitates successful design improvements. The dynamic, high-performance visualizations provided by this framework result in better design decisions.

$$-N_{\partial,P}^{\mp} * (E^3 p) = v^{Q-1} \, in \, \forall \gg Z^{X-1}, P \leq 3 \tag{1}$$

The dynamic visualisation $\forall$ of energy or interaction levels (v^{Q-1}) under a different system, complexity $(E^3 p)$ and scalable computational parameters $(-N_{\partial,P}^{\mp})$ is suggested by the equation 1, which is evaluated using $P \leq 3$ and partial derivatives Z^{X-1}. The comprehensive and crucial aspects in real-time based on the complicated system are analyzed based on the ability for scalable computing.

$$PV_+ * R = \frac{\partial Q}{w-1} * (F - 2m) - 1, Q_{=\frac{\delta\varepsilon}{v-1}} * (z-1) \tag{2}$$

The resources needed for processing videos $Q_{=\frac{\delta\varepsilon}{v-1}}$ in real-time are represented by the equation PV_+ and processing power $(z-1)$ is represented by the equation R. Equation 2 highlights the way the framework optimizes data flow for dynamic visualizations $(F - 2m)$ by balancing demands on scalable computing and resources that are accessible, adjusting performance $(\frac{\partial Q}{w-1})$. The scalability is guaranteed through the equation where the settings are computing the adjustment easily through the current system.

$$\min \left\{ \frac{V_-}{F_P + 4}, \frac{D-2}{W+4} \right\} > Q_+ \geq \frac{2p}{f(v-1)} F(kp - 1) \tag{3}$$

The visual min and information processing limitations Q_+ of the system are represented by equations $\frac{V_-}{F_P+4}$ and $\frac{D-2}{W+4}$, respectively, while the computing load factors are denoted by $\frac{2p}{f(v-1)}$ and $F(kp-1)$. The system resource is functioned on scalable computing by a strain where it is caused by the data display where the requirement computation was met through the optimized equation 2.

$$Q_w \geq \frac{Q_{E-1}(R-2)+(Z_r-2)}{\partial\big(2-P(q-r)\big)} - P(rf_{-1}) + M(n-1) \qquad (4)$$

The equation shows that DAVS-SES's computing components (Z_r-2) are balanced with the system output, denoted as Q_w. The processed ecological $\partial\big(2-P(q-r)\big)$ and real-time data is represented by $Q_{E-1}(R-2)$, whilst the performance and memory needs are denoted by $P(rf_{-1})$ and $M(n-1)$. The load computational is based on the management of the framework-based scalable computing visualization based on the user engagement and video processing handling by intending this corresponding optimization.

