



Autonomy Advantage

The real impact of autonomy in mining and large scale earthworks



Executive Summary

While automation of earthmoving equipment is not new, recent breakthroughs in machine learning have accelerated the development of highly effective autonomous systems for ground-engaging vehicles such as dozers, excavators and loaders. These advancements open up substantial safety improvements by reducing human exposure to hazards and paving the way toward zero-entry mines and jobsites, where no personnel enter active production zones. The same advancements also deliver operational gains through enhanced machine utilization, sustained performance and reduced machine wear.

This paper presents real-world data from production mine sites, demonstrating that autonomous ground-engaging tools are competitive with skilled human operators and can surpass them in key metrics. Autonomous systems exhibit superior consistency while achieving notable improvements in fuel efficiency through optimized operation. This results in +1.6% productivity (BCY/Hr), -2.2% fuel consumption (gal/hr), and +4.0% overall fuel efficiency (BCY/gal) compared to human baselines after normalization for push distance, material hardness, and geological conditions.

When scaled across global earthmoving operations, these incremental advantages compound significantly. Combined with workforce leverage—enabling one operator to supervise multiple machines—these gains translate into substantial economic value. Modeled results from two different sites show that when real empirical results are scaled, annual bottom-line savings and top-line throughput improvements point to an imminent step-change in autonomous earthmoving as a powerful enabler for the ‘dirtworld’ in both safety and performance.

The Time is Now

Autonomous systems have achieved operational scale in specific mining applications well before equivalent progress in on-road vehicles. However, full autonomy for ground-engaging equipment - dozers, excavators, and similar tools - has required recent advancements in perception, adaptive control, and machine learning to handle variable terrain and dynamic environments effectively. These developments now support reliable performance, enabling broader deployment in mining, construction, and beyond.

Established Applications in Autonomous Haulage

Autonomous haulage systems (AHS) have proven effective in controlled, repetitive environments since the late 2000s. Caterpillar's AHS, commercialized in 2013, operates nearly 700 autonomous trucks globally. These have hauled over 11 billion tonnes of material with no systems-related injuries and accumulated more than 380 million autonomous kilometers.^{1,2} Early deployments, such as at Rio Tinto sites in Western Australia, delivered productivity improvements of up to 20% through consistent operation and reduced variability.



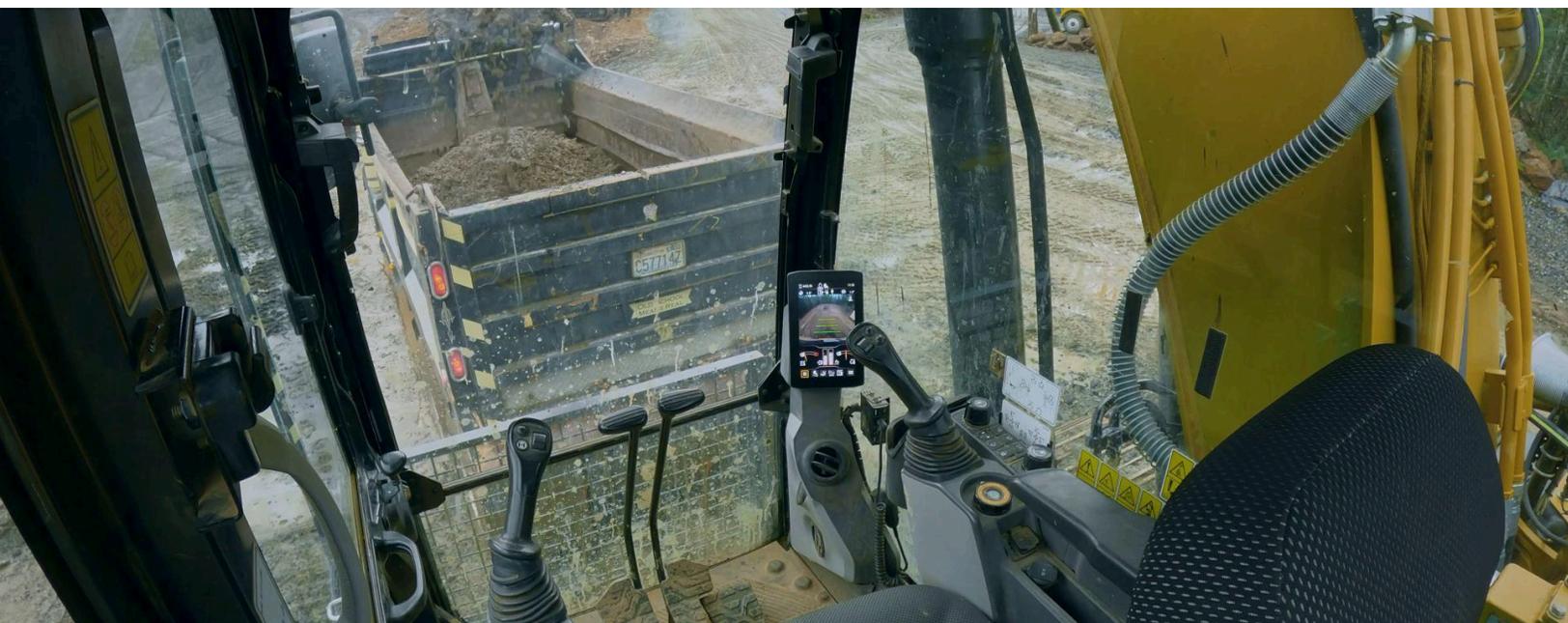
Komatsu's FrontRunner AHS, in use since 2008, has commissioned over 900 trucks, moving more than 10 billion tonnes worldwide with zero systems-related incidents.^{3,4} Other examples include Rio Tinto's Pilbara fleets (over 4.8 billion tonnes moved) and BHP's autonomous haulage and drilling operations, which have shown efficiency and safety gains of 12–30%.⁵ These systems operate on structured routes with predictable cycles, focusing mainly on navigation and avoidance.

