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Article Review

The Role of Generative AI in Agricultural Game Assets Production: A Survey

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Abstract

The growing demand for high-quality visual assets in the gaming industry has created challenges in producing diverse and realistic agricultural-themed content. Traditional techniques, such as procedural content generation (PCG) and early deep learning models—including Autoencoders, Variational Autoencoders, and Deep Convolutional GANs—often struggle with limitations in resolution, realism, and diversity. This study aims to explore how Generative Adversarial Networks (GANs), particularly StyleGAN2, can address these challenges in generating 2D assets for farming games. A systematic literature review was conducted using databases such as Scopus and Google Scholar, covering publications from the last five years. The selection criteria included studies focusing on generative models for visual game asset creation, with an emphasis on domains related to agriculture or the environment. The review highlights StyleGAN2's style-based architecture, which enables fine-grained control over sprites, textures, and environmental elements, leading to more realistic and customizable assets. Key contributions of this work include identifying current technical strengths, outlining socio-economic implications, and discussing practical challenges such as dataset availability and evaluation standards. The findings suggest opportunities for hybrid procedural–AI approaches, domain-specific datasets, and the expansion of content toward dynamic and interactive elements. By consolidating these insights, the paper offers guidance for both researchers and practitioners on leveraging generative AI for the realistic and diverse production of agricultural game assets.

Keywords: *Generative Adversarial Networks, StyleGAN2, Game Asset Generation, Agricultural Games, AI in Game Development*

INTRODUCTION

The rapid growth of the game industry has increased the demand for high-quality visual assets that enhance immersion and player experience (Hendrikx et al., 2019). Agricultural representation in games is gaining attention for its potential to combine entertainment with education. However, creating assets such as crop stages, soil conditions, and farming tools remains a challenge, particularly in procedural or large-scale environments (Attharig et al., 2022).

Existing computational approaches offer partial solutions. Procedural content generation (PCG) is widely used in games such as Minecraft and No Man's Sky (Hidayat et al., 2024). However, its reliance on handcrafted rules often produces repetitive outcomes (Togelius et al., 2020). Deep learning methods such as Autoencoders, VAEs, and DCGANs (Kim et al., 2022; Risi & Togelius, 2020) show promise but still struggle with resolution, realism, and artifact reduction.

Generative Adversarial Networks (GANs), especially StyleGAN2 (Karras et al., 2020), offer a more powerful alternative by enabling high-resolution synthesis with fine-grained style control. Despite successes in face synthesis and digital art, their application to agricultural game assets—particularly 2D sprites and environmental effects—remains limited. This gap underscores the need

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for a systematic review that links game asset generation, procedural approaches, and generative AI.

Accordingly, this paper aims to: (1) summarize current procedural and AI-based methods for game asset creation, (2) identify challenges and limitations in the agricultural game context, and (3) outline research opportunities for leveraging advanced generative models to improve diversity and realism.

LITERATURE REVIEW

Game Theory in Agricultural Simulation

Agricultural simulation games replicate the real-world cycles of farming, resource utilization, and environmental interactions, serving both entertainment and educational purposes. They have been shown to improve understanding of sustainability and agricultural practices (Lu et al., 2019; Klit et al., 2018). However, most rely on static, handcrafted assets that are costly and time-consuming to produce. Even advanced titles, such as *Farming Simulator* (Pavlenko & Argyropoulos, 2024), or AR-based systems like *My-CHIC AR Farm* (Zarraonandia et al., 2021), face scalability limits, as every new crop or environmental effect must be manually created. Thus, the main bottleneck lies not in simulation design but in asset production, which restricts content diversity and accessibility.

Generative Adversarial Networks (GANs)

Generative Adversarial Networks (GANs) are deep learning models designed to synthesize data that closely resembles real-world distributions. A GAN consists of a Generator (G), which produces synthetic data, and a Discriminator (D), which classifies whether data is real or generated (Goodfellow et al., 2014; Creswell et al., 2018). Training follows a minimax adversarial process, where G seeks to minimize detection while D aims to maximize classification accuracy. The equilibrium results in G producing highly realistic samples (Arjovsky et al., 2017).