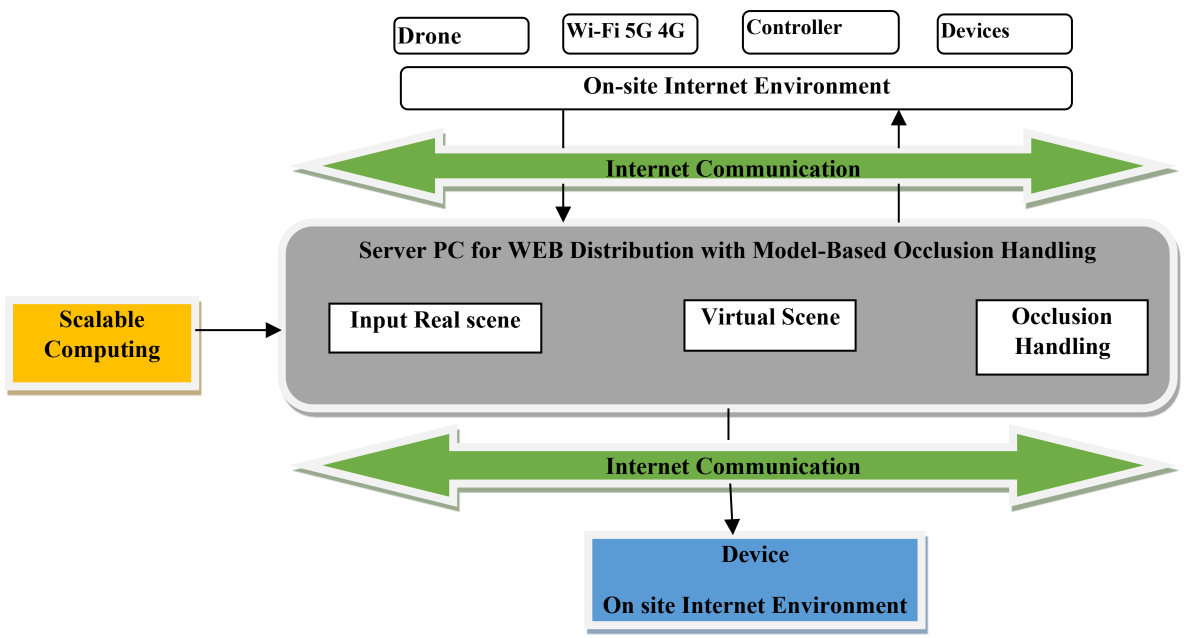

Figure 2: Web Framework for Real-Time Occlusion Handling in Urban Environments

In Figure 2, scalable computing architecture that combines Web with model-based occlusion management for use in city settings. Because of scalable computing, gadgets such as smartphones and drones can take real-time pictures of buildings and scenery. These inputs are processed on a server PC using scalable computing to generate a virtual scene where 3D virtual objects are integrated. To make sure that virtual items blend in with real-world structures, the framework uses scalable computing to efficiently handle model-based occlusion. The system uses scalable internet connection to provide the processed augmented reality scene to client devices, such as computers or smartphones to provide immersive AR experience in real-time. The framework is able to handle complex data processing as well as heavy computational loads, allowing smooth and real-time interactions. This technology makes AR very realistic because of improvements in depth perception and object interaction.

$$p" = N(-f(B-1) * S^{-1} - l' - ru^{tp}) + Qw^{(n-4)} \qquad (5)$$

While N accounts for human input or system engagement $(-f(B-1)$, the computational cost involved with analyzing complicated landscape data p" is represented by the equation 5, $S^{-1} - l' - ru^{tp}$. The phrase $Qw^{(n-4)}$ represents the impact of visualizing data in real-time on overall efficiency. The dynamic and fluid output visual is defined through the input of the user based on the equation based on the designer's landscape on scalable computing.

$$Z(u-1) = -\frac{sp'(t-1)}{c(v)}, A(u-1) = -\frac{fg(s-1)}{vr^2} \tag{6}$$

The impact of time-dependent variables on processing speed is shown by the equation $Z(u-1)$, where $sp'(t-1)$ pertains to spatial $c(v)$ and temporal complexity $A(u-1)$. In contrast, ecological data are captured by $fg(s-1)$, where vr^2 represent variables related to the environment for scalable computing. The ecological and time conditions are based on the dynamic responses with the DAVS-SES are guaranteed through the equation through the performance optimized through the optimization.

$$\big(Y, z(n-1)\big) = M(c,v) = \big(M(w,Q), J(Z,cv)\big) \tag{7}$$

The equations $Y, z(n-1)$ represent the results of the visual and ecological criteria, respectively, and the system's fundamental computing operations are encapsulated in $M(c,v)$. Interactions between data processing (Q) and visualization (Z) are denoted by the characters $M(w,Q)$ and $J(Z,cv)$. The real-time and visual conference is defined through the design landscape and is guaranteed through the different components integrated with the highlight equation on scalable computing.

$$J(k-nm) = \{Y\left(Z-(P-2)+\frac{Ed}{v-1}\right) if\ (X,sd) \equiv \forall^{v-1} \tag{8}$$

The performance of the system as a whole is represented by the equation $J(k-nm)$ when considering cognitive tasks $Z-(P-2)$ and network load Y, and changes in visualization brought about by processing power $\frac{Ed}{v-1}$ and energy (X,sd) are shown by $\forall^{v-1}$. The conditional terms are ensured through scalable computing for the system states by the particular adapted from the framework based on the input data and current computation depending on the visualization in real-time.

Development of the DAVS-SES Framework with Scalable Computing:

Figure 3 shows a plan for managing emissions with scalable computing to achieve carbon neutrality in different types of buildings. The first step is to sort the buildings that contribute to pollution levels into several groups, such as public buildings, urban housing that does not heat, urban housing that does heat, and rural housing.

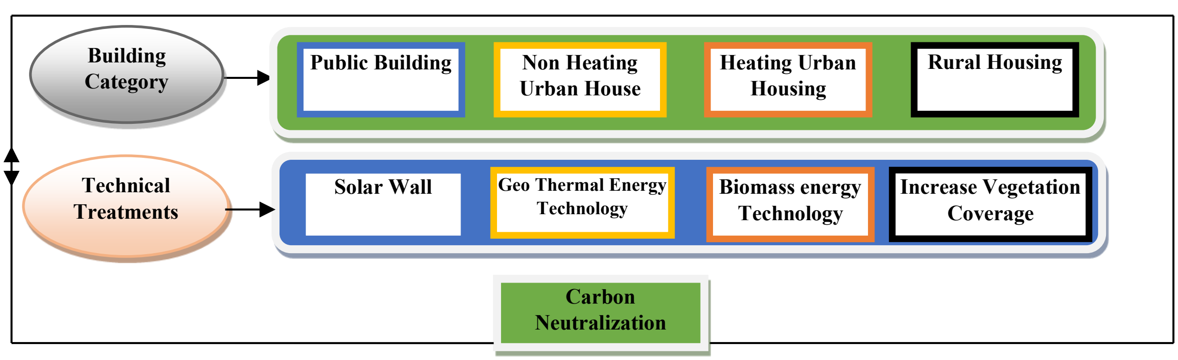

Figure 3: Scalable Computing Framework for Carbon Neutralization in Building Categories