The Greater Complexity of Ground-Engaging Autonomy

Ground-engaging tools present significantly higher technical demands. They must adapt in real time to varying material properties, geological conditions, swell factors, and precise tasks such as ripping, pushing, and grading. This requires sophisticated perception of uneven surfaces, dynamic path planning, force-sensitive control, and management of edge cases like ground instability - challenges beyond the navigation focus of haul trucks. Until recent progress in AI-driven perception and adaptive algorithms, these capabilities were limited to semi-autonomous or remote modes. Validated trials, including those with the AIM platform, now show competitive or improved performance under normalized conditions, indicating readiness for scaled implementation.

Market Opportunity

Adoption of autonomous equipment remains low (typically under 5% in most segments), leaving substantial addressable potential. The autonomous mining equipment market is estimated at approximately USD 4.5-4.9 billion in 2025-2026 and projected to reach USD 11-12 billion by 2033 at a CAGR of 11-12%.^{6,7} In construction, the autonomous equipment market is around USD 16–18 billion in 2026, expected to grow to USD 27-29 billion by 2032 at a CAGR of 8-9%.^{8,9} Combined, these segments offer significant opportunity, driven by needs for safety, productivity, and labor efficiency.



Reversal of the Innovation Flow: Construction Challenges Accelerating Mining Autonomy

While mining delivered the earliest commercial-scale autonomous deployments, construction environments are poised to drive the next wave of advancements in ground-engaging autonomy. Construction sites are typically more dynamic and unstructured than traditional mining operations: frequent changes in layout, diverse material types, tight urban or infrastructure constraints, variable weather exposure, and constant interaction with human workers, pedestrians, and other equipment. These factors demand more robust perception systems, real-time adaptability, edge-case handling, and seamless human-machine collaboration - challenges that exceed the relatively predictable, geofenced cycles of mining haul trucks.

Construction's greater complexity has been highlighted as a key reason why full autonomy until recently has been elusive in this sector compared to mining's more repetitive tasks. As noted in industry analyses, construction requires continuous adaptation to changing site conditions and precise 3D object manipulation in unstructured environments, pushing the development of more advanced AI and perception technologies.¹⁰ These innovations, once refined in construction, will immediately transfer back to mining, enhancing performance in variable overburden, ore zones, and ground-engaging operations where haulage successes have not yet fully extended to dozers, loaders, and excavators.

This feedback loop addresses mining's remaining gaps in ground-engaging tools. As autonomy solutions continue to mature in construction, the resulting technologies will improve mining applications. For example, advanced perception for irregular surfaces, dynamic force control during ripping or grading, and multi-machine coordination in mixed environments will benefit mining's terrain variability.

This reversal is supported by industry frameworks such as the Association of Equipment Manufacturers' (AEM) Levels of Autonomy for Non-Road Equipment and ISO 7334:2025 for earthmoving machinery. Both define levels of automation and autonomy (LAA) with a focus on capabilities and tasks in bounded but

dynamic worksites common to construction and mining. Unlike basic navigation-centric systems (e.g., haul trucks), ground-engaging equipment must handle a broad spectrum of complex, context-dependent functions - material manipulation, force application, precise grading, ripping, adaptive pushing—across diverse use-cases and environmental conditions. This wide range of tasks substantially increases the autonomy challenge.^{11,12} Construction's larger, more fragmented market, combined with acute labor shortages and regulatory pressures for safety and efficiency, is likely to accelerate innovation, channeling transferable improvements (e.g., sensor fusion, adaptive planning algorithms) into mining operations.

The outcome is a virtuous cycle: mining's early wins provided proof-of-concept and scale, while construction's harder problems refine the technology for broader, more resilient application. As these advancements mature, mining stands to gain from construction-driven breakthroughs, enabling faster progress toward full zero-entry sites and optimized ground-engaging fleets.

Learnings from On-Road Autonomy

The commercial rollout of autonomous vehicles on public roads provides important lessons for autonomy in mining and large-scale earthmoving. Although mine sites are more structured and repetitive than public roadways, several core insights transfer directly.

Consistency eliminates human variability

Large-scale deployments of Level 4 autonomous systems (e.g., robotaxis and autonomous trucking) show near-constant performance across 24-hour operations, removing productivity losses from fatigue, shift changes, and breaks.¹³ This aligns with AIM dozer trial results, where normalized productivity displayed lower session-to-session variance than human operators.

