

## AI-Optimized Pyrolysis: A Machine Learning Framework for Predictive Waste-to-Energy Conversion

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### 1. INTRODUCTION & AIM

#### THE DUAL CRISIS

- ▶ Global MSW generation projected to reach 3.4 billion tons/year by 2050
- ▶ Over 60% of waste ends up in landfills, generating methane and contaminating groundwater
- ▶ Fossil fuels represent ~80% of global energy; urgent need for sustainable alternatives
- ▶ Pyrolysis converts waste into bio-oil, syngas & biochar in a zero-oxygen environment

#### RESEARCH GAPS ADDRESSED

- ▶ Existing studies focus on single feedstocks with limited generalizability
- ▶ No standardized predictive yield-optimization tools exist in the literature
- ▶ **This study addresses all three gaps with one unified physics-informed framework**

### 2. RESULTS & DISCUSSION

0.78

SYNGAS R<sup>2</sup>

0.76

BIO-OIL R<sup>2</sup>

0.59

BIOCHAR R<sup>2</sup>

- ✓ XGBoost outperforms RF, SVR, and MLP for pyrolysis data
- ✓ MAE of 2.8–4.3 percentage points across all three outputs
- ✓ Physics constraints enforce mass balance: bio-oil + syngas + biochar ≈ 100%
- ✓ Residual plots confirm unbiased predictions across all phases (Fig. 4)

### 3. METHODOLOGY

#### DATASET

- ▶ 619 validated experimental scenarios
- ▶ 75 biomass feedstock types
- ▶ 12 input features (proximate + ultimate composition, process params)

#### MODEL BENCHMARKING

- ▶ XGBoost vs. RF, SVR, MLP
- ▶ XGBoost selected for superior non-linear performance
- ▶ Multi-output normalization to stabilize gradient behavior

#### VALIDATION

- ▶ 80/20 stratified train-test split
- ▶ Stratified 5-fold cross-validation
- ▶ Stratified by temperature and feedstock class

#### PHYSICS CONSTRAINTS

- ▶ Mass balance enforced post-processing
- ▶ Monotonicity: char yield decreases as T increases
- ▶ Thermochemical consistency maintained throughout