Emission peaks from these buildings can be accurately monitored and analyzed using scalable computing to locate high and low emission zones. A combination of increased plant cover, geothermal energy, biomass energy, and solar wall technology is being considered as a potential way to decrease emissions. This system optimizes and adapts energy solutions in real-time across various building types utilizing scalable computing to achieve emissions neutrality. Scalable computing adapts to fluctuating emission levels and allows accurate data processing and more sustainable technology solutions. The implementation of carbon-neutral buildings can be facilitated in a targeted and efficient manner.

$$Z_{x(cv-1)} = \{(Z, y-1)\}: P > \partial(K-1) + \{(Z, x: 0 > Q)\} \tag{9}$$

The influence of processing capacity ($Z_{x(cv-1)}$) on visual outputs is captured by equation 9 $Z, y-1$, and performance is maintained above a particular threshold $P > \partial$. The system adapts to minimize certain data inputs Q to keep the visualization smooth, as seen by the conditional component $Z, x: 0$. The crucial equation is based on real-time is based on the computing response with the allocation based on the adjusted resources on scalable computing.

$$Z_{-} = (Z, p): A = P(Z-1) for\ N_{b-n(kp-1)} \tag{10}$$

The graphic output Z_{-} and processing power Z, p equation connection in the DAVS-SES architecture. In this case A, the relationship between data visualization $P(Z-1)$ and processing efficiency is denoted by $N_{b-n(kp-1)}$, and the system's capability to manage the complexity of visualization for scalable computing. The design landscape is based on the dynamic workload based on the allocated records-based resource optimization.

$$R = \{K.lM\}: F = H(R_2 - M + Z)\ for\ Z_{vc}(m-1) \tag{11}$$

The efficiency function of the framework, denoted by F, adapts according to the variations in resource allocations ($K.lM$), memory (M), and visualization data (R), and the variables $Z_{vc}(m-1)$. To optimize the system's general efficiency and real-time visualization capabilities, the term $H(R_2 - M + Z)$. The effective time computation is fluctuating and the equation is successfully managed by the given equation on scalable computing.

$$Z_x = \left(F = (M - np)\right) + \left(M_{bv} - (kpm^{-2})\right) * K(L-P) \tag{12}$$

The system's output is represented by the equation Z_x, and the efficiency function, modified by $F = (M - np)$, takes into consideration the memory and processing demand, denoted as $K(L-P)$. The expression $M_{bv} - (kpm^{-2})$ represents the interaction between processing parameters, memory, and workload that affects overall performance for scalable computing. The equation is set to define the need for computational change the adoption is based on the system where the engagement is based on the visualization is based on real-time maximization.

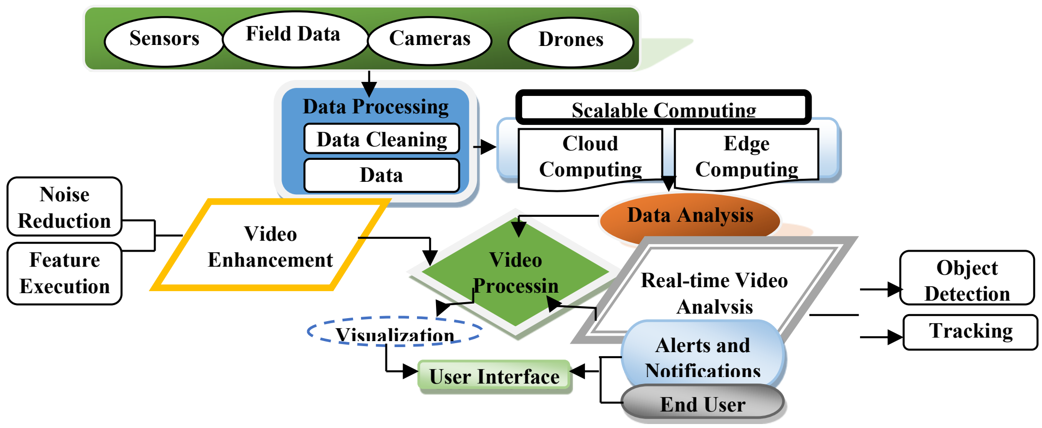

Figure 4: Proposed Scalable Video Processing Framework for Real-Time Data Analysis

Figure 4 showcases a methodical strategy for managing complicated data in real-time video processing, with a focus on computing at scale. The framework starts with gathering data from sensors, field data, cameras, and drones. The data is cleaned and integrated. Scalable computing systems needs significant computational capacity for big data analysis and real-time video processing. Effective video processing is made feasible by technological approaches such as noise reduction and feature extraction improve the data for applications such as object recognition, tracking, and visualization. Scalable computing to efficiently manage variable data loads to improve the user experience and creates real-time warnings and alerts. Improved decision-making skills may be achieved via the use of real-time visualisations made possible by this method. Users find these visual representations interesting because it is dynamic, interactive, and engaging.