Safety improvements from removing human factors

Autonomous trucking pilots in the U.S. have reported intervention rates dropping below 1 per 10,000 miles in mature systems, with most remaining interventions tied to rare edge cases rather than control errors.^{14,15} In mining, eliminating distraction, inattention, and fatigue-related incidents strengthens the case for zero-entry production zones.

Fleet-scale efficiency compounds rapidly

On-road systems coordinate platooning, dynamic routing, and predictive energy management across large fleets — capabilities impossible with human drivers.^{16,17} Similar advantages appear in mining: remote supervision ratios of 1:N, centralized machine allocation, and fleet-wide energy optimization. These effects explain why modeled cost savings accelerate nonlinearly beyond 2–4 autonomous units.

Key challenges to manage

- Edge-case handling remains critical; mining benefits from constrained environments, but failures carry higher consequences (equipment damage, production halts).
- Regulatory approval and workforce transition take longer than expected; on-road autonomy required over a decade for limited commercial operations.

- Transparent communication about safety data, job evolution (operator → supervisor/maintainer), and local economic benefits helps address labor and community concerns.

In summary, on-road autonomy confirms that machine-learning systems deliver superior consistency, safety, and fleet-scale efficiency — outcomes already visible in AIM autonomy deployments as we will demonstrate in this paper.

Next-Generation Operators

Autonomy does not replace operators - it amplifies their impact. Experienced professionals remain indispensable for strategic oversight, nuanced judgment, and fleet optimization. Their role evolves from hands-on machine control to high-leverage supervision, allowing them to shape entire sites while removed from harm's way.

Multiplied Productivity Through Flexible Supervision

One operator can now direct fleets autonomous machines simultaneously - whether from a climate-controlled remote operations center, a pickup truck at a safe vantage point, or even the cab of another machine on site. This 1:N model can deliver the output of multiple traditional crews, with increased machine utilization and consistent performance that eliminates poor human operator performance, fatigue, shift-change delays, and idle time.

Safer, More Versatile Work Environments

Operators are no longer tethered to the machine they control. They can work from secure remote centers, mobile vehicles, or integrated interfaces in other equipment - dramatically reducing exposure to dust, noise, vibration, falling objects, ground instability, and proximity hazards. This flexibility supports true zero-entry zones during active production while preserving on-site presence when needed.

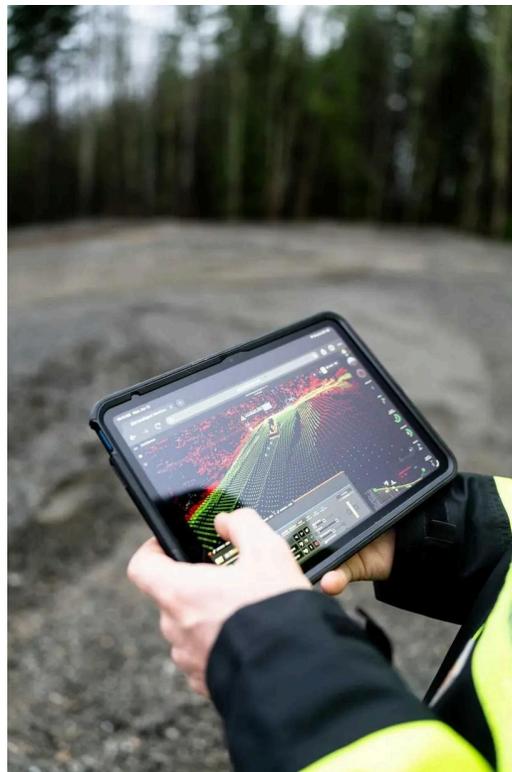
Elevated Expertise at the Center

AI-powered autonomy thrives on human insight. Next-generation operators apply deep knowledge of earthmoving dynamics, material behavior, geotechnics, and equipment limits to handle edge cases, refine AI models, and drive site-level decisions.

Companies are actively upskilling experienced operators for these strategic supervisory roles, creating safer, higher-value career outcomes.

Attracting Fresh Talent

Autonomy creates fresh entry points for today's tech-native youth. Young people who have grown up



immersed in smartphones, apps, social media, AI tools, and digital interfaces as an everyday part of life. Remote supervision, fleet analytics, real-time dashboards, and optimization roles feel intuitive and engaging to this generation, lowering traditional barriers to entering the "dirtworld". This blend of seasoned domain expertise and the natural digital fluency of younger workers broadens and strengthens the industry's talent pipeline, attracting diverse, adaptable new entrants eager to apply their everyday tech comfort to high-impact earthmoving challenges that shape our world.

Real World Results

Production Performance

The primary component of this study focuses on benchmarks conducted as part of pilot projects of the AIM autonomous system. Production performance is an important factor - without strong production performance from each individual autonomous machine, benefits can be eroded at fleet scale. A core principle in designing the AIM system, has been to ensure that performance is competitive with the best human operators.

Methodology

The core objectives of the head-to-head trials were to benchmark the AIM autonomous system against human operators under full operational conditions and to establish the validated metrics required for transitioning to commercial deployments.

