

# Satellite-Driven Crop Type Classification with Deep Generative Models

**Confirmation Assessment Presentation**

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# Outline

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**Research Aims & Objectives**

**SITS-based Crop Analytics**

**Deep Generative Models**

**Benchmark Datasets**

**Thesis Outline**

**Work to Date**

**Future Research Activities**

**Timeline of Completing PhD Thesis**

# Research Aims & Objectives

- **Research Problem:** Variability induced by geographical and temporal changes impedes the generalizability of the existing deep crop type classification models.
- **Hypothesis:** Non-probabilistic deep models cannot identify the underlying generative process that should be sufficiently flexible to account for the variability in observed data.

# Research Aims & Objectives

- **Research Gap:** There is almost no work on probabilistic deep models for SITS-based crop type classification.
- **Contributions of My PhD Research:** Developing crop type classification algorithms that are more generalizable in terms of geographical and temporal variations and more data efficient with latest developments in deep generative models.



# Literature Review: SITS-based Crop Analytics

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## **Conventional Machine Learning Algorithms:**

Support Vector Machines (SVMs), Random Forests (RFs), Probabilistic Graphical Models (PGMs);

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**Deep Learning Models:** Recurrent Neural Networks (RNNs), Temporal Convolution Neural Networks, Transformers, and the hybrid models.