### 4. KEY FINDINGS & FIGURES

Fig. 1 — Model Performance: Predicted vs. Actual Yields

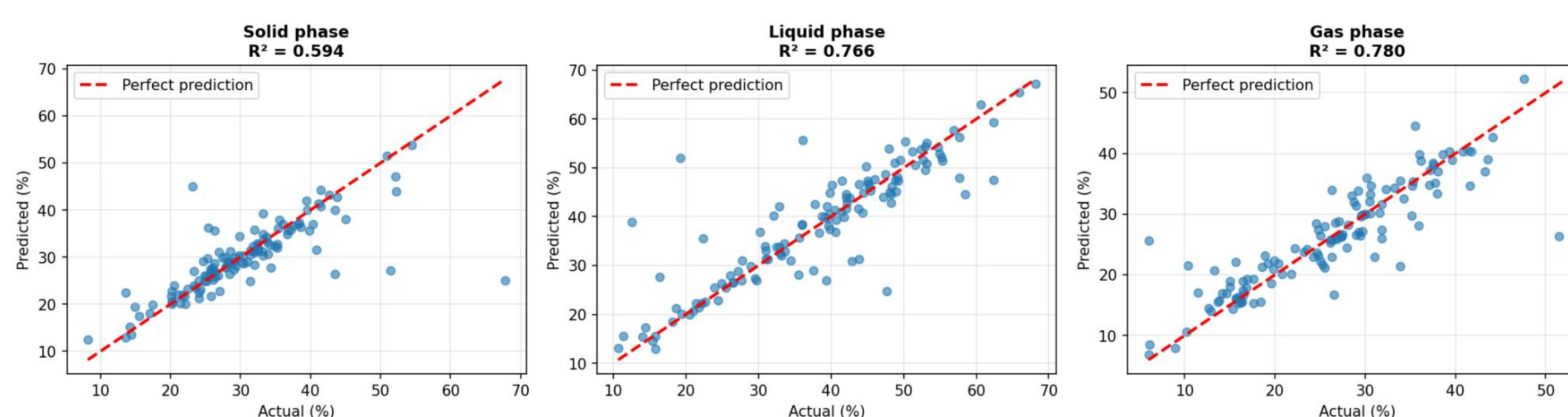


Fig. 2 — Temperature Effect on Product Distribution

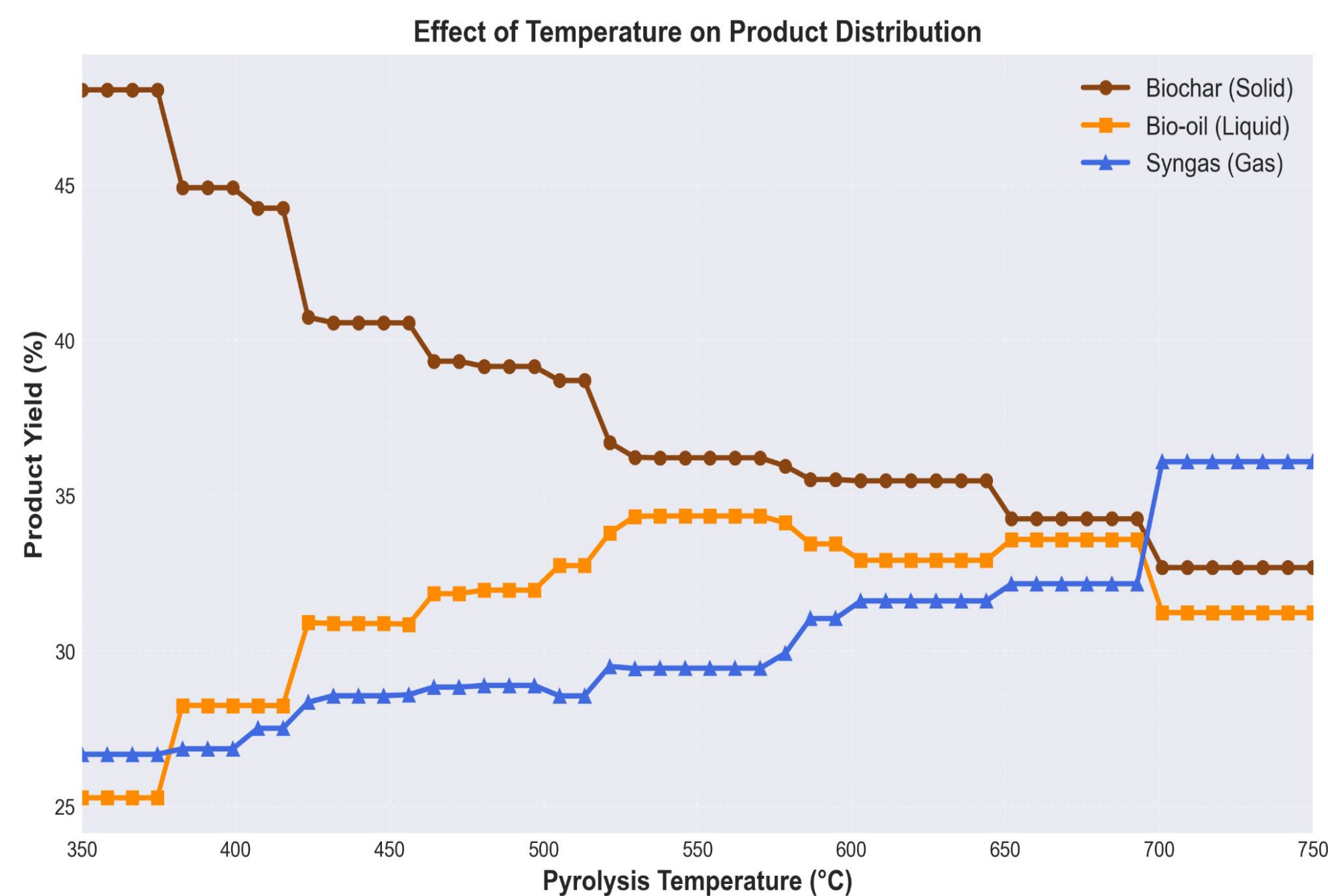


Fig. 3 — Feature Importance Rankings (All Phases)