Specifically, the trial aimed to:

- **Execute a Full Cycle Trial:** Conduct a comprehensive slot dozing autonomy trial encompassing the full cycle of dozer mining activities (ripping, slot dozing, windrow cleaning) over a continuous shift of no less than six hours.
- **Establish Accurate Volume Metrics:** Begin and end the trial with cleaned cut surfaces. This precise conditioning allows for accurate differentiation between Bank Cubic Yards (BCY) and Loose Cubic Yards (LCY), providing a robust measure of swell factor by comparing the change in cut volume to the change in fill volume.
- **Establish Reliable Human Baseline:** Measure the dozing performance of a number of human operators to establish a more accurate and representative average human baseline productivity. *(Note: Acknowledging a potential positive productivity bias from operators aware of being monitored during a single shift.)*
- **Validate Data Integrity:** Validate the AI-reported productivity data against multiple independent external sources, including drone survey data, CAT VisionLink data, and manually collected data.
- **Verify Real-Time AI Accuracy:** Validate the accuracy of the AI system's real-time data collection capabilities for determining instantaneous and cumulative productivity.

Data Collection

The primary objective was to utilise external sources to measure key metrics. This involved

- A total of 6 trial shifts using CAT D10T dozers
- Autonomous dozer shifts supervised by a remote operator completed ripping & slot dozing components of the full cycle (see Total Hours vs AI hours below). The windrow cleaning component of the cycle was completed via manned operation.
- Lidar Drone Survey at the start and end of each shift
- Metered fuel reading at the start and end of shift
- Shift start and end time

Data Processing

- Drone data was processed to generate a surface model for each session survey
- Work regions were defined within the survey area
- Volume difference were compared
- Average push distance was calculated based on center of Mass change between start and end
- Data was then processed to determine production performance

Data Outputs

Raw Processed

Session	Type	Total Hours	AI Hours	Volume Cut (C.Y)	Rate (BCY/Hr)	Volume Fill (C.Y)	Rate (LCY/Hr)	Distance (ft)	Fuel (gal)	Fuel (gal/hr)
1	AIM	10.1	7	2,839.0	281.1	3,545.0	351.0	301.5	251	24.85
2	Human	8.9	0	2,233.6	251.0	2,442.2	274.4	309.6	227	25.51
3	AIM	10.4	7.6	3,063.9	294.6	3,305.6	317.8	336.3	264.0	25.38
4	Human	10.4	0	2,992.9	287.8	4,265.3	410.1	289.7	269	25.87
5	AIM	8.3	5.1	1,908.5	229.9	2,507.4	302.1	280.4	210	25.30
6	AIM	8.3	8.1	2,531.2	305.0	2,778.6	334.8	372.4	207	24.94

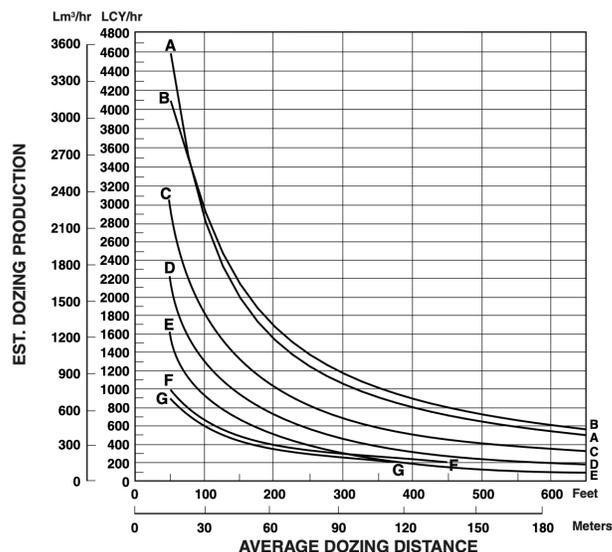


Push Distance Normalization

Normalising for push distance is a critical factor in comparing like-for-like in dozer push operations. The figure on the right from the CAT performance handbook demonstrates the relationship from real-world data. Pushing shorter distances reduces cycle time and fuel burn. Shorter push distances yield higher production rates.

When **normalized** for distance, the Human operator on session 4 becomes the highest performer (296.3 BCY/hr). However, the AIM system shows high consistency (clustering around 245–281 range) even as the actual push distances varied significantly (280ft to 372ft). Note that the raw data for AIM in session 6 (305 BCY/hr at 372ft) was significantly adjusted down because the model identified the long distance as an "advantage" in this specific dataset.

ESTIMATED DOZING PRODUCTION • Universal Blades • D7G through D11T



KEY
 A — D11T-11U
 B — D11T CD
 C — D10T-10U
 D — D9R/D9T-9U
 E — D8R/D8T-8U
 F — D7R Series 2-7U
 G — D7G-7U

NOTE: This chart is based on numerous field studies made under varying job conditions. Refer to correction factors following these charts.

CAT Performance Handbook (Edition 40)

Session	Type	Total Hours	Cut (C.Y)	BCY/Hr (Actual)	Distance (Ft)	BCY/Hr (Norm)	Fuel (gal/hr)
1	AIM	10.1	2,839.00	281.1	301.5	281.1	24.85
2	Human	8.9	2,233.60	251	309.6	245.1	25.51
3	AIM	10.4	3,063.90	294.6	336.3	269.5	25.38
4	Human	10.4	2,992.90	287.8	289.7	296.3	25.87
5	AIM	8.3	1,908.50	229.9	280.4	245.1	25.3
6	AIM	8.3	2,531.20	305	372.4	253.8	24.94

Correcting for Slate

To ensure "apples-to-apples" comparison across trial zones with varying geological content, the field data was normalized to account for material hardness. Specifically, the presence of **Slate**—a significantly harder material capping the orebody creates a measurable drag on dozer productivity.

