

1 **Agentic Modelling Pipeline: Reproducible Rapid Stormwater Modelling Management**

2 **System with OpenClaw**

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8 **ABSTRACT**

9 Configuring urban hydrological models, such as SWMM, for operational or real-time
10 modelling remains onerous for many models. We propose an Agentic SWMM workflow,
11 which embeds 'Skills' and model context protocols to automate model configuration,
12 execution, and extract and plot quantities of interest. To ensure that the entire Agentic
13 SWMM workflow is auditable and reproducible, each run will create an independent
14 manifest file that documents the SWMM version used, parameter mappings, input file
15 hashes, and quality gate (e.g., continuity diagnostics). We demonstrate the workflow on the
16 Tod Creek watershed (located on the Saanich Peninsula, British Columbia) and verified the
17 equivalence between EPA SWMM® command line execution and model context protocol
18 triggered SWMM execution, and between SWMM GUI workflow and the Agentic SWMM
19 workflow. Validation was demonstrated through identical peak. The overall automation
20 workflow (Skills and model context protocol setting), along with plotting services and

21 evaluation protocols are available as Open Source to support a reproducible Agentic SWMM
22 workflow triggered by natural language.

23 **Keywords:** Hydrological Modelling, Agentic AI, SWMM, MCP, Agent Skills

24 HIGHLIGHTS

- 25 • Proposed a new Agentic SWMM framework that integrates SWMM–GIS, SWMM-
26 runner, and SWMM-plot Skills (MCPs embedded for each Skill), thus enabling natural
27 language driven SWMM model setup, orchestration, and standardized result and
28 figure generation, which also mitigates large language model (LLM) hallucination
29 from operational level.
- 30 • Proposed reproducibility and reliability Agentic AI running check through a manifest
31 and an automated continuity/consistency quality verification component, which
32 provides Agentic SWMM action audits.
- 33 • A multi-layer verification protocol was established to verify the equivalence of
34 Agentic SWMM and SWMM GUI.

35

36 INTRODUCTION

37 OpenClaw is a typical Agentic AI and designed for complex goals (Acharya et al., 2025). It
38 was released by Peter Steinberger on January 29, 2026, in a GitHub repository (Steinberger,
39 2026; OpenClaw contributors, 2026). Unlike conventional chat-oriented systems (e.g.,
40 ChatGPT or Gemini) that primarily optimize for natural-language responses, OpenClaw is
41 designed to complete tasks by orchestrating external tools (e.g., web retrieval, scripts, APIs,

42 file operations) under explicit permissions (Steinberger, 2026). Currently, a major pain point
43 in hydrological modelling is that physics-based modelling software, such as PCSWMM® and
44 MIKE+®, require users to extensively interact with the user interface (UI) and constantly
45 adjust various parameters during the modelling process (Chawanda et al., 2020; Gan et al.,
46 2020). The visualization capabilities are excellent and built-in physics formulas make the
47 process and results interpretable, while the multiple scenarios simulation can lead the
48 modelling running time to be excessively long (Ahmadi et al., 2025). As well, users often
49 need a significant amount of time to understand and familiarize themselves with the
50 interface and to debug software errors. Conversely, with the development of machine
51 learning, hydrology is currently focusing on various alternative models such as long short-
52 term memory (LSTM) and physics-informed neural networks (PINNs), increasing their time
53 series recognition capabilities or adding physical constraints based on PDE residuals (Feng et
54 al., 2024; Qi et al., 2024; Sakar et al., 2026). This allows for the training of data-driven
55 models that can match physics-based models in most contexts, thereby increasing
56 operational efficiency. However, the defining weakness of these models is their poor
57 generalization ability (Panda et al., 2025). Their near-black-box training characteristics make
58 accurate representation of interpretability and physical consistency very difficult, often
59 leading to overfitting issues in data scarce situations (Baniya & Maity, 2026; De La Fuente et
60 al., 2024; Li et al., 2024).

61 With the development of Generative AI technology, some open-source software, such as
62 SWMM®, can expose communication methods to Generative AI through model context
63 protocol (MCP), enabling software invocation (Anthropic, 2024; Xu et al., 2025). Currently,
64 various AI technologies are flourishing. For example, Claude Code's Agent Skills can package

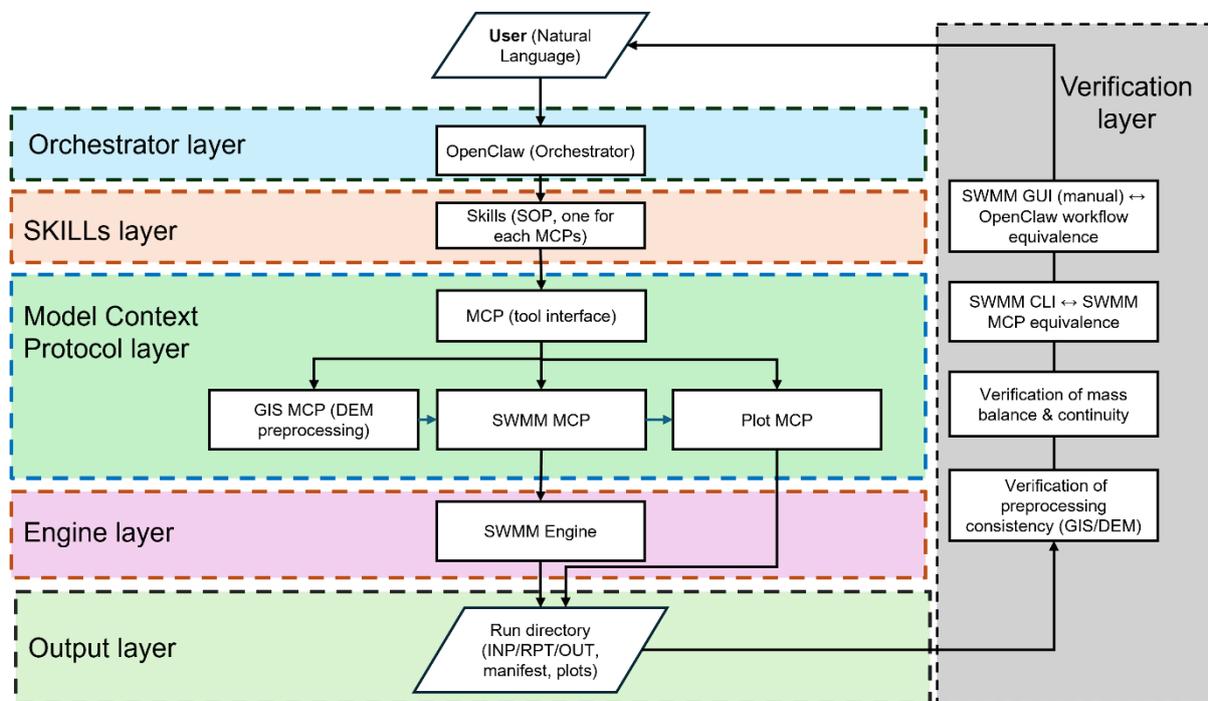
65 workflows together that an agent can recognize, thus achieving simple migration of
66 automated workflows (Anthropic, 2024). The idea of fully automated workflows originated
67 from N8N, which aims to create simple chatbots or replace humans by triggering specific
68 workflows at specific times (Pawar, 2025); however, its configuration process is often highly
69 complex.

