Stockminnow is a decision-support tool designed to help guide augmentation practice for the endangered Rio Grande silvery minnow. It is based on a deep reinforcement learning (DRL) framework developed to make near-optimal augmentation decisions using the same noisy and irregular monitoring data and hydrological forecasts available to managers in practice.

The tool focuses on two recurring management decisions:
(1) how many fish to produce each spring based on recent catch data and spring flow forecasts that determine expected recruitment capacity, and
(2) how to allocate the produced fish each fall across the three river reaches where the species currently persists (Angostura, Isleta, and San Acacia).

The underlying decision models were trained using a realistic simulation of silvery minnow population dynamics, hydrology, monitoring processes, and hatchery operations. Through repeated simulated management over long time horizons, the DRL models learned strategies that balance two competing objectives: maintaining population persistence across river reaches and minimizing operational costs associated with hatchery production.

Across a range of management priorities, the trained DRL models produced a clear performance frontier describing the trade-off between population persistence and hatchery production cost, yielding a portfolio of alternative supplementation strategies. From this frontier, a decision model was selected in consultation with managers that emphasizes high persistence while substantially reducing unnecessary production, and this selected policy is implemented in Stockminnow. This strategy achieved higher mean population persistence at a lower average production level than the previously operational supplementation strategy currently in use (Archdeacon et al. 2022), demonstrating that improved conservation outcomes can be achieved with lower management cost.

Stockminnow does not replace expert judgment. Instead, it provides a transparent and interpretable policy engine that synthesizes complex ecological dynamics, monitoring uncertainty, and long-term trade-offs between objectives into actionable guidance.

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