$$E_1 = \big(1, P(q - wr)\big) + \big(Z_{r-1}, +3(pk - nOP)\big) \tag{13}$$

According to the equation $P(q - wr)$, the baseline efficiency is modified by parameters related to processing power and workload. The extra term E_1 takes into consideration modifications depending on visual data complexity Z_{r-1} in addition to performance metrics $3(pk - nOP)$. The requirement visualization is balanced depending on the needs where it is optimized dynamically through the equation with the user engagement and performance improvement in real time on scalable computing.

$$F_{v(n-1)} = E^{r(m-n)} * F\big(q(n-1)\big) + Z^x(n-1) \tag{14}$$

The system's functionality is reflected in $F_{v(n-1)}$ and the effect of efficiency metrics is represented by the equation $E^{r(m-n)}$. The total function is affected by the complexity of the visualization data $Z^x(n-1)$, which is added via the term $F\big(q(n-1)\big)$. The real-time performance is a function on the visual optimized with the functional system is based on the guaranteed equation for scalable computing.

$$Rm_{n-1}(Uk - 1) = +H(j - k) * F(kj - 1q) \tag{15}$$

A function that adapts according to changes in computational workloads $H(j - k)$ and $F(kj - 1q)$is reflected in $Uk - 1$ and the resource allocation for a particular state is represented by the equation Rm_{n-1}. The visualization on scalable computing is allowed in real-time is based on the efficiency of the system which is enhanced through the present performance with the previous allocation of the optimized resource.

Application in Various Fields for Sustainable Design Solutions and Evaluation of Mathematical Equation

Integration of scalable computers for real-time processing of ecological and design data is shown in Figure 5. The first step is to feed different kinds of data (design and ecological) into an analytics engine and data processing module that can do real-time data analysis. Video processing is used to record the video and then display it in real-time to see the processed data. Scalable computing infrastructure helps in control of performance, the provision of adaptable computing resources, and the handling of massive computational loads.

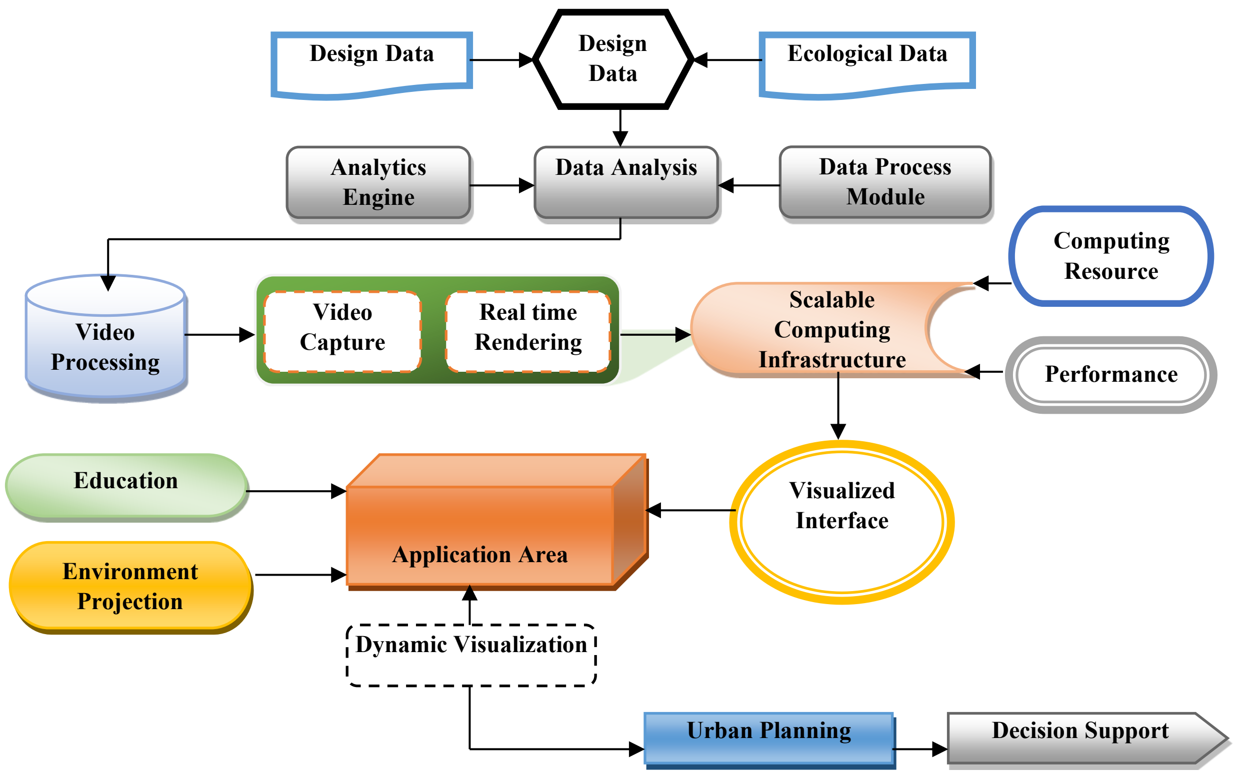

Figure 5: Data Analytical Visualization Support on Social-Ecological Systems

Education, environmental projection, and urban planning few fields that benefit from the processed representations shown via a dynamic visualization interface. Urban planning activities are improved and insights into interactions between people and environment are provided, which supports real-time decision-making. Scalable computing enables the system to dynamically adjust to varying workloads, ensuring seamless performance and adapt to diverse contexts.