Since their introduction, various improvements have been proposed to stabilize training and improve output quality. DCGAN introduced convolutional architectures for higher-quality images (Radford et al., 2015), while WGAN employed the Wasserstein distance to mitigate mode collapse (Arjovsky et al., 2017). GANs have since been applied across domains, including medical imaging (Nie et al., 2018), synthetic training data generation (Frid-Adar et al., 2018), and video super-resolution (Wang et al., 2018). Since their introduction, various improvements have been proposed to stabilize training and improve output quality. DCGAN introduced convolutional architectures for higher-quality images (Radford et al., 2015), while WGAN employed the Wasserstein distance to mitigate mode collapse (Arjovsky et al., 2017). GANs have since been applied across domains, including medical imaging (Nie et al., 2018), synthetic training data generation (Frid-Adar et al., 2018), and video super-resolution (Wang et al., 2018).

StyleGAN and StyleGAN2

StyleGAN introduced a paradigm shift with its disentangled latent space, allowing independent manipulation of features such as shape, color, and texture (Karras et al., 2020). This was groundbreaking compared to earlier GANs, which lacked such control. However, StyleGAN outputs still exhibited distortions, particularly at high resolutions, undermining their usability in production pipelines.

StyleGAN2 addressed these issues by redesigning normalization layers and introducing per-layer noise, thereby enhancing texture variation. The result is not just incremental improvement but a qualitative leap:

- Compared to DCGAN, StyleGAN2 avoids blurriness.

- Compared to WGAN, it retains fine detail without sacrificing stability.
- Compared to StyleGAN, it minimizes artifacts and enables smoother attribute editing.

For agricultural games, this means that entire libraries of crops, soil textures, or seasonal environments can be generated with both diversity and consistency. In practice, a farming game developer could generate hundreds of visually coherent yet unique sprites in minutes—a task previously requiring weeks of manual work. Thus, StyleGAN2 directly addresses the bottleneck identified in Section Game Theory in Agricultural Simulation.

Game Asset Evaluation

Evaluation is another area where prior work falls short. Conventional metrics, such as the Frechet Inception Distance (FID) and Structural Similarity Index (SSIM), provide statistical benchmarks (Karras et al., 2019). However, they do not align with the subjective criteria of game design. For example, an asset with low FID may statistically resemble the training distribution but appear stylistically inconsistent with the art direction of a farming game. SSIM, while effective in restoration tasks, fails to measure the relevance of creativity or playability.

UX studies (Smith & Jones, 2019) aim to fill this gap, but their methodologies vary widely, which prevents a systematic comparison. This disconnection between numerical evaluation and player-centered quality reflects a core weakness in current literature. Without metrics that capture both technical fidelity and gameplay immersion, the impact of generative models on asset pipelines remains only partially understood.

Prior Studies on Sprite Generation

Sprite production is a prime example of asset bottlenecks. Manual sprite creation is a labor-intensive process that requires pixel-level editing across multiple animation frames (Serpa & Rodrigues, 2019). Procedural methods for maps and characters (Guzdial et al., 2018; Hong et al., 2019) reduce effort but often yield repetitive patterns, unsuitable for diverse farming environments.

GAN-based approaches brought efficiency gains, especially style transfer with label conditioning (Isola et al., 2017; Kim et al., 2022). However, their dependence on labeled data restricts flexibility and often fails to capture fine-grained artistic variation. In this regard, StyleGAN2's disentangled style representation is crucial. It enables controlled variation without strict reliance on labels, allowing generation of assets that are both diverse and consistent with the overall aesthetic (Odena et al., 2017; Karras et al., 2020).

The literature, however, lacks comprehensive comparative studies. While isolated experiments suggest StyleGAN2's superiority, systematic reviews evaluating its role specifically in agricultural sprite generation are absent. This absence highlights the need for the present study: to consolidate fragmented findings, critically evaluate strengths and weaknesses, and chart directions for future research.

RESEARCH METHOD

This study employs a systematic literature review (SLR) approach to identify, evaluate, and synthesize research on Generative Adversarial Networks (GANs) for generating agricultural game assets. An SLR was chosen because it provides transparency, replicability, and comprehensive coverage of existing evidence, which is essential for a rapidly evolving field such as generative AI. Unlike narrative reviews, the SLR methodology follows predefined procedures to minimize bias and ensure that the findings are based on a rigorous and reproducible process.

Data Sources and Search Strategy

To ensure the breadth and depth of coverage, publications were retrieved from multiple scientific databases, including Scopus, Web of Science, IEEE Xplore, ACM Digital Library, and Google Scholar. These databases were selected for their comprehensive coverage of computer science, artificial intelligence, and applied domains, including educational technologies and digital game studies.

