



GeoAI

The next frontier in
digital transformation



Whitepaper.

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The opportunity & challenges of AI & ML

IDC forecasts the Artificial Intelligence (AI) will contribute \$19.9 trillion to the global economy through 2030 and drive 3.5% of global GCP in 2030. In a recent [McKinsey Global Survey](#) on AI, 65% of respondents report that their organizations are regularly using GenAI. Unsurprisingly, companies across industries are investing in capabilities to take advantage of this commercial opportunity.

However, as AI and ML applications become popular, companies are realizing that the process for developing, deploying, and continuously improving them is complex. In fact, [Forbes](#) reports that 85% of ML projects never make it into production.

When you consider the basic infrastructure needed to get started with traditional approaches to ML, it makes sense why the investment can take years to reach a positive return:



Data science know-how



ML lifecycle management process



High-performance hardware



Data management (storage, cleaning, etc.)



Data security measures

\$19.9

trillion contributed to global economy through 2030 by AI

65%

of McKinsey survey respondents report their organizations are regularly using GenAI

85%

ML projects that never make into production

What is GeoAI?

As GenAI transforms internal data, GeoAI unlocks external intelligence.

In an era where GenAI has transformed internal data management, GeoAI is the next leap forward. It brings tailored, actionable insights on your physical assets anywhere in the world—fast, cost-effectively, and without the need for large investments.

Unlike traditional solutions that are costly and unpredictable, Picterra offers the only fully productized GeoAI system:



Collaboration & communication tools



Streamlined ML training process



Cloud-based infrastructure



No headache production scaling



Easy data management



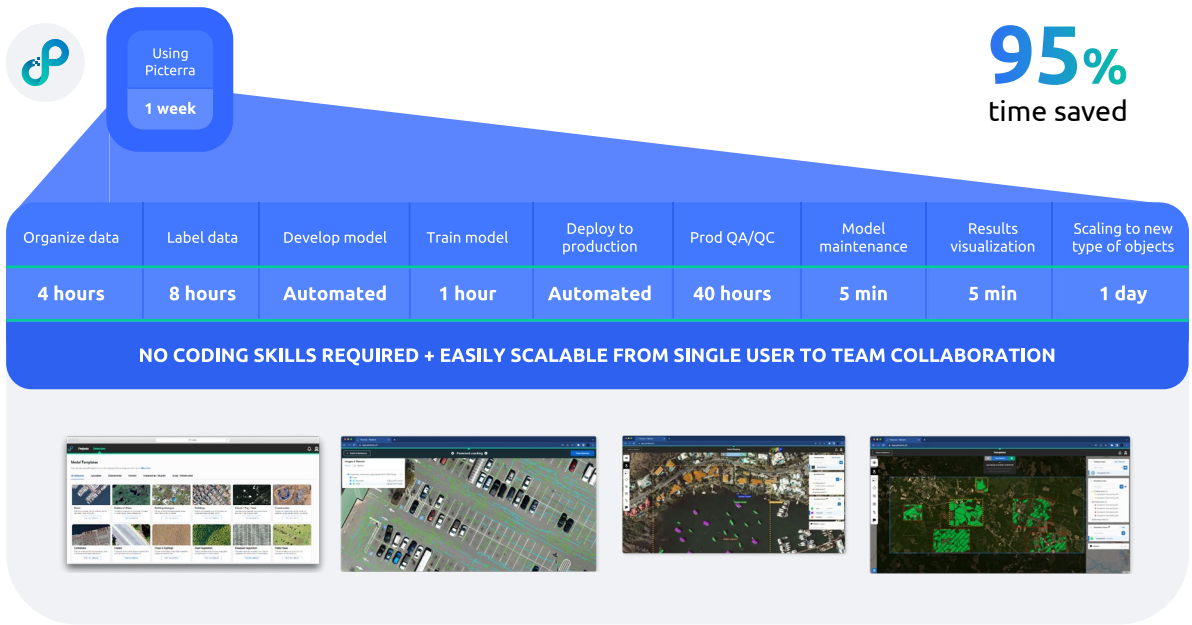
[Read on to get the full comparison between Picterra's ML lifecycle and the traditional ML workflow.](#)

Picterra vs. traditional ML

This graphic depicts the typical workflow and resources required for productionizing one ML model compared to the same project in Picterra. Resource estimates are based on industry knowledge and client interviews to reflect the effort of bringing one standard ML application to life.