The analysis utilizes a **Material Normalization Formula** to convert "Normalised Productivity" (observed performance) into "Equivalent Productivity" (projected performance in standard overburden). This adjustment isolates machine performance from geological variance.

The Calculation

$$\text{Adjusted BCY/hr} = \text{Actual BCY/hr} + (\text{Slate \%} \times \text{Difficulty Factor})$$

Key Components

- **Actual BCY/Hr:** The raw production rate measured during the specific trial block (e.g., *281.1 BCY/hr*).
- **Slate %:** The geological composition of the cut zone (e.g., *50% Slate*).
- **Difficulty Factor (1.43):** The "Slate Coefficient." Derived from baseline resistance data, this coefficient indicates that for every **1% increase in slate composition**, dozer productivity decreases by approximately **1.43 BCY/hr**.

Session	Type	Slate %	Raw BCY/Hr	Slate Corr. BCY/Hr	Distance (Ft)	Fully Norm. BCY/Hr
1	AIM	50%	281.1	352.6	301.5	352.6
2	Human	50%	251	322.5	309.6	327.8
3	AIM	10%	294.6	308.9	336.3	331.8
4	Human	50%	287.8	359.3	289.7	351.5
5	AIM	90%	229.9	358.6	280.4	344.7
6	AIM	0%	305	305	372.4	351.6

Performance Comparison

Metric	Human Operator (Avg)	Autonomous (AIM) (Avg)	Performance Delta
Productivity (Yd ³ /Hr)	339.7	345.2	1.62%
Fuel Consumption (gal/hr)	25.69	25.12	-2.23%
Fuel Efficiency (Yd ³ /gal)	13.22	13.75	3.98%

Key Takeaways

1. **Productivity (+1.6%):** The autonomous system maintains a slightly higher pace of work when normalized for conditions.
2. **Fuel Consumption (-2.2%):** The AIM system burns less fuel per hour than the human operator. This reduction is driven by the system's ability to maintain optimal engine RPMs.
3. **Fuel Efficiency (+4.0%):** The combination of moving more dirt (numerator) while burning less fuel (denominator) creates a compounding efficiency gain of nearly 4%. This is the "double win" of autonomy: faster production with a lower cost footprint.

Performance at Scale

The trial performance data shows that with an albeit small sample size, that for individual machines autonomy can be competitive with humans in benchmark conditions. This section explores how single machine data could be scaled to fleets of autonomous vehicles.

Modeling Scale

To generate an understanding of the impact of autonomy when deployed at scale, the unit production performance improvements were used as inputs into a larger model designed to emulate large-scale autonomous earthmoving operations.

The following is a breakdown of the input parameters. These inputs serve as the baseline for calculating operational costs, productivity, and the scaled impact of autonomous earthmoving.

Operational Inputs

These parameters define the schedule and labor structure of the site operation.

Metric	Site 1	Site 2
Production Availability (days)	200	350
Labor Cost (\$)	\$35.00	\$9.00
Shift Structure	12 x 2	8 x 3
Shift Utilization	90%	90%

Production & Material Inputs

These metrics describe the material being moved and the value associated with it.

Metric	Site 1	Site 2
Ore Value (\$)	\$100	\$150
Stripping Ratio (Yd ³ /raw tonne)	9.00	2.82
Baseline Human Yield (Yd ³)	340	440

Fuel & Efficiency Inputs

These figures establish the current energy costs and consumption rates.

Metric	Site 1	Site 2
Fuel Cost (\$/US gal)	\$3.40	\$4.40
Baseline Consumption (US gal/hr)	25	27

Savings: The Bottom Line

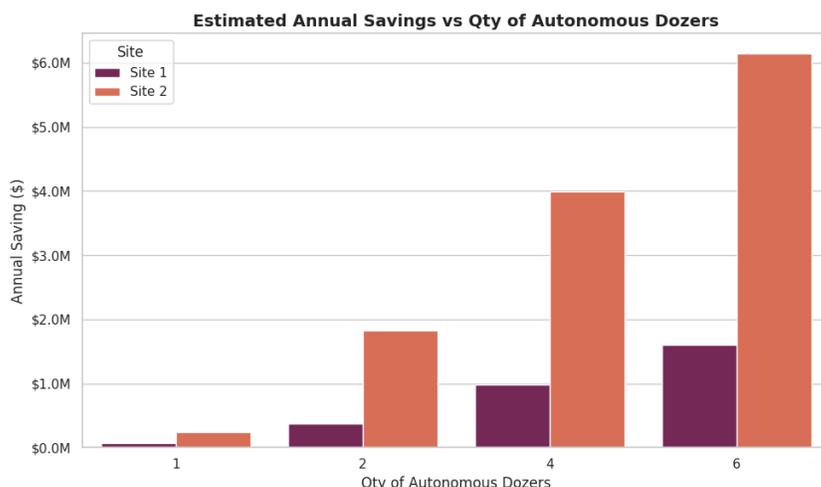
By decoupling the traditional 1:1 ratio of operator to machine, autonomy is shown to transform labor from a variable cost constraint into a fixed oversight function. To quantify this, our modeling emulates two distinct site profiles, illustrating how autonomous deployment can systematically drive down unit costs while exponentially increasing total yield.