70 To address the current pain points in hydrology, we propose a configuration framework
71 based on OpenClaw, SKILL, MCP, and SWMM. This enables the configuration of SWMM and
72 the definition of user-defined plots using natural language. In addition, we verified the
73 consistency of the entire system using the Tod Creek Watershed, Saanich, BC, Canada. The
74 results showed that the SWMM configured through natural language was consistent with
75 the results configured manually through the SWMM graphical user interface (GUI), which
76 verified that the core hydrological derivation process does not depend on the Agentic AI, but
77 on the SWMM engine that is invoked.

78 This paper proposes and demonstrates a practical architecture that integrates (i) OpenClaw
79 as an execution runtime; (ii) Skills as reusable workflow modules; and (iii) MCP as a standard
80 interface layer, to operate the SWMM engine and downstream plotting in a controlled and
81 auditable manner via nature language. The novelty of this work lies in an Agentic
82 orchestrated, end-to-end workflow that encodes the standard operating procedure (SOP) as
83 reusable Skills and invokes SWMM and plotting via MCP tools, enforcing provenance for
84 each run (recorded hash locked inputs, parameter mappings, and continuity-based quality
85 assurance (QA). Thus, the overall pipeline enables repeatable, auditable SWMM
86 experiments beyond GUI-centric operation.

87 **METHODS**

88 The methodology is depicted in Figure 1 to indicate how the Agentic AI (OpenClaw)
 89 orchestrated tasks, starting with input Geo-layers data for the case study watershed. As
 90 shown in Figure 1, we present a complete workflow that packages the initial multi-source
 91 data (DEM, landuse, soil, rainfall) required for modeling into an input package for GIS MCP.
 92 End users can interact with SWMM by issuing commands via natural language. In the middle
 93 layer, we packaged SWMM's commands as callable tools through the MCP. Since SWMM
 94 lacks the lookup table capability to transform raw data layers into model parameters, we
 95 generate a built-in transformation lookup table through dialogue in the GIS MCP as well.



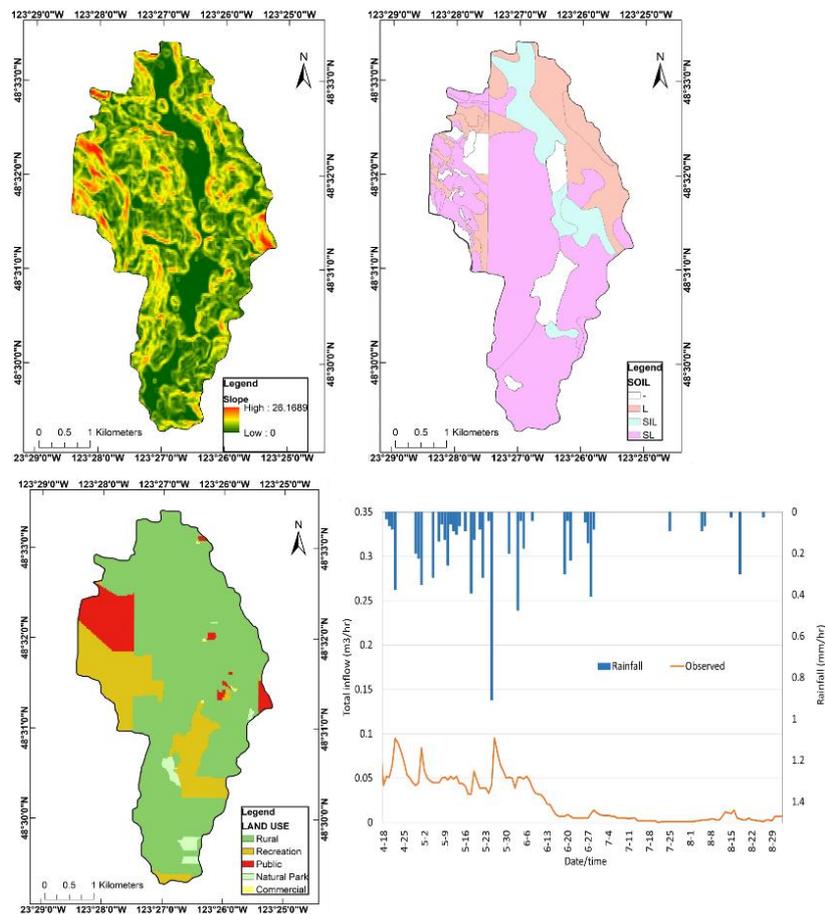
96

97 Figure 1: Methodology Flowchart for the whole proposed pipeline.

98 2.1 Study Site

99 The Todd Creek watershed, which spans about 17 km², is situated on Vancouver Island's
 100 Saanich Peninsula in British Columbia, Canada. The covered region is mostly rural with a few
 101 tiny residential villages scattered throughout the watershed's undulating terrain (see Figure

102 2a in the digital elevation model). The 1000–1200 mm of annual precipitation is mostly
103 concentrated between October and March of the following year. The soil types range from
104 poorly draining clays to well-drained soils that are rich in organic matter (see Figure 2b). The
105 resolution of the digital elevation model is 27 meters.