Organize data	Label data	Develop Model	Train model	Deploy to production	Prod QA/QC	Model Maintenance	Results visualization	Scaling to new type of objects
1 week	4 weeks	4 weeks	2 weeks	8 weeks	2 weeks	1 week	1 day	3 weeks
Data scientist GIS associate	Data scientist Annotator	Data scientist	Data scientist	Software engineer Developer engineer	Data scientist GIS associate	Data scientist	GIS associate	Data scientist



 [Let's dive into how each step compares](#)

Build powerful ML models

Organize & label the data

In terms of resource intensity, the first part of the traditional ML workflow is the most expensive. Data acquisition, feature extraction, and transformation to fit specific business needs are complex processes that traditionally would require a team of skilled data scientists collaborating with the commercial side of the business.

First, the team must prepare and normalize the data. Then, the model needs to be fed examples and training data so it can recognize relationships and patterns, learn from them, and infer. The data science team must also supply enough annotations to develop the model. Some companies choose to outsource the annotation process with varying results.

Here follows a breakdown of the process of developing a model and the resources it requires:

	Traditional ML Requires a GIS associate, data scientist, annotator(s)	Picterra Requires a GIS associate and optional annotator(s)
Organize data	• Transferring data to shared servers • Harmonizing various file formats • Creating secure backups • Normalizing georeferenced information • Performing GSD/ resolution normalization	• Uploading images to Picterra through drag & drop • ML-ready and easily visualizable
Time required	40 hours	4 hours
Label data	• Deploying labelling software • Creating guidelines for the labelling team • Managing the labelling team • Normalizing labels and completing missing files	• Creating a detector in minutes • Assigning regions to annotators • Tracking annotation progress 40 hours
Time required	160 hours	8 hours



95%
total time
savings



Build powerful ML models

Develop & train a model

When the data is prepared, it's time to develop and train the model. It requires infrastructure, both in terms of high-performing hardware (GPUs) and storage, often involving the IT team.

	Traditional ML	Picterra
	Requires a data scientist	Requires a GIS associate
Develop model	- Preparing data for machine learning - Installing ML framework - Trying various architectures - Developing pre/post-processing	- Automated architecture search - Smart pre/post-processing
Time required	160 hours	Fully automated
Train model	- Getting GPU access from IT - Transferring data to training machine - Tracking training progress - Troubleshooting errors	One-click training of detector
Time required	80 hours	1 hours

99%
total time
savings



Build powerful ML models

Productionize the model

After building the model, the data science team transfers the model to a software engineering or DevOps team to bring it into production. This is typically the riskiest part of the lifecycle, as many projects fail due to poor communication, lack of resources, and lengthy lead times

	Traditional ML Requires a GIS associate, data scientist, software engineer, and DevOps Engineer	Picterra Requires a GIS associate
Deploy to production	• Get GPU server access from IT • Containerize the model • Data handling code (upload, etc.) • Setup Tensorflow Serving • Setup logging monitoring • API or UI development	• Trained models are immediately available for production
Time required	320 hours	Fully automated
Production QA / QC	• Getting GPU access from IT • Transferring data to training machine • Tracking training progress • Troubleshooting errors	• One-click training of detector
Time required	80 hours	40 hours
Model maintenance & documentation	• Setup version control • Create documentation	• Share the detector with other users
Time required	40 hours	5 mins



91%
total time
savings



Build powerful ML models

Report & scale

The point of analysis is to create actionable insights for the business. Visualizing results in an easy-to-understand manner enables decision-makers to incorporate the analysis into their work. But this often requires custom work to integrate with existing reporting tools. In Picterra, you can build attractive change reports in minutes.

Picterra also makes it easy to scale your work. Your model can be used as a base for new ones and applied to new data sets forever. In fact, it will just get more intelligent the more you use it.

	Traditional ML	Picterra
	Requires a GIS associate	Requires a GIS associate
Results visualization	• Data management in GIS • Import into a visualization solution	• Built-in interactive shareable reports
Time required	8 hours	5 mins
Scale to new objects	• Model adaptation • New deployment • API/UI modification	• Easily use existing detectors as a base for new ones
Time required	120 hours	8 hours

94%
total time
savings



Conclusions

Overall it is up to 95% faster to deliver an operational ML model with Picterra compared to with the traditional ML workflow. That means ML and operational IT staff teams have more time to focus on higher-value tasks including:



Integration

Integrating the results in existing workflows and business applications, which usually requires close work with stakeholders.



Collaboration

Working with business managers to find new applications for machine learning that will drive business results



Experimentation

Testing new ideas in minutes without expending internal resources and create PoCs with ready-to-go infrastructure.

With GeoAI in place, enterprises have a scalable, reliable way to operate geospatial ML models in production and continuously develop them. Over time, the company will have a library of strategic ML assets that will enable it to act on timely data, fast.



Find out more at

picterra.ch