The Decoupling of Labor and Production

In a manual environment, increasing production necessitates a linear increase in labor costs. Autonomy breaks this link. As demonstrated in the scaling models for both Site 1 and Site 2, the introduction of multi-machine control allows a single operator to manage multiple units.

This shift results in a compounding economic benefit:

- **Yield Acceleration:** At the maximum modeled scale (6x Auto), both sites realized a production increase of **over 500%** compared to baseline human-operated dozers.
- **Unit Cost Optimization:** Cost per yard drops consistently as the autonomous fleet grows.
 - Site 1: from **\$0.683** to **\$0.525**
 - Site 2 (350-day schedule): from **\$0.450** to **\$0.374**



Site 1

Metric	Baseline Dozer	1 x Auto	2 x Auto	4 x Auto	6 x Auto
Operators	1 / dozer	1	1	1	1
Total Yield /hr	340	345	691	1382	2073
Cost Per Yd ³ \$	0.683	0.643	0.572	0.537	0.525
Saving/ hr \$	-	14.06	77.78	205.23	332.68
Saving/hr %	-	6.05	33.49	88.36	143.24
Shift Saving \$	-	168.71	933.40	2,462.77	3,992.15
Year Saving \$	-	67,484	373,359	985,109	1,596,858

High-Cost Labor Efficiency

Site 1 represents a higher labor cost environment (**\$35.00/hr**) with a standard **200-day** production window. The primary driver of savings is reduced cost-per-yard through higher utilization and machine density.

- **Incremental Gains:** Transitioning from manual to one autonomous unit yields a **6.05%** saving per hour.
- **The 6x Multiplier:** At full scale, the site achieves nearly **\$4,000** in savings per shift, delivering an annual bottom-line impact of **\$1,596,858**.

Site 2

Metric	Baseline Dozer	1 x Auto	2 x Auto	4 x Auto	6 x Auto
Operators	2 / dozer	1	1	1	1
Total Yield/hr	523	539	1,077	2,155	3,232
Cost Per Yd ³ \$	0.450	0.395	0.382	0.376	0.374
Saving/ hr \$	-	29.32	72.26	158.14	244.01
Saving/hr %	-	12.47	30.73	67.26	103.78
Shift Saving \$	-	234.59	578.09	1265.10	1952.10
Year Saving \$	-	246,316	1,820,982	3,985,051	6,149,120

High-Utilization Impact

Site 2 demonstrates autonomy's value in a high-utilization environment (**350 days**, 3-shift structure). The baseline required **two operators per dozer** for shift coverage and rotation - autonomy's single-operator oversight model unlocks massive financial headroom.

- **Total Scaled Savings:** The progression from 1x Auto to 6x Auto drives annual savings from roughly **\$246,000** to **over \$6.1 Million**.
- **Cost Efficiency:** At the 6x Auto phase, the operation achieves a **103.78%** saving per hour relative to baseline, effectively doubling the economic efficiency of the earthmoving fleet.

From Cost Center to Value Driver

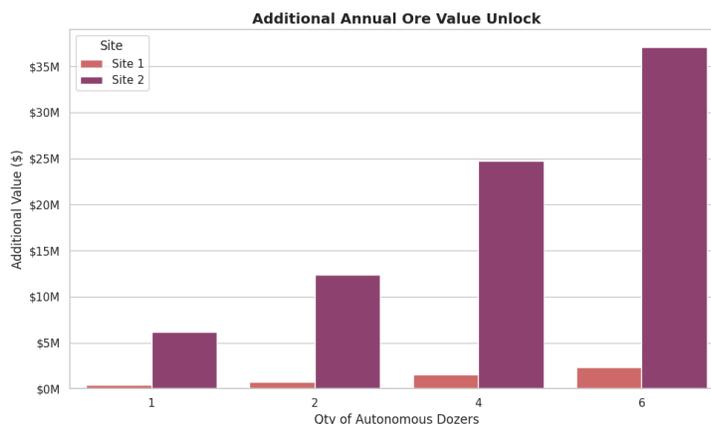
The savings from autonomy extend far beyond fuel or maintenance - they stem from the radical optimization of the cost-to-yield ratio.

Key Takeaway: For large-scale operations, scaling to a 6x autonomous fleet does not merely reduce expenses; it delivers a structural competitive advantage - lowering the cost of every yard moved by up to **23%** while simultaneously maximizing total material throughput across the site.

Throughput: Unlocking Latent Asset Value

In modern mining operations, overburden removal frequently bottlenecks ore access. As ore bodies deepen and stripping ratios rise, the velocity of the dozer fleet can directly dictate a site's Net Present Value (NPV).

While scaling traditional manual fleets multiplies management overhead, safety risks, and performance variability, autonomy offers a structural solution centered on operational consistency. Human operators inherently exhibit volatility in the production cycle which can be removed with effective autonomous deployments.