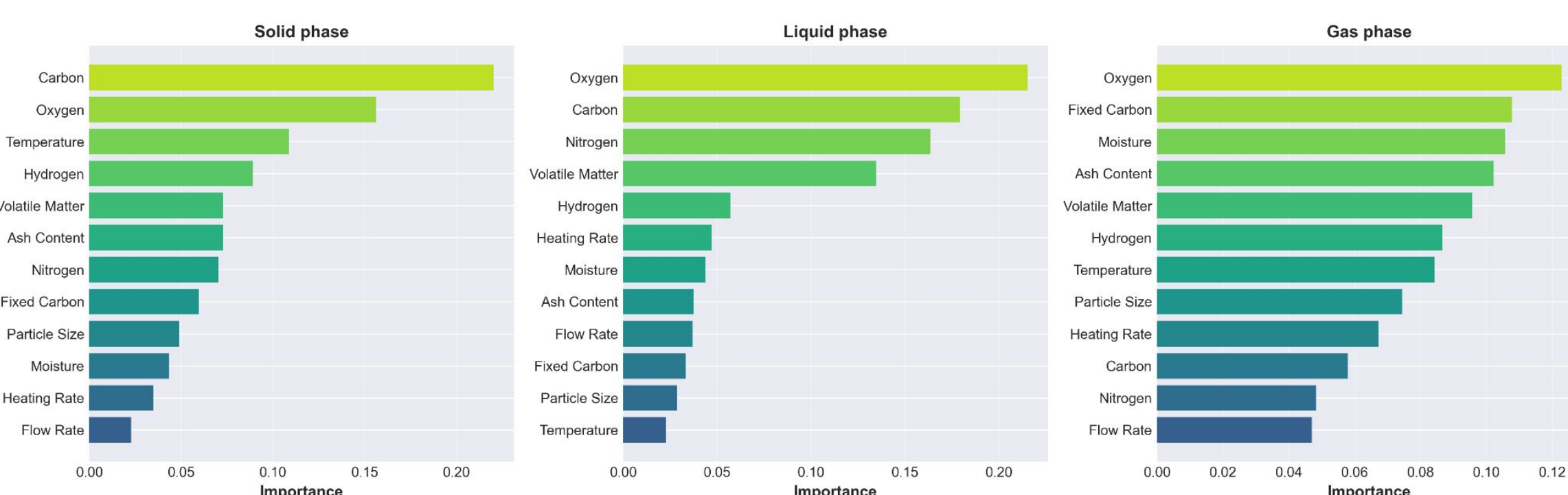


Fig. 4 — Residual Plots (Unbiased Predictions)