106
107 Figure 2: Slope, landuse and soil as well as timeseries rainfall in 1984.

108 The Tod Creek database contained a) digital elevation model (DEM); b) soil type
109 polygons with texture attributes; c) land use polygons (zoning-style categories; used as a
110 land-use proxy); and d) 1984 rainfall records (daily totals in units of mm). For demonstration
111 purposes, a lumped model representation of Saanich was used to validate the end-to-end
112 workflow. The outlet location was selected algorithmically on the DEM boundary (minimum
113 elevation candidate) to obtain a consistent reference outfall point for the stormwater
114 simulation.

115 **2.2 Methodology of Agentic SWMM System**

116 Our research compiles the SWMM command-line program (v5.2.4) from the EPA SWMM
117 source code on macOS and executes simulations using the standard command “swmm5
118 <inp> <rpt> <out>”. Our SWMM Skill workflow automatically creates a separate run
119 directory for each run, uniformly saving the input file (INP), report file (RPT), and binary
120 output (OUT), and additionally generating a manifest file as shown in the Supplementary file
121 Section S1. The biggest difference from the traditional UI approach is that while users can
122 see the modifications made in a UI, this manifest, based on OpenClaw (Version 2026.2.17), is
123 mandatory and written into the Skill. This log records the software version, key user
124 configurations and parameter mappings, rainfall event information, and a summary of key
125 results (such as continuity error, peak flow, etc.), thus, achieving transparency, reverse
126 tracing, and auditability for each experiment. In addition, the same INP file is run
127 synchronously in the SWMM GUI, and the consistency of key indicators and resulting
128 statistics is used as the basis for equivalence verification to ensure that the automated
129 command line process and the GUI run in terms of numerical behavior are consistent. After
130 establishing this equivalence, we invoke the SWMM MCP via natural-language instructions
131 that specify the original locations of the required datasets to trigger automated execution
132 and subsequently call the plot Skill to generate the runoff comparison results shown in
133 Section 3 of this paper.

134 *2.2.1 OpenClaw*

135 OpenClaw is used as an orchestration environment that executes commands, reads and
136 writes artifacts, and invokes external programs. Within this work, OpenClaw does not
137 replace SWMM; it standardizes the execution and bookkeeping around it. It is currently

138 compatible with most large language models through the application programming interface
139 (API) for analysis complex tasks. In our case study, we are using GPT 5.2 as the primary
140 model of OpenClaw. In practice, OpenClaw workflow is triggered by a natural language
141 prompt. This will invoke the available Skills and orchestrates the MCP service to run the
142 SWMM engine automatically and generates the model outputs. The natural language
143 prompt input format we recommend is:

144 *“Run the full Agentic SWMM workflow using your GIS, SWMM runner, and plotting skills. My*
145 *input data folder is located at <PROJECT_ROOT>:*

- 146 *1. Use swmm-gis to select an outlet (document the method) and export the outlet*
147 *(GeoJSON + preview).*
- 148 *2. Use swmm-runner to build and run a baseline SWMM simulation from the provided*
149 *inputs and assumptions and save a self-contained run folder with all artifacts and a*
150 *manifest.json.*
- 151 *3. Use swmm-plot to generate figures for the QoIs on dd-MM-YYYY.*
- 152 *4. Return: the output folder path, the manifest.json path, and a short list of assumptions*
153 *(if you have).”*

154 Note that, swmm-gis, swmm-runner, and swmm-plot in the prompts are Skill modules (tool
155 bundles). The Skills we used have been standardized as Standard Operating Procedures (SOP);
156 therefore, the workflow does not require high quality user prompts. The dependence on the
157 overall prompting process is significantly reduced because the capability boundaries,
158 parameter structure, and output formats are all “well designed” by the Skill/MCP interfaces.
159 As a result, the Agentic AI does not need to guess the user’s meaning, which maximizes
160 portability and reproducibility as well as minimizes the LLM hallucination.

161 2.2.2 MCP

162 MCP provides a consistent protocol for exposing local capabilities as callable tools. In the
 163 proposed design, three MCP servers are used: a) swmm-gis-mcp for DEM data
 164 preprocessing; b) swmm-runner-mcp: generates inputs, runs swmm5, extracts quantities of
 165 interest (QoIs) and continuity metrics; and c) swmm-plot-mcp: reads INP/OUT artifacts and
 166 produces figures that conform to a fixed user’s specification. Moreover, OpenClaw can
 167 automatically configure MCP services after configuring the API of any Large Language model.
 168 Therefore, users can use OpenClaw to configure the required MCP services for different
 169 analysis scenarios, such as pollutant diffusion or water quality modules. In this study, we
 170 only encapsulated the peak flows we were interested in to demonstrate the overall effect of
 171 Agentic SWMM. Table 1 shows an interface catalogue for a SWMM-focused MCP toolchain.
 172 Table 1 lists six MCP servers, which are designed for the entire Agentic AI workflow.