Accelerated Material Velocity & Projected Scaling

By consistently increasing the hourly volume moved per machine, scaled autonomous fleets accelerate the mining cycle and expedite ore access. The models below project the throughput and financial delta between a manual baseline and scaled autonomous operations.

Site 1: Standard 200-Day Production Schedule

At a 6x scale, a modest hourly per machine performance uplift yields over 269,280 additional cubic yards annually, unlocking nearly \$3 million in accessible ore value.

Metric	Baseline Dozer	1 x Auto	2 x Auto	4 x Auto	6 x Auto
Total Yield /hr	340	350	700	1,401	2,073
Yearly Throughput Change Yd ³	-	44,880	89,760	179,520	269,280
Additional Ore Access Tons	-	4,987	9,973	19,947	29,920
Additional Ore Value \$	-	498,667	997,333	1,994,667	2,992,00

Site 2: Continuous High-Utilization Environment

In high-utilization environments, the compounding effect is severe. A 6x autonomous fleet moves an additional 679,000 yards annually, accelerating access to over \$37 million in ore.

Metric	Baseline Dozer	1 x Auto	2 x Auto	4 x Auto	6 x Auto
Total Yield /hr	523	539	1,077	2,155	3,232
Yearly Throughput Change Yd ³	-	113,262	226,524	453,049	679,573
Additional Ore Access Tons	-	40,164	80,328	160,656	240,983
Additional Ore Value \$	-	6,185,240	12,370,480	24,740,960	37,111,440

Operational Realities: Scaling Beyond the Algorithm

Realizing these proven Opex and projected NPV gains requires navigating the practical realities of real world site-wide deployments. Technology providers and operators of autonomy must actively manage and navigate several systemic variables and acknowledge potential technological drawbacks to validate the data:

- Clarifying "Additional Ore Value":** While gross throughput can always be increased simply by deploying more manual dozers or extending shift hours, the "Additional Ore Value" projected in the models above does not represent newly discovered, free market tons. Rather, it quantifies the financial impact of accelerated access and incrementally lower unit costs. The true value lies in maximizing asset utilization - extracting the ore faster and at a significantly higher margin by avoiding the compounding Operating Expenditure (OpEx) penalties of scaling a human fleet.
- Infrastructure & CapEx:** Traditionally, the site bottleneck shifts from physical labor to digital infrastructure, requiring front-loaded CapEx in reliable low-latency connectivity (e.g., private LTE/5G). Contained solutions that can be deployed effectively with low-to-no dedicated site infrastructure can ease deployment. These systems, enabled by high speed satellite internet for example, mitigate upfront network costs and accelerate time-to-value by operating independently of site infrastructure while acknowledging the need for interoperability requirements for operating at established sites with autonomy air-gap and private on-premises network requirements.
- OEE Payback (Hardware & Installation):** While autonomy can dramatically boost the *Performance* metric of Overall Equipment Effectiveness (OEE), adding complex computational hardware to a machine introduces new risks to *Availability*. The initial installation and calibration of these systems require planned downtime. The harsh realities of the pit - extreme vibration, dust, and temperatures can induce failures, leading to unplanned stops. Fast installation of environment-validated hardware with predictive diagnostics are critical to ensuring these technological additions do not degrade overall machine OEE and delay time to value.

- **Machine Health Multiplier:** Conversely to the above, by executing optimized blade paths and eliminating human-induced wear and shock-loading, autonomy promises to reduce mechanical unscheduled maintenance and extend drivetrain lifecycles to positively impact OEE.
- **Rework Reduction Opportunity:** Human-operated dozers can frequently and inadvertently rehandle material due to variability in operator technique, fatigue, and inconsistent material management. Autonomy may (though not included in this study) eliminate these inconsistencies through precise, repeatable blade control and real-time adaptive material management, achieving the intended result in fewer passes. This directly reduces cycle time, fuel consumption, and cumulative machine wear.
- **The Interoperability Imperative:** Autonomy cannot exist in a silo. As operations scale, autonomous systems must integrate seamlessly with a wide array of existing Fleet Management Systems (FMS) and multi-OEM environments. Achieving true "open autonomy" without vendor lock-in relies on systems to be flexible with support for bi-directional APIs.
- **Mixed-Fleet Dynamics:** Autonomous machines will initially share the pit with manned equipment and likely always have, successful scaling requires safe interaction of autonomous fleets with non-intelligent machines with self-contained perception and robust operational processes to prevent degradation of the autonomous fleet's optimal cycle times.
- **Trust & Safety as a Catalyst:** Removing operators from hazardous zones establishes true zero-entry operations. This protects personnel while systematically eliminating the costly, site-halting downtime associated with safety incidents. Developing trust amongst ground crews in safety systems is paramount to easing adoption and scaling.
- **Interventions and Supervisor Duty Cycle:** In autonomous operations, minimizing intervention rate is essential for maintaining high supervisor duty cycles, where a single supervisor can oversee multiple machines efficiently. A system's capability to reliably complete full operational cycles without frequent interruptions must reach a critical mass, and surpassing this threshold ensures that as the fleet scales to large numbers, the human oversight ratio remains sustainable.