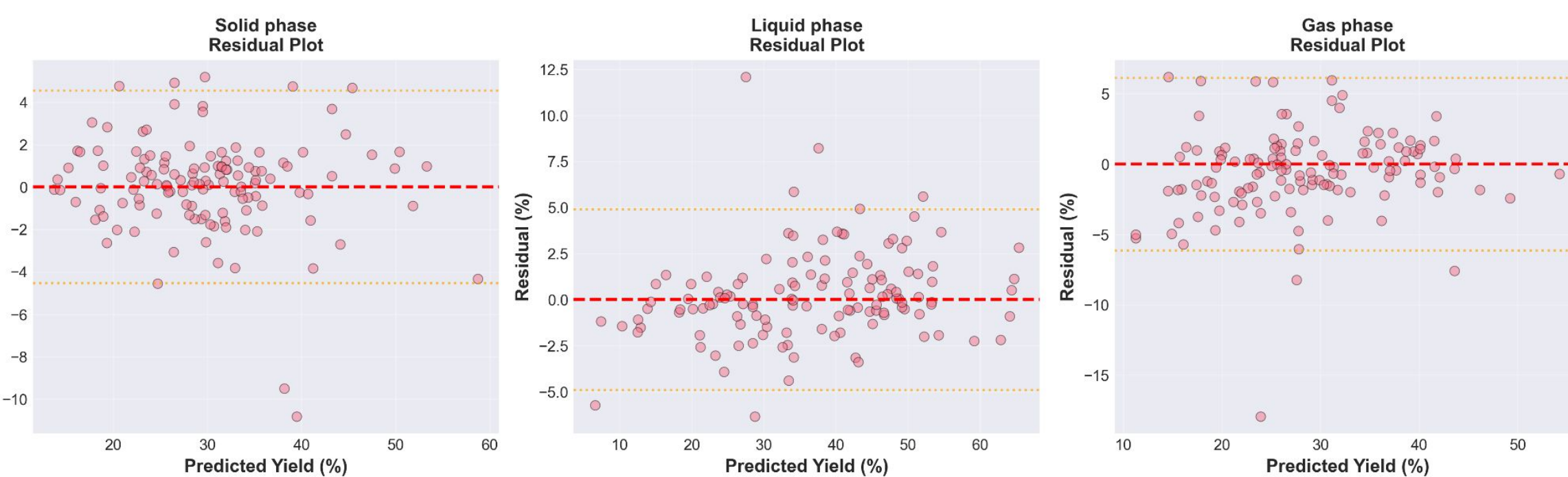
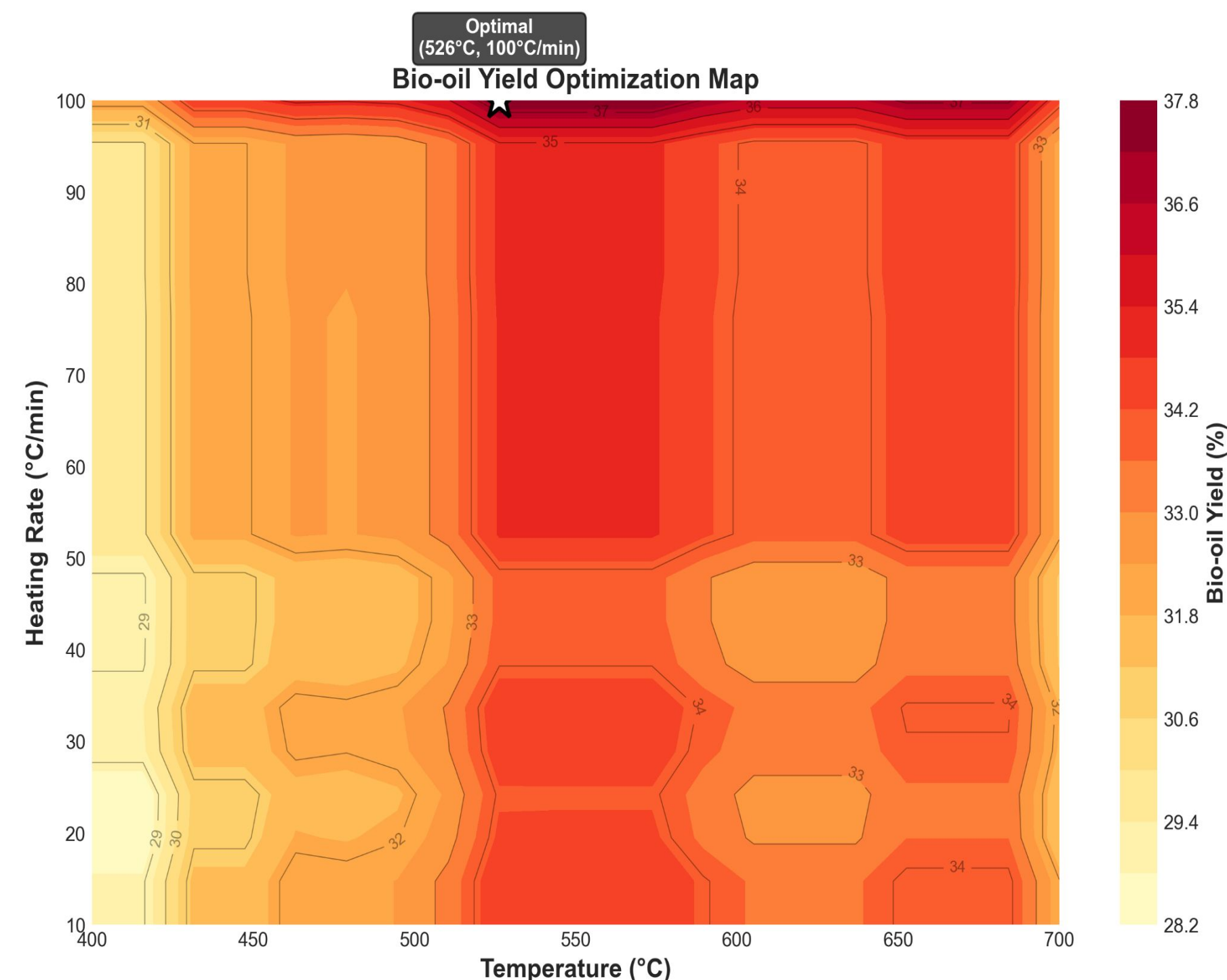


Fig. 5 — Bio-oil Yield Optimization Map | Optimal: 526°C, 100°C/min → Peak Yield ~37.8%



### 5. CONCLUSIONS

- ✓ First physics-informed ML framework combining multi-feedstock benchmarking with thermodynamic constraints
- ✓ XGBoost outperforms RF, SVR, MLP for high-dimensional chemical pyrolysis data
- ✓ **Optimal bio-oil at 526°C and 100°C/min — peak yield ~37.8%**
- ✓ 50–70% fewer GHG emissions vs. incineration; biochar sequesters C for 500+ years
- ✓ Plant payback 3–6 years; capital ~\$5–10M for a mid-size facility

### 6. FUTURE WORK

- Expand dataset to co-pyrolysis (plastic-biomass blends) and catalytic cases
- Integrate real-time sensor data for closed-loop reactor control
- Apply reinforcement learning for fully autonomous process optimization
- Develop hybrid physics-ML architectures with uncertainty quantification
- Link framework to urban circular economy deployment strategies