173 Table 1. MCP tool interface specification for the Agentic SWMM workflow

MCP Server	Tool name	Required inputs	Outputs	Units / assumptions	Failure modes
swmm-gis-mcp	gis_find_point	dem (path); outGeojson (path); outPng (path)	JSON: x,y,row,col,crs,score; GeoJSON; PNG preview	Coordinates in DEM CRS; score=min elev or max accum index	DEM unreadable/NoData boundary; pysheds missing (maxAccum); output path not writable
swmm-runner-mcp	swmm_run	inp (path); runDir (path)	JSON manifest; writes rpt/out/log/manifest	Flow units follow INP FLOW_UNITS (CMS → m ³ /s)	swmm5 missing; INP errors; runDir not writable; nonzero return code
swmm-runner-mcp	swmm_peak	rpt (path)	JSON: node, peak, timeHHMM, source	peak in SWMM flow units; time in report timebase	RPT parse mismatch; node not found and return null; encoding issues
swmm-runner-mcp	swmm_continuity	rpt (path)	JSON: runoff table; routing table; continuityErrorPct	SWMM report units; continuity in percent	Continuity blocks missing; parser mismatch across SWMM versions

swmm-runner-mcp	swmm_compare	rpt (path); rpt2 (path)	JSON: aErr, bErr (headline continuity)	percent (%)	Same as continuity; different INPs/steps and return expected differences
swmm-plot-mcp	plot_rain_runoff_si	inp (path); out (path); outPng (path)	writes PNG; JSON: ok,outPng	Rain as mm/ Δt (default 5 min); flow m ³ /s if CMS	OUT missing/corrupt; TS_RAIN missing; swmmtoolbox missing; font fallback

174

175 **2.2.3 Skills**

176 Beyond MCP, Skills package scripts, configuration, and conventions for specific tasks or
 177 workflow (e.g., generating INP files Via MCP, running SWMM, extracting outputs, and
 178 producing figures). This packaging ensures the workflow can be repeated and shared with
 179 minimal manual setup. The shortcoming to MCP is that it only addresses the interface issue
 180 of "how the tools are called" (encapsulating SWMM execution, result extraction, and
 181 plotting capabilities into callable tools), thus failing to accurately implement the Standard
 182 Operating Procedure (SOP) process. We adopt Skill to render commands of "what to call, in
 183 what order, using what specifications; how to implement quality gates; and how to produce
 184 reproducible workpieces" into a reusable methodology. This is shown in Table 2.

185 Table 2. OpenClaw SWMM Capability Skill CatLog

Skill name	Purpose	Key scripts	MCP server	Main tools	Outputs
swmm-gis	GIS/DEM preprocessing (pour point/outlet selection) for reproducible SWMM workflows	scripts/find_pour_point.py	scripts/mcp/server.js (swmm-gis-mcp)	gis_find_pour_point	GeoJSON pour point + DEM preview PNG
swmm-runner	Run swmm5 reproducibly and extract peak/continuity + write manifest.json	scripts/swmm_runner.py	scripts/mcp/server.js (swmm-runner-mcp)	swmm_run, swmm_peak, swmm_continuity, swmm_compare	run directory: rpt/out/stdout/stderr/manifest.json; metrics JSON

swmm-plot	Publication-grade plotting	scripts/plot_rain_runoff_si.py	scripts/mcp/server.js (swmm-plot-mcp)	plot_rain_runoff_si	figure PNG/PDF
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186

187 In the Agentic SWMM scenario, Skill orchestrates the corresponding MCP to autogenerate
 188 the INPs file; runs the swmm engine, extracts indicators such as peaks and continuity;
 189 performs conservation/continuity checks and GUI-CLI equivalence comparisons; includes
 190 built-in plotting specifications (units, axes, fonts, and window clipping, etc.) and automatic
 191 repair rules for common pitfalls; and enforces standardized run directories and manifests
 192 (version, hash, parameter mapping, key results, plots, etc.). Therefore, simply relying on
 193 MCP can easily degenerate into a set of "bare tools", which can be called but are difficult to
 194 manage and reproduce stably over a long period of time. This also makes it difficult to
 195 quickly port the entire workflow. Skill, however, organizes interface capabilities into
 196 reproducible experimental packages that are auditable, shareable, and maintainable; thus,
 197 enabling workflows to run repeatedly and be reliably reused with minimal manual setup. As
 198 well, in the data preprocessing part, because DEM-based preprocessing is often required for
 199 hydrologic model setup (e.g., identifying a pour point and delineating subcatchments) and
 200 EPA SWMM does not provide these GIS functions, we implemented a dedicated swmm-gis
 201 Skill to automate this step. We use two methods from the DEM to find candidate outlets:
 202 one is the lowest point on the boundary, and the other is the point with the largest flow
 203 accumulation. This skill saves the pour point with coordinate system as a reproducible
 204 geographic file, which can be directly used for SWMM model configuration.

205 **2.3 Verification, Reproducibility and Repeatability**

206 *2.3.1 Verification of DEM-based Preprocessing (Automatic Pour Point Detection)*

207 Because EPA SWMM does not provide necessary GIS pre-processing utilities, we
208 implemented an automated pour-point detection routine as an independent SWMM–GIS
209 MCP and Skill (as shown in Table 1 and Table 2) to reproduce key preprocessing steps in a
210 traceable, script-driven workflow, and to verify consistency against a conventional GUI-based
211 approach (PCSWMM). Its pseudocode implementation logic has been included in Section S3
212 of the Supporting file.