The search was limited to articles published between 2018 and 2025, aligning with the period when GAN variants (including StyleGAN and StyleGAN2) matured and became widely applied. Search strings were constructed using Boolean operators and synonyms to maximize retrieval:

- "Generative Adversarial Networks" OR "GAN" OR "StyleGAN" OR "StyleGAN2"
- "game assets" OR "sprite generation" OR "procedural content generation"
- "agriculture" OR "farming games" OR "simulation games"

Search results from each database were exported into a reference manager, and duplicates were removed prior to screening.

Inclusion and Exclusion Criteria

The retrieved records were screened based on the following inclusion criteria:

- Peer-reviewed journal or conference papers.
- Publications in English.
- Studies explicitly addressing generative models for visual asset creation, with at least partial relevance to simulation, gaming, or agricultural domains.
- Publications from 2018 onwards, ensuring alignment with state-of-the-art developments.

Exclusion criteria included:

- Non-scholarly works (blogs, opinion papers).
- Articles without full-text availability.
- Studies focused solely on unrelated applications (e.g., GANs in finance or unrelated domains).

This protocol ensures that the review captures both technical contributions and interdisciplinary perspectives relevant to agricultural simulation.

Screening and Selection Process

The initial search yielded 134 records across all databases. After removing 17 duplicates, 117 unique studies remained. Title and abstract screening excluded 56 studies due to lack of relevance. Full-text screening of the remaining 61 papers was conducted, applying the inclusion and exclusion criteria, which resulted in 29 primary studies for final analysis. A PRISMA flow diagram (Figure 1) illustrates this multi-stage screening process, showing the number of records included and excluded at each stage. This stepwise documentation enhances transparency, enabling future researchers to replicate or build upon this review.

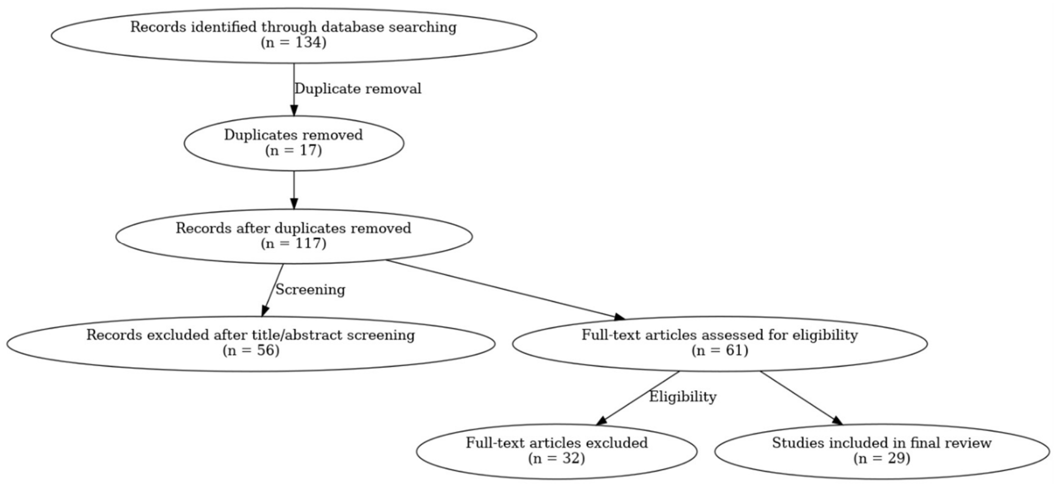

Figure 1. A PRISMA flow diagram used in this research.

Data Extraction and Analysis

From each included study, a structured data extraction template was applied to record:

- Bibliographic details (author, year, publication type).
- GAN variant used (e.g., DCGAN, WGAN, StyleGAN, StyleGAN2).
- Application domain (e.g., sprite generation, map design, environmental textures).
- Evaluation methods (e.g., FID, SSIM, UX testing).
- Reported strengths, limitations, and contributions.

This systematic extraction enables consistent comparison across studies, ensuring that conclusions are not based on selective evidence.

Analysis Framework

The extracted data were analyzed using a thematic synthesis approach. Findings were grouped into three dimensions:

- Technological Developments – architectural improvements and their implications for game assets.
- Social Value – accessibility, democratization of game development, and educational benefits.
- Economic Value – resource efficiency, cost reduction, and market competitiveness.

Within each dimension, evidence was compared across studies to identify converging trends, discrepancies, and research gaps. Special attention was given to the comparative advantages of StyleGAN2 over earlier GAN variants and to the shortcomings of existing evaluation metrics.