# Literature Review: Deep Generative Models

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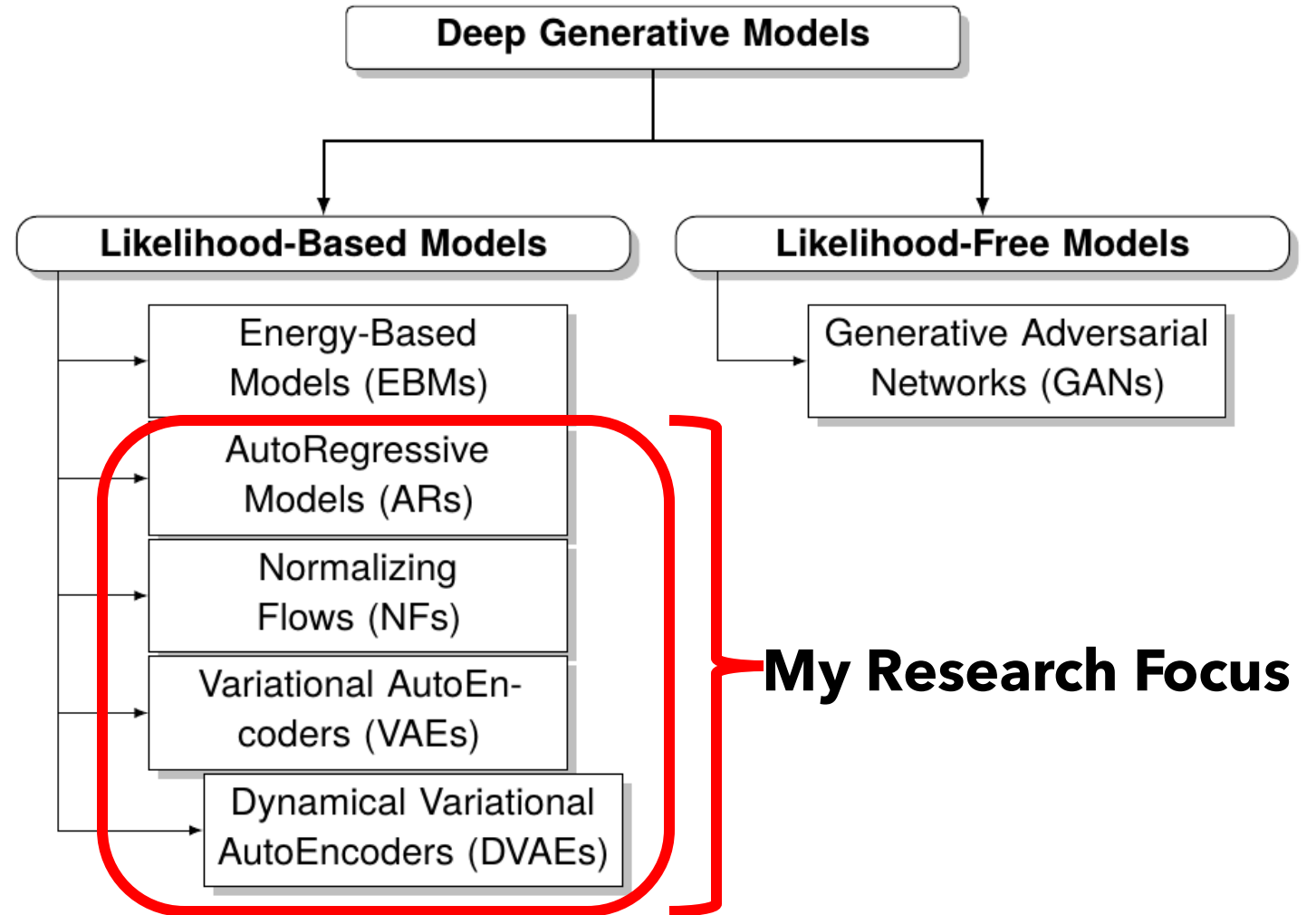
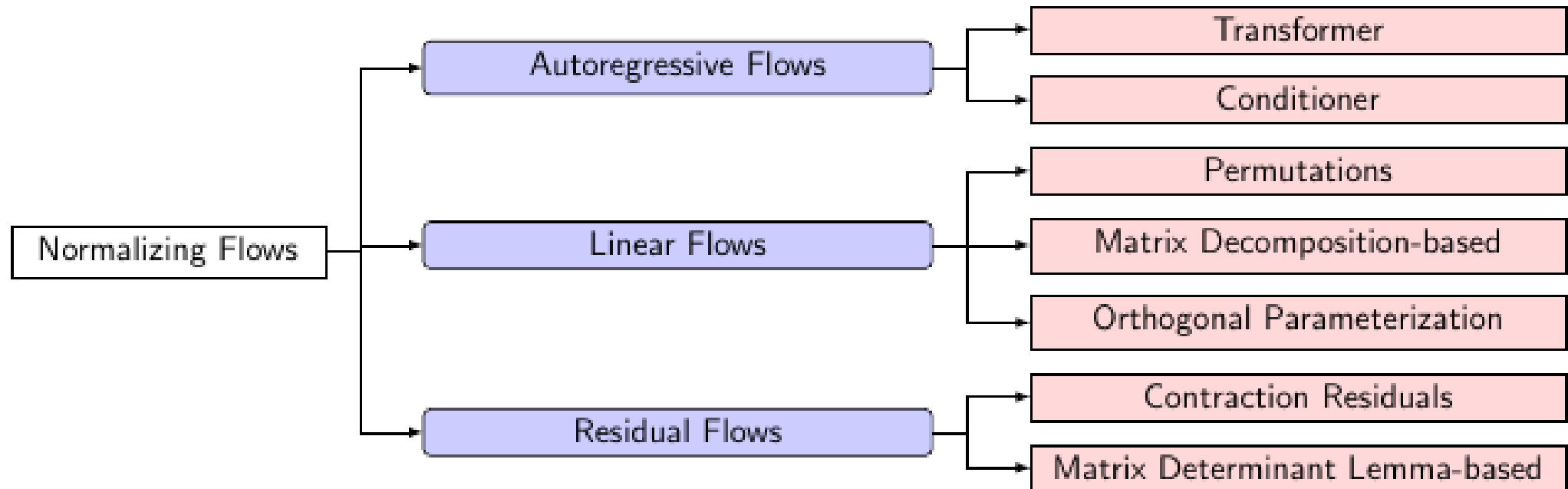


Figure 1: The taxonomy of deep generative models.