213 *2.3.2 Repeatability: equivalence validation between CLI and MCP*

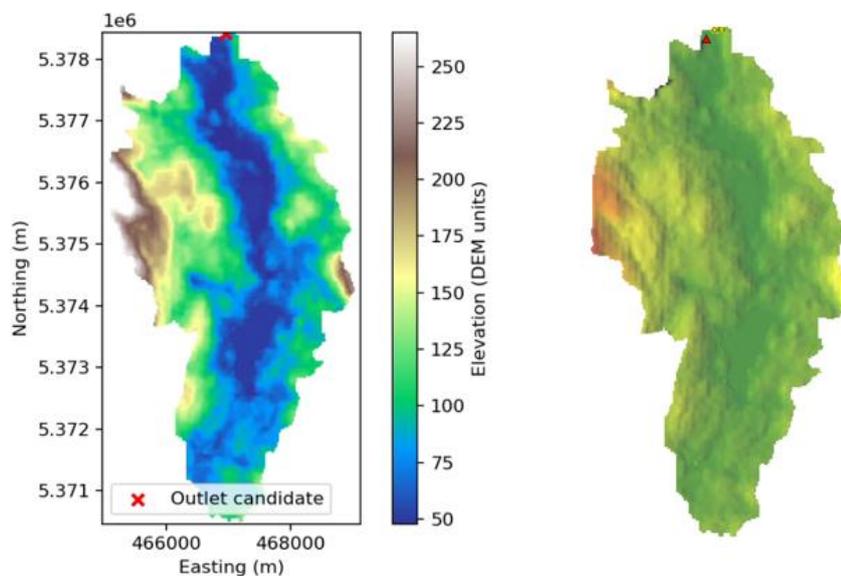
214 In this section, we tested whether the results produced by the packaged MCP service are
215 numerically consistent with a direct command-line interface (CLI) SWMM execution under
216 identical model inputs. Our baseline model is a lumped model with a timestep of 5 minutes,
217 representing the Chicago storm (which is the same INP structure and parameters for
218 hydrology/hydraulics). Two types of tests were performed. In Test 1, a total of 30 runs is
219 conducted where the Chicago storm-shape parameter r (time to peak $r \in [0.30, 0.50]$ f) is
220 increased from 0.30 by an increment of $(0.50-0.30)/30$ in each run while holding all other
221 model settings constant. Test 2 is similarly 30 runs where the percentage of imperviousness
222 (I) is varied by a factor ranging from $[0.9, 1.1]$ while holding all other model settings
223 constant. Note that there are 30 samples in each test, but we run the test in two different
224 ways (CLI and MCP), resulting in a total of 120 runs. We then compare the degree of
225 agreement of the computed peak flow at the outlet for each run using R^2 and the Nash and
226 Sutcliffe Efficiency (NSE). Theoretically, if CLI and MCP are equivalent, then R^2 and NSE
227 should both be exactly 1.

228 *2.3.3 Reproducibility: SWMM GUI vs Agentic SWMM*

229 To verify cross-system consistency, we manually recreated the baseline model in the SWMM
230 GUI and note that the baseline model is generated by the Agentic SWMM from the user
231 prompt. After the manual configuration, we ran the SWMM GUI and compared the results
232 with the Agentic AI generated baseline model to verify whether its ability to automate
233 configuration using natural language was consistent with manual configuration.

234 RESULTS

235 3.1 Verification of data preprocessing tools

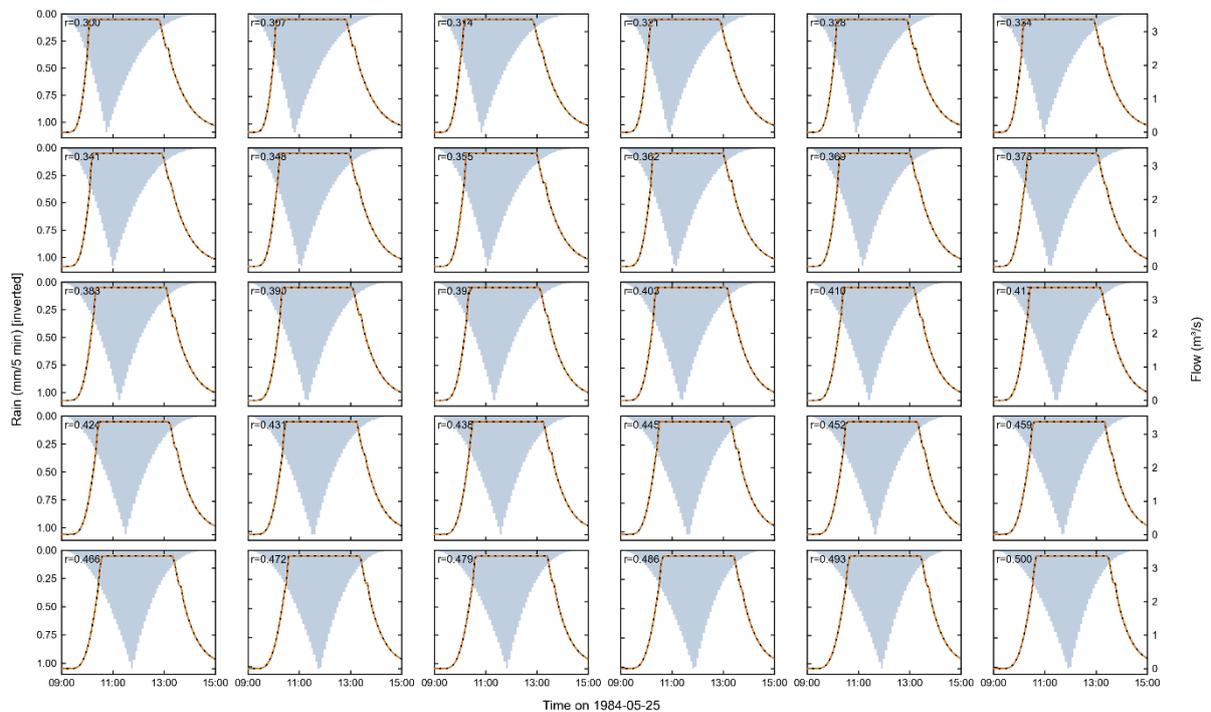


236
237 Figure 3: The comparison of boundary minimum-elevation outlet detection. Left panel
238 shows the pour-point and watershed boundary generated via and the right panel is the
239 corresponding watershed and pour-point generated with the PCSWMM GUI.