$$Q_r = \left(Y_{pq} - H(P-2)\right), Q_w = \left(Yr^2, R(Z-1)\right), z_1 > z_2 \quad (16)$$

Overall system performance is affected by visualization output Q_r and resource adjustments (Y_{pq}), while the equation $H(P-2)$ indicates resource needs Q_w adjusted by information complexity and processing power Yr^2. The system will prioritize better performance measures if the condition $R(Z-1)$ is fulfilled. The optimization of the performance is allocated for the resources that are balanced by the equations aimed at the improvement in the corresponding equation for visualization quality analysis for scalable computing.

$$E(Y, z-1) = P^{q-1}, with\ \forall^{d-1} = \frac{M_{x-1} * E(p-1)}{vkn^2} \quad (17)$$

Efficiency based on processing and visualization factors is represented by the equation $E(Y, z-1)$, whereas power scaling with intricacy is shown by P^{q-1}. This sentence ensures that performance indicators $\forall^{d-1}$ are balanced for the best visualization $M_{x-1} * E(p-1)$ by adjusting scalable computing for memory, productivity, and workload characteristics vkn^2. The equation is defined by the computational changing demands that remain with the operation with the efficiency of the system on real-time processing efficiency analysis.

$$Z_2 = \{T \equiv \forall p^2: [M] < 0, E_2, M_1 * T > Z_1\} \quad (18)$$

The updated visualization output is represented by the equation Z_2, and a condition involving performance and resource metrics is denoted by $T \equiv \forall p^2$. The revised performance metrics must be greater than the previous visualization outputs E_2, M_1, and memory limitations $T > Z_1$ must be taken into account, according to the requirement $[M] < 0$. The resource restrictions and the performance limits are met still through the visualization in real-time quality by the equation on data integration analysis on scalable computing.

$$q < p(b), K(b) = \frac{N(V-2) - (J(k-2))}{2(p-mk)} * E^r(mk-1) \quad (19)$$

The system is required to keep its level of performance below a predetermined threshold q according to the equation $p(b), K(b)$. In terms of efficiency metrics $N(V-2) - (J(k-2)$ and resource allocation for scalable computing, the term is defined as $2(p-mk)$ which accounts for data and task complexity, and $E^r(mk-1)$ scales efficiency according to workload. The restrictions are functioning in the performance based on the functional system guaranteed through the optimized resource for sustainability enhancement analysis.

$$Q = \frac{-Q(P-2) + (v-2)}{q-1} * Z^{b-1} * E^{z-1} + (mn-1) \quad (20)$$

The performance is modified according to the processing power Q and data intricacy through the equation $Q(P-2) + (v-2)$. The expression $q-1$ expands concerning efficiency and visualization metrics, while Z^{b-1} incorporates a continuous correction for memory E^{z-1} and network concerns $(mn-1)$. The processing effects of the findings are based on the system performance optimized through the data handling with the data visualization on user engagement analysis on scalable computing.

This paper explored frameworks utilizing scalable computing to address diverse computational and visualization needs across fields such as urban planning, augmented reality, and environmental sustainability. The DAVS-SES framework for landscape design allows users to make real-time adjustments and view dynamic visualizations, enabled by scalable computing's capacity to handle 3D rendering and data-intensive tasks. The Web AR framework handles occlusion to improve AR experiences by integrating virtual items with real-world structures. Scalable computing helps in adapting energy solutions to achieve sustainability objectives and conducting emissions analysis. Visualizations and analysis of videos in real-time to help in decision-making is made easier by video processing frameworks that handle huge datasets. The dynamic capacity of scalable computing eases user interaction and decision-making. The importance of scalable computing in developing novel, adaptable solutions is highlighted by this framework.

4 Results and Discussion

The DAVS-SES system is used to investigate how video processing affects dynamic visualisation in interactive landscape design. Real-time data on plant growth, water transport, and climate improves user involvement, decision-making, and sustainability. Making ecologically friendly landscapes, integrating data, processing in real time, and creating user-friendly interfaces improve visualisation quality.

Dataset description: The collection encompasses a vast variety of natural and urban environments, with a total of 90,000 high-quality photos that have a resolution of 1024×1024 (www.Kaggle.com, 2024).