FINDINGS AND DISCUSSION

Overview of Selected Studies

From the 29 studies that passed the inclusion criteria, an apparent increase in publications was observed between 2019 and 2024, reflecting the growing interest in applying GANs to creative and entertainment domains. While early studies (2018–2020) were dominated by DCGAN and WGAN implementations, more recent works increasingly adopted StyleGAN and StyleGAN2. Notably, only three studies explicitly examined agricultural or environmental game contexts, confirming the relative novelty and underexplored nature of this domain.

Technological Trends

The analysis reveals a consistent pattern: early GAN variants, such as DCGAN, produced acceptable results for low-resolution sprites but failed at higher resolutions, resulting in blurred textures. WGAN improved training stability but produced outputs lacking fine detail, which limited suitability for detailed farming environments. By contrast, StyleGAN introduced a disentangled latent space that enabled feature-level control, though still with artifacts. StyleGAN2 represents the most significant advancement, combining high-resolution fidelity, stability without progressive growing, and flexible style manipulation. Compared to published results in procedural content generation or VAE-based models, StyleGAN2 consistently delivers assets with higher realism and diversity, making it the most promising tool for agricultural games.

Evaluation Approaches

Most studies relied on machine learning metrics such as FID and SSIM. However, these metrics often failed to reflect subjective quality or gameplay relevance. For example, sprites with substantial statistical similarity sometimes appeared visually inconsistent within farming game aesthetics. Studies incorporating user experience (UX) testing have reported a more reliable alignment with gameplay immersion, suggesting that future evaluation frameworks should integrate both computational and perceptual measures to enhance the overall experience. This review, therefore, identifies a methodological gap in the literature: no standardized evaluation framework yet exists for GAN-generated game assets.

Novelty and Contribution of This Review

The novelty of this study lies in its systematic synthesis of GAN-based methods specifically for agricultural game assets. To the best of our knowledge, no prior survey has critically consolidated technological, social, and economic findings in this niche domain. Compared with existing reviews of procedural content generation or general GAN applications, this paper offers three unique contributions:

1. A critical evaluation of why earlier GANs failed and how StyleGAN2 surpasses them in practice.
2. An integrated perspective that bridges technical metrics with social and economic implications for game developers.
3. Identification of research gaps, including the lack of domain-specific datasets and standardized evaluation methods.

Overall, the findings demonstrate that StyleGAN2's style-based architecture and artifact-free synthesis make it the most viable current approach for generating agricultural game assets. At the same time, the review highlights avenues for future research, including hybrid AI-procedural models, perceptual evaluation frameworks, and the expansion of dynamic interactive content.

CONCLUSIONS

This review of 29 studies highlights the role of Generative Adversarial Networks (GANs) in game asset generation, with emphasis on agricultural contexts. While early models such as DCGAN and WGAN struggled with resolution and detail, StyleGAN2 stands out as the most robust, enabling high-fidelity and controllable sprite generation. Nonetheless, gaps remain in evaluation frameworks and in the availability of domain-specific datasets.

The contributions of this study are: (1) a critical comparison of GAN variants, (2) an integrated view of technological, social, and economic impacts, and (3) identification of research gaps. Looking forward, the implications differ for researchers and practitioners:

- For researchers: future work should prioritize the construction of domain-specific datasets for agricultural sprites, the design of hybrid models that combine procedural content generation with GAN-based approaches, and the development of evaluation frameworks that integrate computational metrics with human-centered UX measures. These directions will strengthen the academic foundation and address current methodological limitations.

- For practitioners: StyleGAN2 and related generative models can already be applied to accelerate sprite production, reduce costs, and diversify asset libraries in farming and educational games. Developers and educators are encouraged to experiment with generative models to expand content variety, while being mindful of ethical and design considerations such as dataset biases and gameplay coherence.

In summary, this study offers a comprehensive understanding of GAN-based approaches for agricultural game assets. It provides a roadmap tailored to the needs of both the academic community and industry practitioners. By bridging these perspectives, the review advances the discourse on how generative AI can contribute not only to technological innovation but also to sustainable and accessible game development.

LIMITATIONS & FURTHER RESEARCH

Despite the systematic process, this review acknowledges several limitations. First, only English-language publications were included, which may exclude relevant studies published in languages other than English. Second, while the chosen databases are comprehensive, coverage bias cannot be eliminated. Third, the reliance on published literature introduces potential publication bias, as negative results are less likely to be reported. Finally, the fast pace of GAN research means that new developments may have emerged after the cut-off date of this review. By explicitly stating these limitations, this review provides a balanced methodological foundation for interpreting its findings and encourages future scholars to replicate or extend its findings.

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