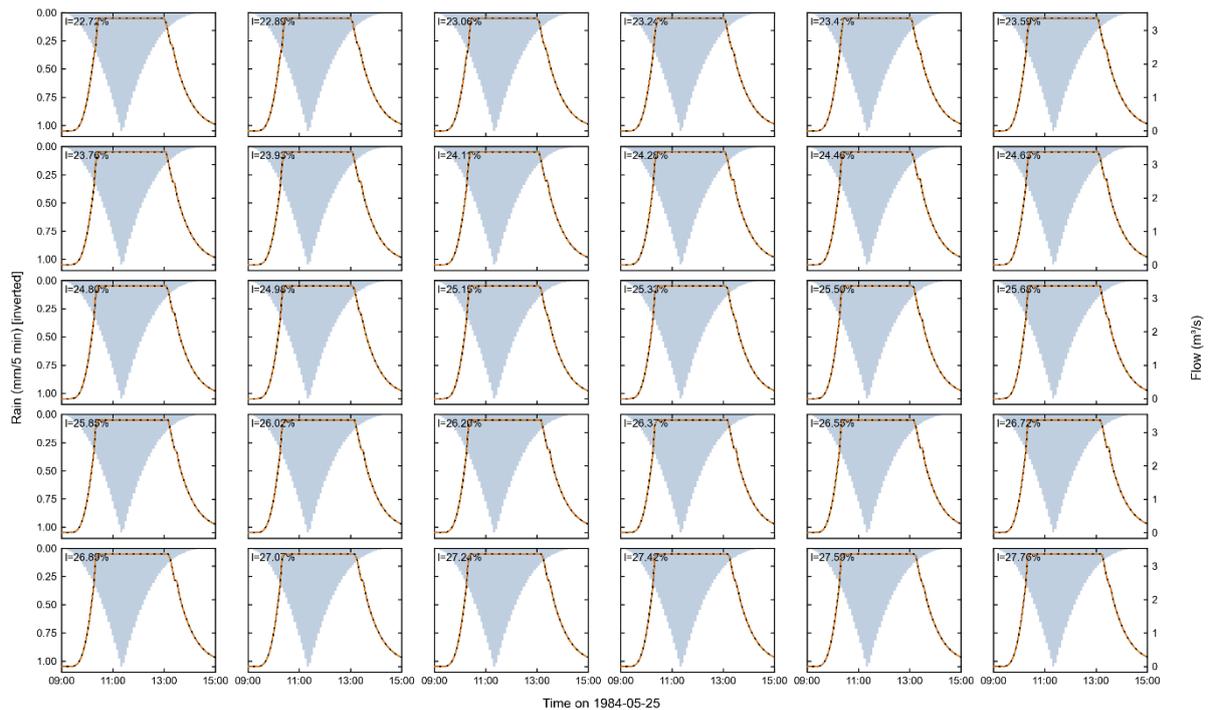
240 Because SWMM itself does not integrate DEM-related GIS preprocessing functions, we
241 implemented "automatic pour point identification" as an independent script logic SWMM-
242 GIS Skill to extract key spatial features before modeling. Specifically, we used rasterio/numpy
243 generated by OpenClaw to search for the lowest elevation point on the study area boundary
244 as a candidate pour point and automatically output it as a point. In Figure 3, the left panel

245 shows the DEM visualization generated by the OpenClaw SWMM–GIS Skill. The
 246 automatically identified candidate pour point is shown as a red mark. The right panel
 247 visualization of the pour point location in the same area was generated in PCSWMM using
 248 manually identified pour points from (Zhang and Valeo, 2022). The results show that the two
 249 methods exhibit high consistency in spatial location and topographical consistency,
 250 indicating that Skill can stably produce pour point results similar to those of the traditional
 251 GUI workflow.

252 **3.2 Repeatability: SWMM CLI and SWMM MCP**



253
 254 (a)

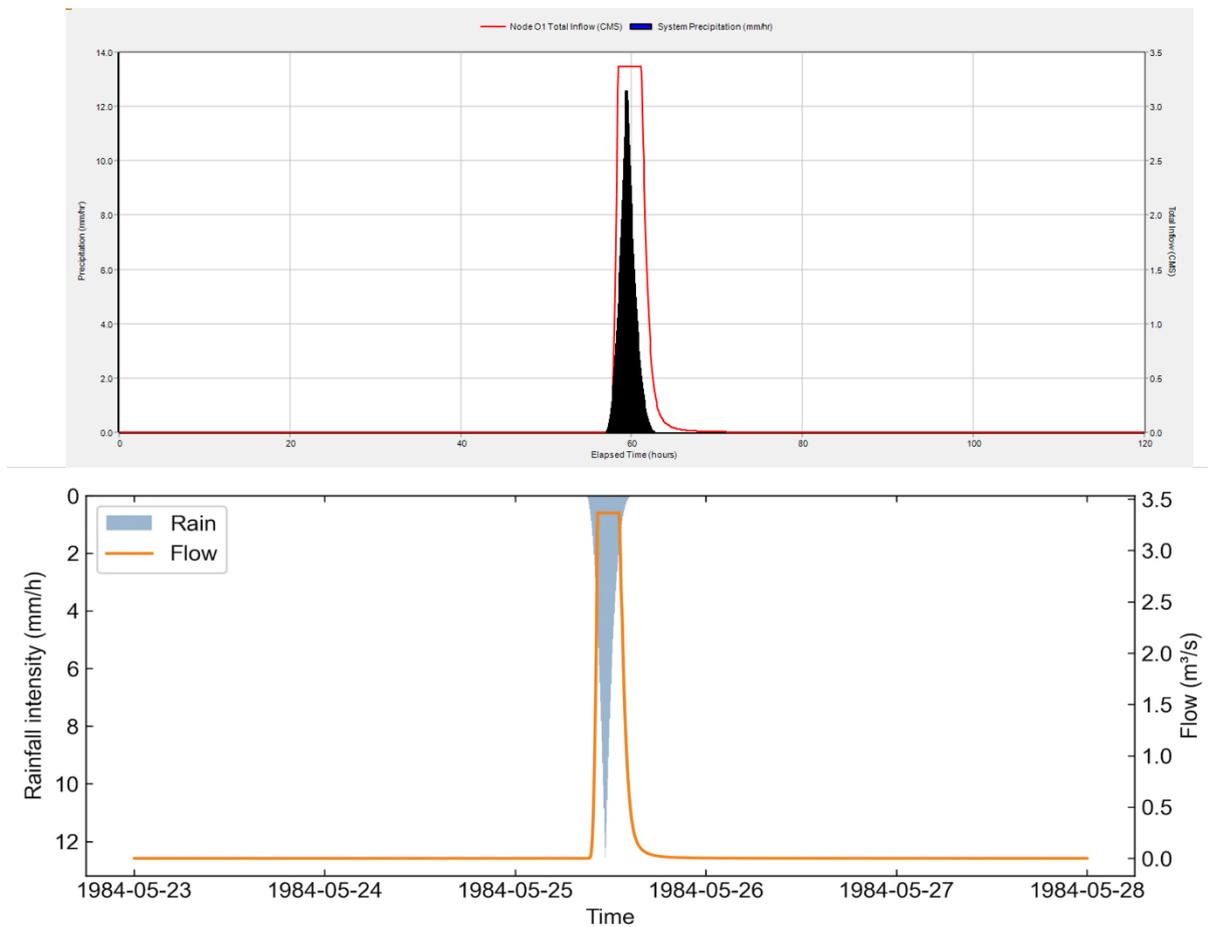


255
256 (b)

257 Figure 4: Computed hydrographs at the outlet for all 30 runs with hyetograph shown in blue
258 on the left axis (inverted) for (a) Test 1; and (b) Test 2. CLI results are shown as black solid
259 lines and MCP results are orange dashed lines overlaid on top.