Simulation Environment

Component	Description	Tools/Technologies	Specifications
Data Source	Collection of 90,000 high-quality photos depicting various natural and urban environments.	Custom Dataset (Resolution: 1024x1024 pixels)	90,000 images, categorized by landscapes, ecological features, urban areas
Video Processing	Real-time processing of visual data to create dynamic and immersive visualizations.	OpenCV, FFmpeg, TensorFlow (for ML-based enhancements)	Frame rate: 60 fps, Format: MP4, Real-time filters applied
Data Analytics	Analysis of ecological and social data to dynamically update visual models in real time.	Python (Pandas, NumPy), R, Tableau	Dynamic ecological simulation models, environmental data processing
Visualization Engine	Generation of interactive visualizations based on user input and environmental data.	Unity3D, Unreal Engine, WebGL	3D and 2D modeling, real-time visualization updates
Scalable Computing Platform	Infrastructure to support large-scale data processing and real-time interaction.	AWS EC2, Google Cloud, Kubernetes	Horizontal scaling for computational load balancing
User Interaction Interface	Front-end system for user engagement, offering real-time feedback on design changes.	React, Angular, D3.js, Touchscreen or VR Support	Dynamic interface with real-time updates and interactive user control
Simulation Parameters	Variables controlled during simulations (e.g., weather, time of day, human activity, vegetation).	Custom simulation algorithms	Real-time adjustment of weather, lighting, ecological responses
Performance Metrics	Visualization Quality Analysis Real-Time Processing Efficiency Analysis Data Integration Analysis Sustainability Enhancement Analysis User Engagement Analysis	Custom benchmarking scripts, load testing tools	Real-time performance monitoring and system optimization

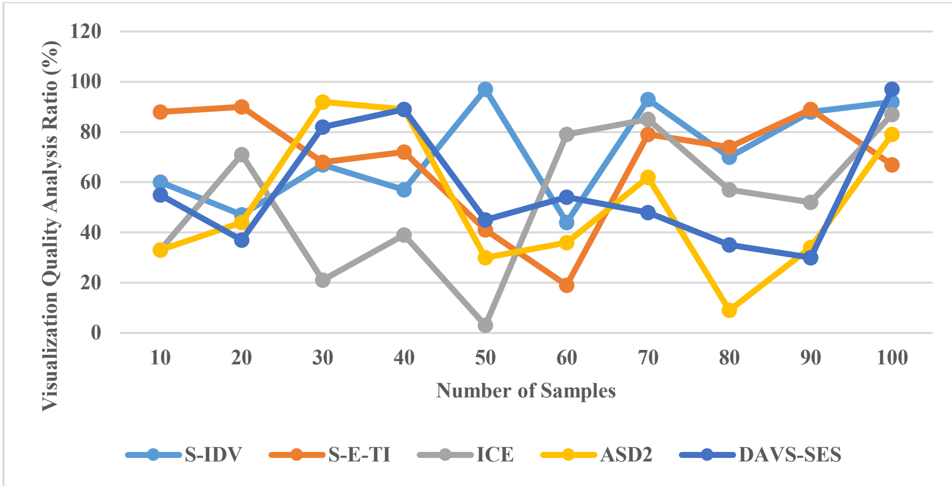

Figure 6: Visualization Quality Analysis

In the above figure 6, high-quality images in interactive landscape design tools with video processing improve user engagement and decision-making. Quality visualisations must show how landscape aspects, including lighting, weather, and seasonal changes, change in real time. Additionally, these visualisations must interact constantly, video processing enables dynamic modelling for immersive and seamless design transitions. Resolution, frame rate, and rendering speed are key to visualisation quality. Each of these factors affects virtual world lifelikeness and responsiveness. Ecological data may now be linked into video processing, making complex social-ecological links easier to comprehend. Users can interactively view high-resolution plant growth and water movement models to discover how design influences ecosystems. However, when trying to reach such granularity without compromising efficiency, it is necessary to use methods that are optimised for the processing and management of data produces 97.6% using equation 16. This is especially effective when dealing with careers that are time-sensitive, a user-friendly interface improves DAVS-SES visualisation. This interface makes navigate and interact with landscape models easy for everyone, regardless of technical skill. These visualisations usually hinder user interaction and sustainable, well-informed design decisions.