# Literature Review: Deep Generative Models

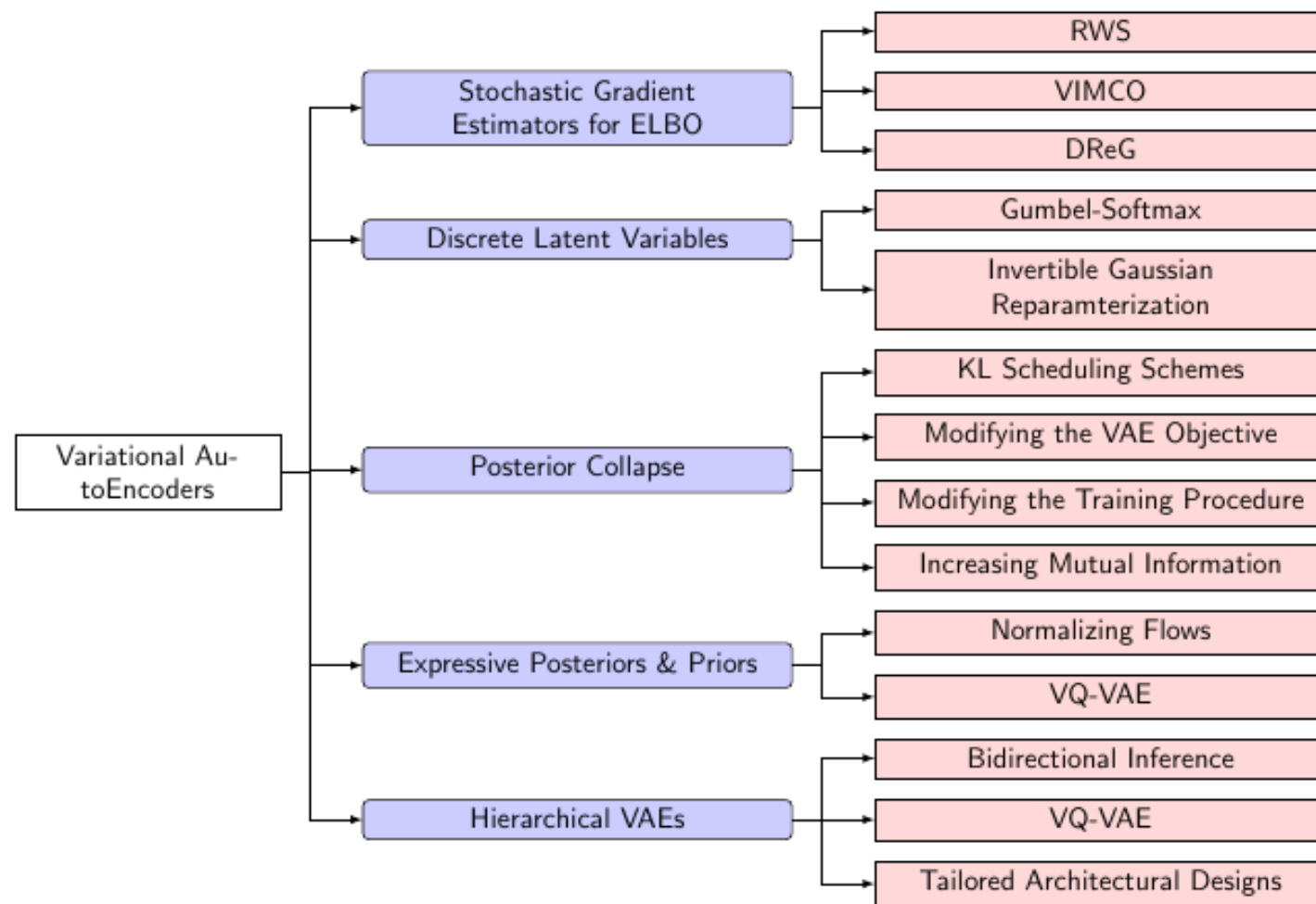
- Normalizing Flows (NFs)