260 Figure 4 a and b, and Figure S2 in the Supplementary file show that the evaluation metrics,
261 R2 and NSE are all identically 1.0, demonstrating consistent predictions across all 30
262 simulations. Therefore, we can reasonably conclude that the model called by the MCP
263 server, and the model used via the command line through the CLI port are consistent, and
264 that the core hydrological computation based on Openclaw is entirely based on the SWMM
265 engine rather than the large language model itself. Furthermore, the secure hash algorithm
266 256-bit (SHA256) hashes of the manifest.json files for both tests are all identical; the return
267 code is all 0, and $\max|\Delta Q_{\text{peak}}|=0.0$, proving that the CLI and MCP have completely identical
268 INPs (same hash). Further indications of the robustness of the MCP service in shown in Table
269 S2 and S4 in the Supplementary file.

270 3.3 Reproducibility: Agentic SWMM and SWMM GUI



271

272 Figure 5: Equivalence between OpenClaw workflow (bottom panel) results and SWMM GUI
273 generated results (top panel).

274 Using identical INP files we conducted equivalence verification on two execution paths.

275 Figure 5 top panel shows the GUI interface display obtained through manual parameter
276 configuration and execution using the traditional SWMM GUI. Figure 5's bottom panel shows
277 the workflow from Figure 1, entirely driven by OpenClaw through natural language dialogue,
278 utilizing the SWMM Skill and MCP toolchain. Agentic AI automatically generates/verifies
279 inputs from the original dataset, calls swmm5 to execute simulations, and extracts key
280 outputs. As the comparison in Figure 5 shows, the peak flow results obtained from both

281 paths are completely identical, indicating that the OpenClaw driven SWMM modeling
282 approach is practically consistent with GUI execution. This demonstrates that, given the
283 current level of AI development, OpenClaw orchestrated end-to-end workflows can produce
284 event response results are identical to manual GUI operations, greatly expanding the
285 model's usability.

286 **DISCUSSION AND CONCLUSIONS**

287 The MCP and Skills described in this paper suggest that Agentic AI offers a highly effective
288 real-time prediction capability for hydrological modeling in place of traditional GUI modes of
289 parameter modification. OpenClaw is an Agentic AI runtime that orchestrates tool-based
290 workflows (via Skills and MCP) to execute, verify, and reproduce domain tasks beyond
291 conversational responses. This paper details how the OpenClaw architecture, leveraging
292 mainstream MCP services and Skills, can completely replicate the previously manually driven
293 GUI operation process. This application-level implementation greatly facilitates subsequent
294 researchers or users unfamiliar with model deployment and operation to configure their
295 own hydrological models in a very short time. This enables hydrological analysis and
296 modelling, and to the authors' knowledge, this is the first time Agentic AI (OpenClaw) has
297 been applied to peak runoff prediction. In this study, our MCP servers and Skills are primarily
298 prototyped and iterated rapidly through a dialogue-driven workflow, rather than being
299 implemented from scratch with extensive engineering code, enabling a high degree of
300 flexibility and adaptability across different tasks. This offers a high degree of freedom and
301 flexibility, distinguishing it from traditional large language models like GPT in terms of task-
302 specific capabilities. It excels at "act" rather than "answer." Furthermore, OpenClaw is
303 completely open source, allowing it to use local Ollama® models (open-weights LLMs) for

304 inference. This largely ensures data privacy, which is why we chose it as one of our core
305 frameworks.

306 The interpretability of our results does not arise from Agentic AI itself or from the underlying
307 LLM. Rather, interpretability is grounded in the physical model and its explicit, inspectable
308 input/output files. In our framework, SWMM constitutes the computational core: all
309 hydrologic calculations are executed by SWMM, while the Agentic layer is responsible for
310 orchestration, tracking, and standardized output generation. To mitigate LLM hallucinations,
311 we first established the full end-to-end workflow and then performed manual checks to
312 confirm consistency between automated and reference runs. Moreover, after exposing the
313 MCP interfaces, we packaged the workflow as a standardized Skill (SOP) with mandatory
314 artifacts and quality gates (e.g., continuity diagnostics and consistent QoI definitions),
315 improving portability and substantially reducing the risk of hallucination errors. In practice,
316 while poor prompting can lead to variability in how non-expert users specify tasks, the Skill
317 constrains execution to validated procedures and specifications, thereby shielding the
318 workflow from failures caused by ambiguous or low-quality prompts.

319 The MCP services or Skills in this paper can be recreated and adjusted according to the
320 needs of end users (such as adjusting quantity of interests like water quality or any function
321 available in SWMM, for example). Future researchers can consider building QGIS MCP as the
322 QGIS is an open-source software, which naturally makes function calls easier compared to
323 commercial software like ArcGIS.

324 **ABBREVIATIONS**

SWMM®	Storm Water Management Model
MCP	Model Context Protocol
CLI	command-line interface
GUI	graphical user interface
QoI	quantity(ies) of interest
DEM	digital elevation model
GIS	geographic information system
INP / RPT / OUT	SWMM input / report / binary output files
SOP	standard operating procedure
API	application programming interface
LLM	large language model
NSE	Nash – Sutcliffe efficiency
SHA-256	Secure Hash Algorithm 256-bit

325

326 **ACKNOWLEDGEMENTS**

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 328 Ontario, Canada for providing the PCSWMM software used in this work.