While the financial models prove the unprecedented potential of autonomous throughput, ultimate success will be dictated by how well an operation integrates these digital, mechanical, and human variables across the pit's lifecycle.

The Opportunity Ahead

The earthmoving industry faces a decisive opportunity. Advances in AI-driven perception and adaptive control are steadily transitioning autonomous equipment from conceptual prototypes to viable field systems. Early controlled trials suggest these systems are beginning to match—and in some metrics, exceed skilled human operators in performance. Normalized data from initial deployments indicates autonomous fleets can yield up to a 1.6% increase in productivity and a 4.0% improvement in fuel efficiency.

As this technology matures, it offers a realistic pathway to break the linear constraints of traditional expansion, where scaling throughput has historically required proportional increases in labor, training, and safety liabilities. By building towards predictable high utilization rates and OEE, companies can begin modeling near-linear growth against fixed supervisory costs. The projected economic impact is significant: for a supervised six-machine fleet in continuous multi-shift operations, models indicate potential annual net savings of up to \$6.1 million, driving cost per yard down by as much as 23%. At scale, this structural shift promises to shorten stripping cycles, expedite ore access, and improve project Net Present Value (NPV).

Autonomy is the present multiplier redefining the dirtworld. Autonomy for ground-engaging vehicles is evolving from a distant concept into a real-world operational multiplier. Early adopters who deploy these ground-engaging fleets today are laying the essential groundwork for lower unit costs and greater resilience against persistent labor shortages.

References

1. Caterpillar. Cat® Autonomy Solutions. January 2026. Available from: <https://www.caterpillar.com/en/news/caterpillarNews/2026/cat-autonomy-solutions.html>
2. Caterpillar. Caterpillar Unveils the Next Era of Autonomy in Construction. January 7, 2026. Available from: <https://www.caterpillar.com/en/news/corporate-press-releases/h/next-era-autonomy.html>
3. Komatsu. FrontRunner Autonomous Haulage System. October 2025. Available from: <https://www.komatsu.com/en-us/technology/smart-mining/loading-and-haulage/autonomous-haulage-system>
4. Komatsu. Komatsu achieves major autonomous milestones. July 30, 2024. Available from: <https://www.komatsu.com/en-us/newsroom/2024/komatsu-achieves-major-autonomous-milestones>
5. Komatsu and Rio Tinto celebrate 300th AHS delivery. August 12, 2024. Available from: <https://www.komatsu.com.au/company/news-media/news/komatsu-and-rio-tinto-celebrate-300th-ahs-delivery>
6. Grand View Research. Autonomous Mining Equipment Market Report. 2025–2033 projections.
7. Dimension Market Research. Autonomous Mining Equipment Market. 2025–2033 projections.
8. Fortune Business Insights. Autonomous Construction Equipment Market. 2024–2032 projections.
9. SNS Insider. Autonomous Construction Equipment Market. 2024–2032 projections.
10. The Elusive Dream of Fully Autonomous Construction Vehicles. WIRED. 2023 Apr 16. Available from: <https://www.wired.com/story/the-elusive-dream-of-fully-autonomous-construction-vehicles>
11. Association of Equipment Manufacturers (AEM). Levels of Autonomy for Non-Road Equipment. December 15, 2025. Available from: <https://www.aem.org/getmedia/b318a244-839f-49a1-892d-1dfaf372f9cb/AEM-Guidance-Documents-Autonomy.pdf>
12. ISO 7334:2025. Earth-moving machinery — Vocabulary and taxonomy for automation and autonomy. International Organization for Standardization; 2025. Available from: <https://www.iso.org/standard/82754.html>
13. Waymo. Waymo Safety Impact. 2025. Available from: <https://waymo.com/safety/impact> (Data through September 2025 shows 127 million rider-only miles with consistent performance metrics and reductions in variability compared to human benchmarks.)
14. Waymo. Comparison of Waymo Rider-Only crash rates by crash type to human benchmarks at 56.7 million miles. Traffic Injury Prevention. 2025. Available from: <https://www.tandfonline.com/doi/full/10.1080/15389588.2025.2499887> (Peer-reviewed analysis of disengagement/intervention trends and safety improvements in mature systems.)
15. California DMV. Autonomous Vehicle Disengagement Reports. 2024–2025. Available from: <https://www.dmv.ca.gov/portal/vehicle-industry-services/autonomous-vehicles/disengagement-reports/> (Reports show declining disengagement rates, with mature operators like Waymo achieving thousands of miles per intervention.)
16. Concurrent optimization of routing and platooning decisions for autonomous truck fleets. Alexandria Engineering Journal. 2025. Available from: <https://www.sciencedirect.com/science/article/pii/S1029313225000028> (Discusses platooning, dynamic routing, and fuel/energy efficiency gains in fleet coordination.)
17. A Predictive Framework for Dynamic Heavy-Duty Vehicle Platoon Coordination. ACM Transactions on Cyber-Physical Systems. 2019 (updated analyses in 2025 contexts). Available from: <https://dl.acm.org/doi/10.1145/3299110> (Foundational work on predictive energy management and platooning for fleet-scale benefits, referenced in recent autonomous trucking studies.)