# Literature Review: Deep Generative Models

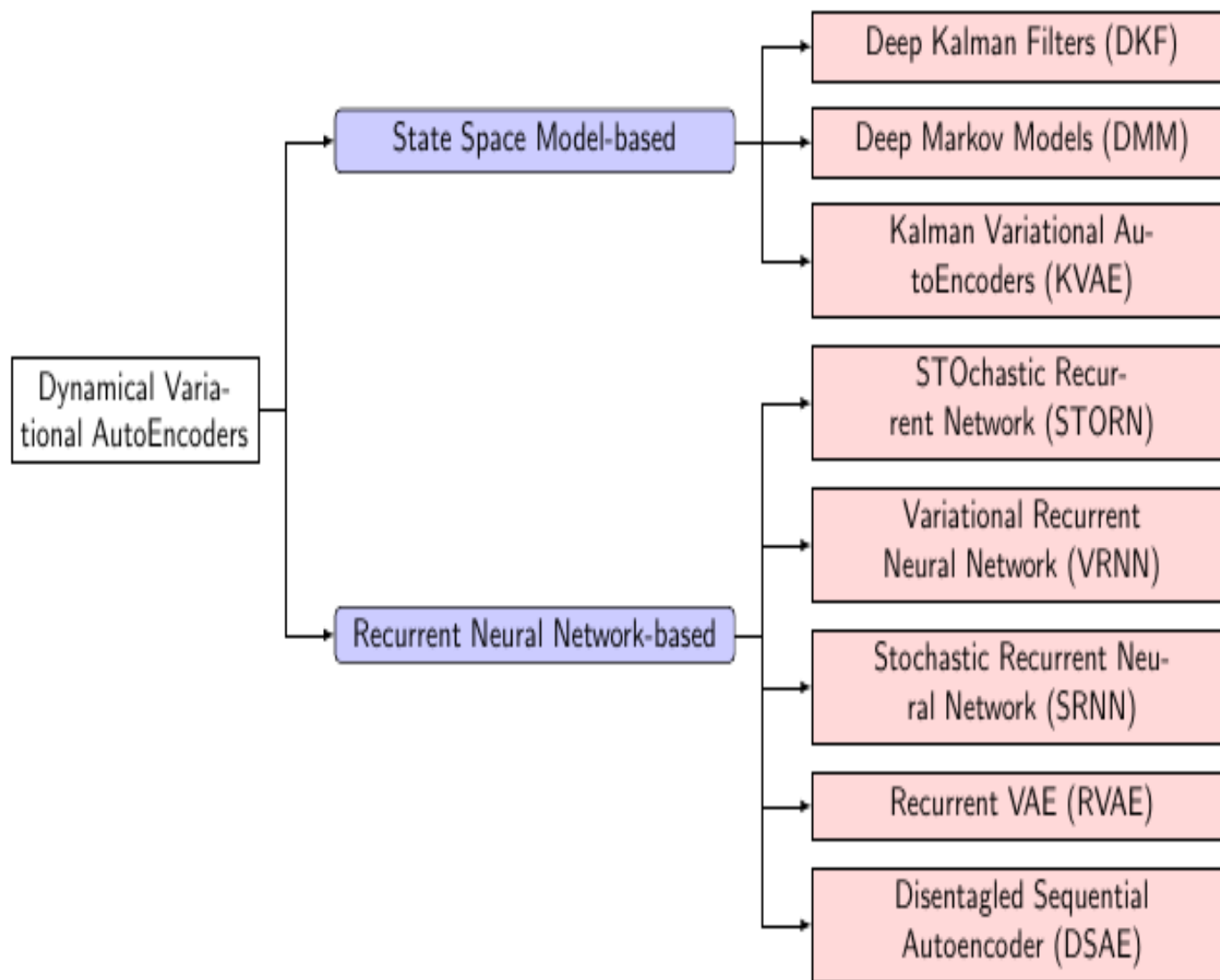
- **Variational  
AutoEncoders (VAEs)**





# Literature Review: Deep Generative Models

- **Dynamical Variational AutoEncoders (DVAEs)**



# A Preprint Paper on VAEs

- Applying VAEs with discrete latent variables to improve accuracy for crop type classification and extend the model to perform semi-supervised learning.
- Making technical improvements in mitigating posterior collapse problem.

Table 5: Comparison of our proposed and state-of-the-art models on DENETHOR test dataset.

	O.A.%	Precision%	Recall%	F1 Score%
PSE+TAE <sup>8</sup>	64.95	-	-	54.50
PSE+L-TAE <sup>7</sup>	67.25	-	-	58.12
PTST	70.29	61.27	56.72	56.14
<b>VAE-PTST</b>	<b>73.78</b>	<b>70.37</b>	<b>65.96</b>	<b>65.50</b>