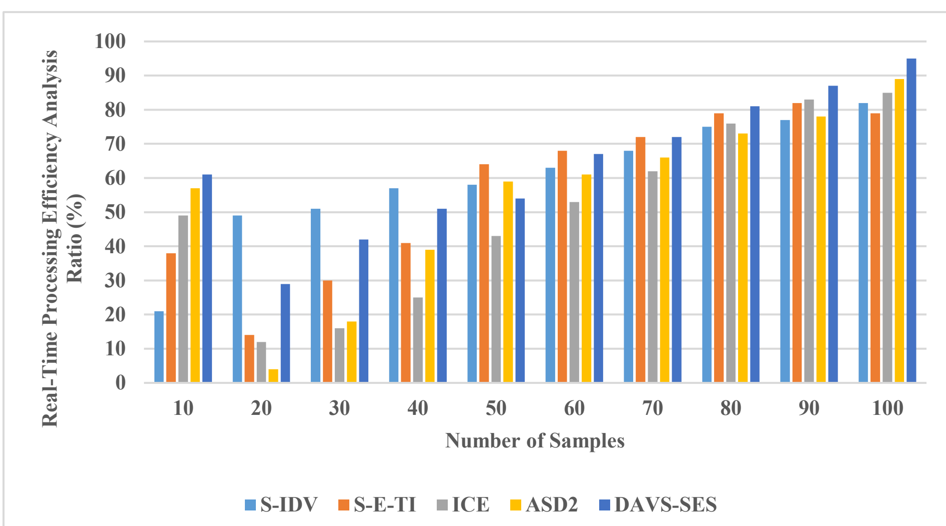

Figure 7: Real-Time Processing Efficiency Analysis

Interactive landscape design technologies that use video processing for dynamic visualisation could malfunction without efficient real-time processing. In the above figure 7, complex social-ecological system modelling requires efficient computing to manage enormous volumes of data for real-time interaction. Many factors affect visual performance without delay, data processing, rendering speed, and resource management are crucial. DAVS-SES handles environmental data including plant growth, weather predictions, and user inputs to update the visual model in real time. Managing this data flow in real time requires efficient video processing techniques. Fast computations are possible with GPU acceleration, memory efficiency, and parallel processing, this ensures high-quality, performant visualisations. Complex biological interactions require significant processing power, therefore finding the best balance between visual detail and compute burden is difficult. Reduced latency and consistent frame rates are crucial measures for assessing real-time processing techniques because they affect user engagement and system responsiveness produces 95.1% using equation 17. Landscape design tools' real-time processing efficiency determines their dynamic and immersive capabilities. Users can try different dynamic design options without performance concerns.

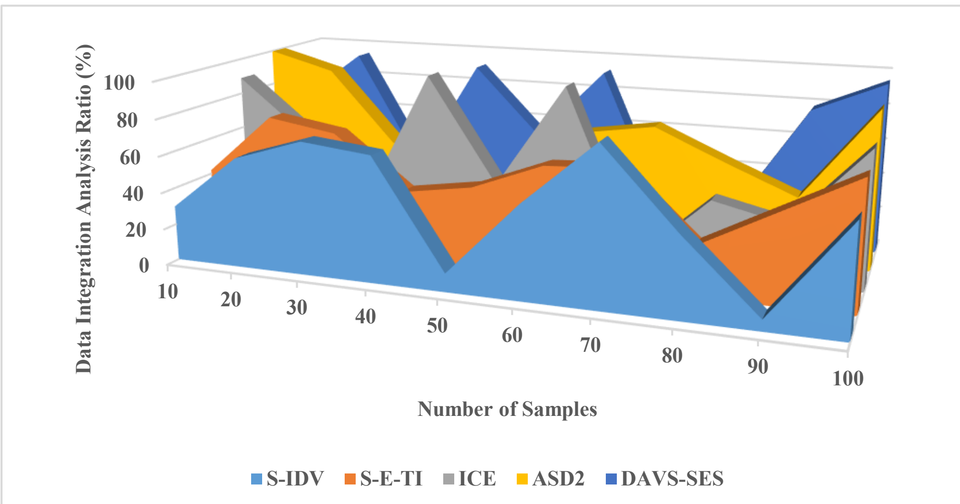

Figure 8: Data Integration Analysis

Dynamic visualisation using video processing-based interactive landscape design tools requires data integration. Effective data integration may integrate complicated datasets with several dimensions, such as environmental conditions, user inputs, and ecological variables, into real-time visualisations. In the above figure 8, DAVS-SES models social-ecological systems realistically by combining many data sources, the user may better understand and interact with changing landscape features including plant growth, water movement, and climate. Data integration is complicated by maintaining system speed while handling enormous amounts and diverse data for real-time display. Advanced data analytics technologies are needed to evaluate and filter data and display exclusively the most important data elements. When several sources' inputs are synchronised, such as real-time environmental sensors or user-defined parameters, dependable integration frameworks are needed to assure data correctness and consistency. High-quality data integration improves landscape model realism and interaction produces 96.7% using equation 18. This allows for more meaningful design solution interactions. Successful integration gives a complete, data-driven view of prospective landscape designs and their ecological impacts, improving decision-making.