329 **DATA AVAILABILITY STATEMENT**

330 The source codes are available for downloading at the link:
 331 <https://github.com/Zhonghao1995/agent-swmm-workflow>

332 **CONFLICT OF INTEREST**

333 The authors declare there exist no financial interests/personal relationships which may be
 334 considered as potential competing interests.

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Section S1 Manifest Schema

Table S1. Run Manifest Schema for Reproducible SWMM Execution

Field	Type	Required	Description
manifest_version	string	YES	Manifest schema version.
created_at	string (ISO-8601)	YES	Timestamp when the run record was created.
swmm5.cmd	string	YES	Command used to invoke SWMM engine (e.g., swmm5).
swmm5.version	string/null	RECOMMEND	SWMM engine version if detectable (e.g., 5.2.4).
inp	string (path)	YES	Path to the SWMM input file (.inp).
inp_sha256	string	YES	SHA256 hash of the input INP to guarantee input equivalence (GUI vs CLI).
files.rpt	string (path)	YES	Path to SWMM report file (.rpt).
files.out	string (path)	YES	Path to SWMM binary output (.out).
files.stdout	string (path)	YES	Captured stdout from swmm5 execution.
files.stderr	string (path)	YES	Captured stderr from swmm5 execution.
metrics.peak.node	string	YES	Node/outfall identifier used for peak extraction (e.g., O1).
metrics.peak.peak	number/null	YES	Peak flow value parsed from SWMM report; unit follows INP FLOW_UNITS (paper uses m ³ /s).
metrics.peak.time_hhmm	string/null	YES	Time of peak in HH:MM if available in report summary.
metrics.peak.source	string/null	YES	Which SWMM report section provided the peak (e.g., Node Inflow Summary).
metrics.continuity	object	YES	Parsed continuity blocks including continuity_error_percent and underlying tables.
return_code	integer	YES	Return code from swmm5 (0 indicates success).

This table defines the required and recommended fields of the run-level manifest used to record provenance and key metrics for each SWMM simulation by using OpenClaw. The manifest captures execution metadata (timestamp, engine command/version), input identity (INP path and SHA256 hash), generated artifacts (RPT/OUT and logs), extracted peak-flow metrics, continuity check results, and return status, enabling auditable reproduction and GUI–CLI equivalence verification. As well, the Json file are provided as following:

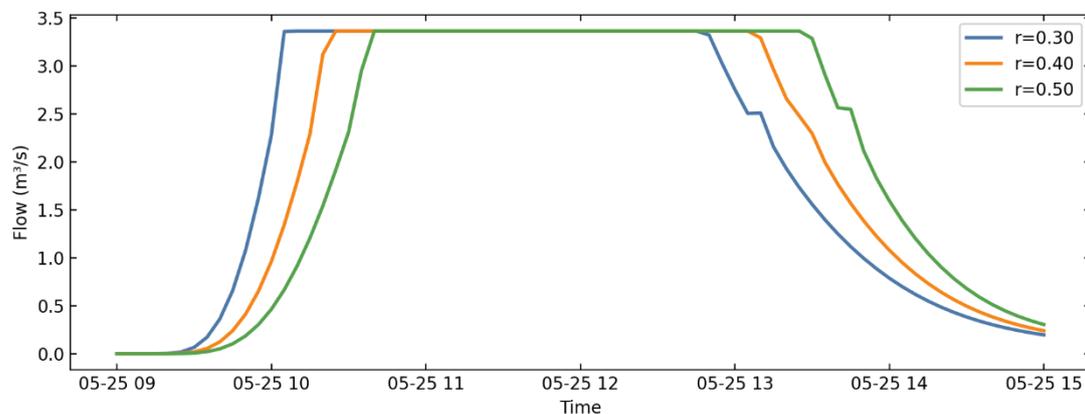
```
{
  "manifest_version": "1.0",
  "created_at": "2026-02-25T09:40:12",
  "swmm5": {
    "cmd": "swmm5",
    "version": "5.2.4"
  },
  "inp": "/path/to/model_chicago5min.inp",
  "inp_sha256": "...",
```

```
"files": {  
  
  "rpt": "/path/to/model.rpt",  
  
  "out": "/path/to/model.out",  
  
  "stdout": "/path/to/stdout.txt",  
  
  "stderr": "/path/to/stderr.txt"  
  
},  
  
"metrics": {  
  
  "peak": {  
  
    "node": "O1",  
  
    "peak_m3s": 3.366,  
  
    "time_hhmm": "10:31",  
  
    "source": "Node Inflow Summary"  
  
  },  
  
  "continuity_error_percent": {  
  
    "runoff_quantity": 0.003,  
  
    "flow_routing": 0.003  
  
  }  
  
},  
  
"return_code": 0  
  
}
```

Section S2 Sensitivity analysis to Chicago peak-time ratio (r)

To demonstrate how the agentic workflow supports controlled experimentation, we conducted a supplementary sensitivity test in which only the Chicago hyetograph peak-time ratio r was changed while holding constant: (i) total rainfall depth (21.8 mm), (ii) lookup-table parameterization, (iii) outlet selection method, (iv) SWMM version and time stepping, and (v) extraction procedures.

Three cases were evaluated: $r = 0.30$, 0.40 (baseline), and 0.50. Across these runs, the peak flow magnitude at the outfall remained unchanged in this simplified v0 configuration (3.366 m³/s), while the time of peak shifted systematically (10:11, 10:28, and 10:45, respectively). SWMM-reported continuity errors remained small ($\leq 0.003\%$). This experiment illustrates that the proposed pipeline can generate, run, verify, and summarize controlled scenario variants with minimal manual effort and with complete provenance.



Section S3 Automatic Pour Point Detection Algorithm

Algorithm: FindPourPoint_BoundaryMinElev_ImageFrame(Z , M , T)

Input : $Z[H,W]$, $M[H,W]$ (True=valid), affine transform T