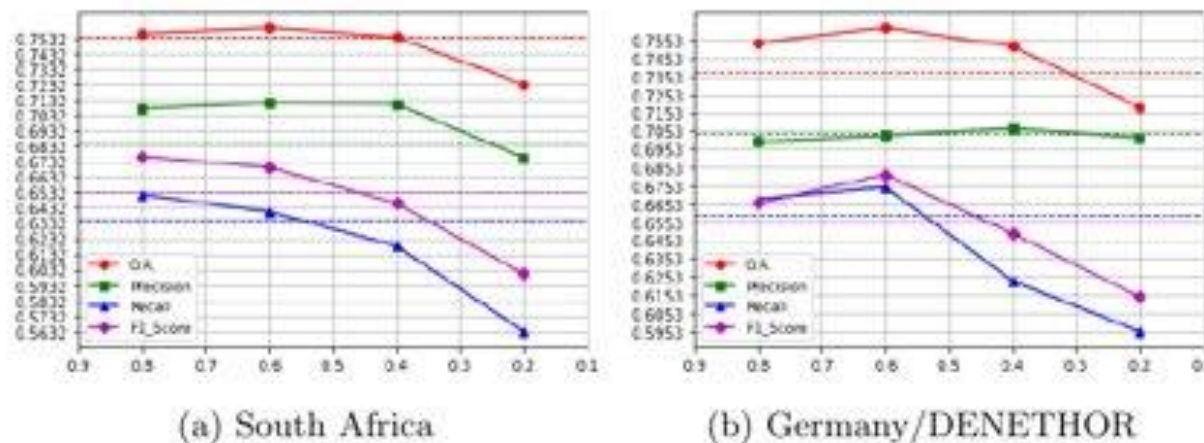


Fig. 1: Classification performance of VAE-PTST on South Africa and Germany test datasets with partially labelled data. N.B., figures are based on predictions of the recognition component. Please refer to Tab. 3 and 4 in the Supplementary Material for detailed results.



# Benchmark Datasets

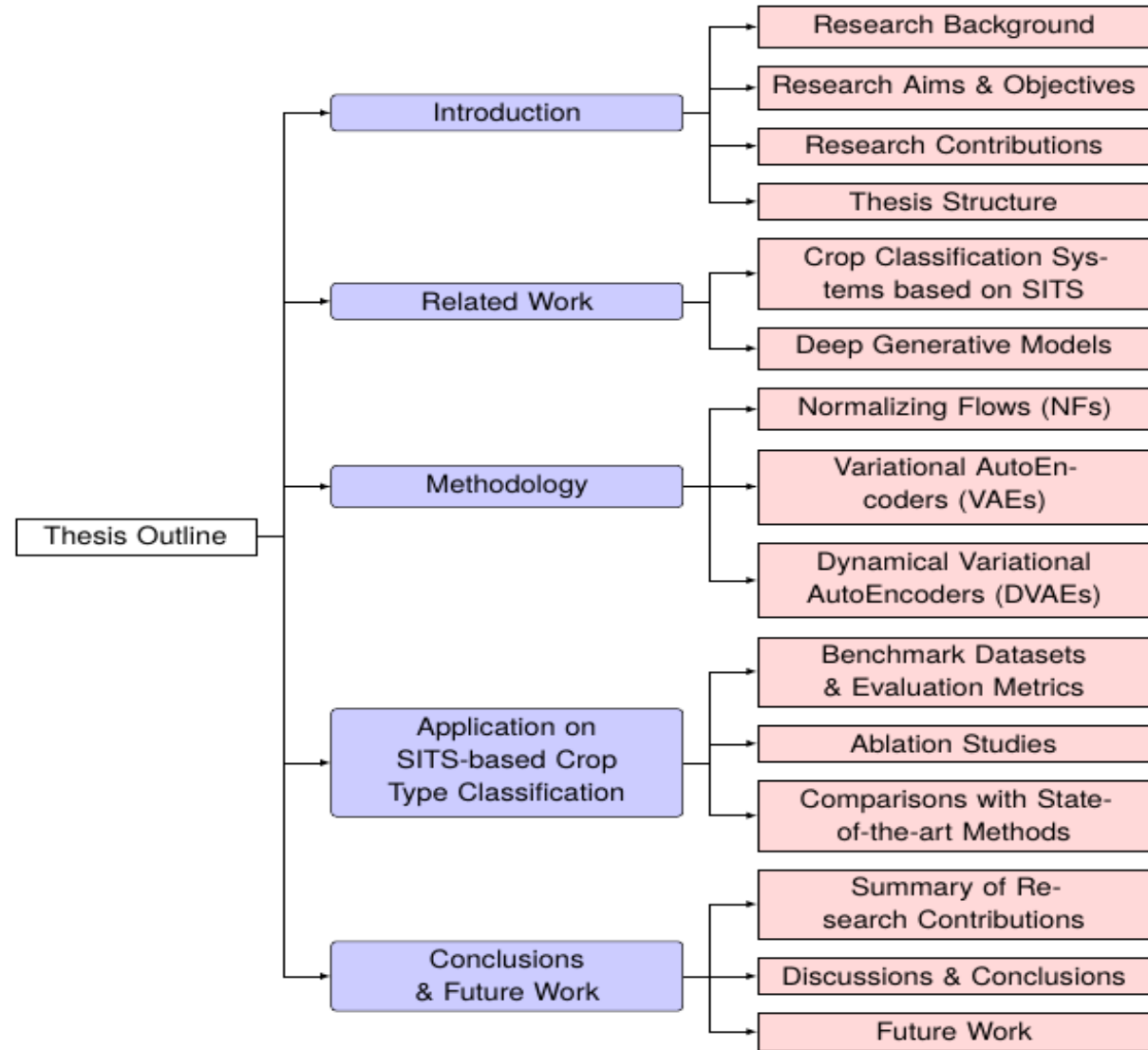
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Table 1: An overview of publicly available benchmark datasets for crop type mapping. “TS” and “ST” in the column “Format” stand for *Time Series* and *Spatio-Temporal*, respectively. “S1”, “S2”, “PF”, “M”, and “T” in the column “Modality” denote *Sentinel-1*, *Sentinel-2*, *Planet Fusion*, *Meteorological Data*, and *Topographic Data*, respectively.