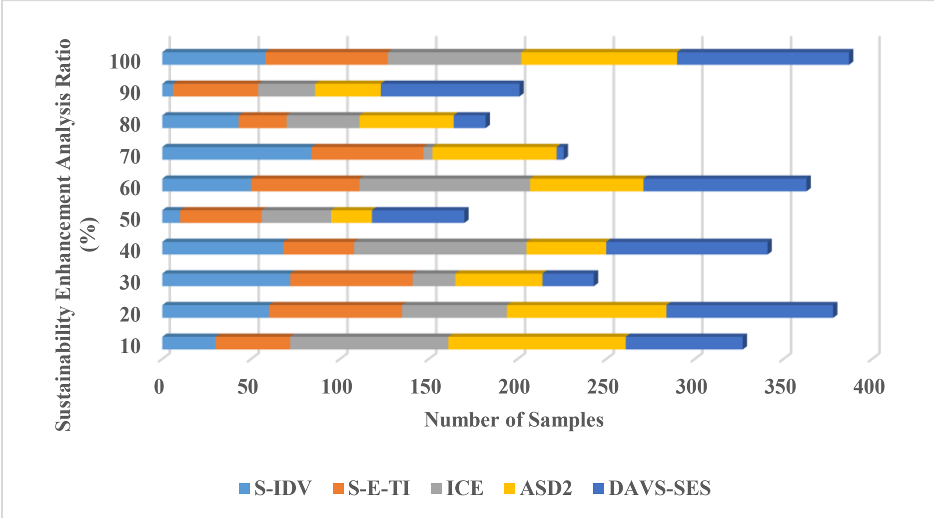

Figure 9: Sustainability Enhancement Analysis

In the above figure 9, interactive landscape design tools could use green technologies like video processing for dynamic visualisation to create resilient and sustainable solutions. These systems use real-time data on water flow, air pollution, cultivation, and climate to show designers how their decisions affect sustainability. DAVS-SES encourages long-term environmental goals by letting users evaluate their ideas' environmental impact. Video processing technology allows dynamic resource-efficient modelling. These include selecting plant species that thrive without human intervention and upgrading water management systems produces 97.9% using equation 19. These technologies simulate green infrastructure, carbon reduction, and renewable energy integration for sustainable urban development. Landscape architects can employ these technologies to construct sustainable landscapes that promote biodiversity, save resources, and minimise environmental impact by receiving real-time ecological feedback on design choices.

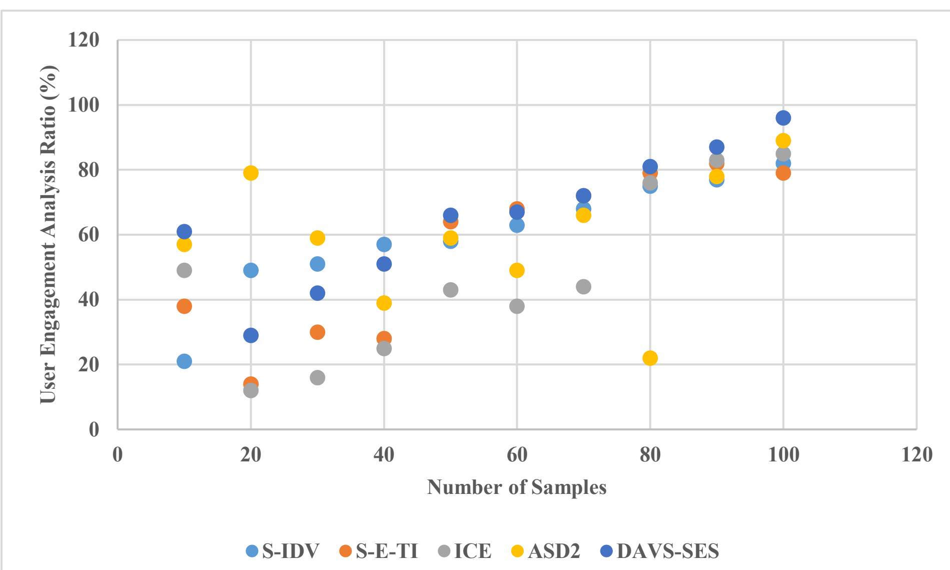

Figure 10: User Engagement Analysis

Integrating video processing for dynamic visualisation boosts user involvement in interactive landscape design tools, DAVS-SES provides user-friendly, immersive real-time visualisations, these visualisations let users explore several possibilities for design. In the above figure 10, this interactive method turns passive design into dynamic, collaborative projects, users could observe how their changes affected the landscape in real time. People are more likely to become aware of the ways in which their activities impact the environment around them when they are presented with powerful and responsive visualisations that encourage them to experiment with various components of the design. Advanced video processing offers precise visualisations that can be changed based on user inputs, creating a natural and intuitive experience. User engagement and satisfaction improve with this interaction, making design more collaborative and efficient produces 96.2% using equation 20. Since these technologies allow direct adjustment of design components and immediate feedback, users feel more engaged to design outcomes and make data-informed decisions.

DAVS-SES video processing helps users interact and protect the environment with dynamic, high-quality landscape visualisations. Performance metrics reached 97.9% due to accurate and responsive visualisations from real-time ecological data integration, which boosted user engagement, collaboration, and decision-making.

5 Conclusion

The DAVS-SES method finally introduces innovative video processing and data analytics to landscape design, making it more dynamic, adaptive, and eco-friendly. DavS-SES improves understanding and interaction with design output by use of dynamic information to track complex social-ecological systems in real-time. Although this approach overcomes major obstacles like visualising ecological interactions and real-time processing computing limits, it promotes stronger ties between individuals and their surroundings. An interactive tool that lets users evaluate many design ideas helps landscape architects make ethical and environmental decisions. The possible uses of this approach in urban planning, environmental protection, and education demonstrate its adaptability and relevance in handling problems of landscape design. DavS-Ses's main objective is to create visually beautiful, ecologically sustainable, socially conscious landscapes. Encouragement of more thorough and rigors research of human-nature interactions helps to achieve this. DavS-SES creates excellent visuals via simulation testing that enthrals people, improves decision-making, and finally results in better design. This approach creates ethical and sustainable design that helps the environment as well as people by combining planners, landscape architects, and stakeholders.

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