Source	Area of Focus	Format	Modality	# Fields	Temporal Density	Temporal Shift
BREIZHCROPS [98]	France	TS	S2	$6.1 \times 10^5$	$\geq 5$ days	✓
TimeSen2Crop [99]	Austria	TS	S2	$1.1 \times 10^6$	$\geq 5$ days	✓
DENETHOR [1]	Germany	ST	S1+S2+PF	$4.5 \times 10^3$	Daily	✓
EUROCROPS [100]	EU Member States	TS	S2	$8 \times 10^5$	$\geq 5$ days	✓
CropHarvest [101]	Global	TS	S1+S2+M+T	$9 \times 10^4$	Monthly	✓

# Thesis Outline

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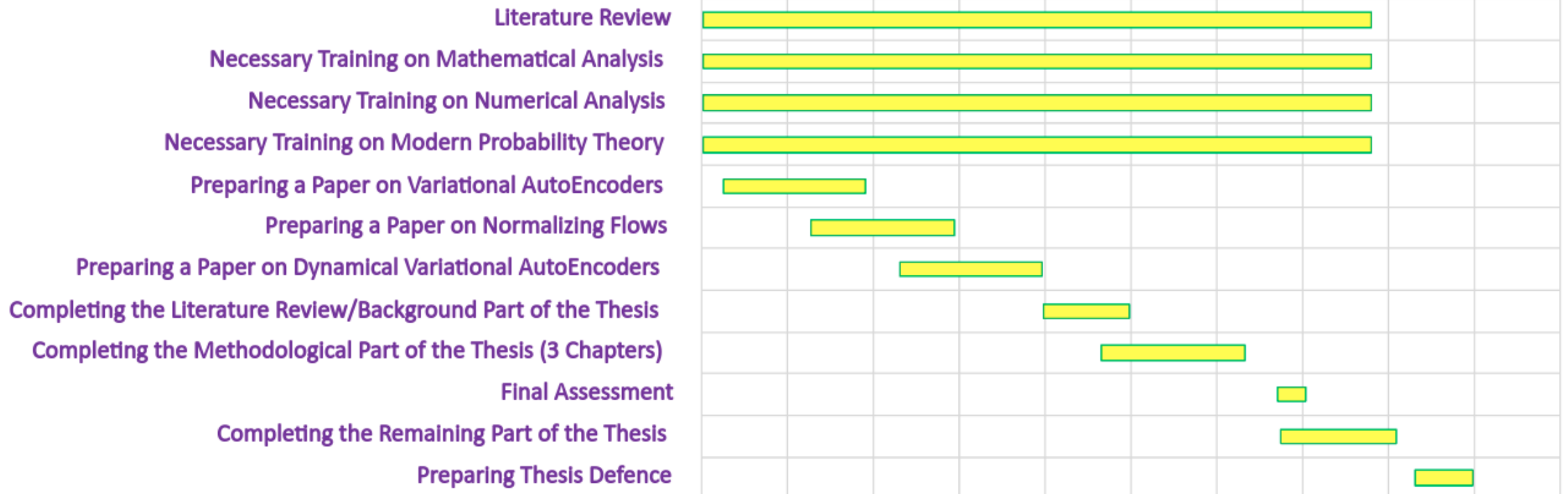
# Work to Date

- Conducted a literature review on crop type classification, SITS analysis, deep generative models, deep semi-/un-supervised learning, and deep neural architecture designs;
- Acquired an intermediate level of knowledge and skill in performing parallel training of deep neural nets on SLURM-based High-Performance Computing (HPC) facilities;
- Built a pipeline to process raw SITS for crop type classification;
- Participated in AI4Food Security Challenge and submitted final solutions;
- Had a preprint entitled "Tampered VAE for Improved Satellite Image Time Series Classification" on arXiv.

# Future Research Activities

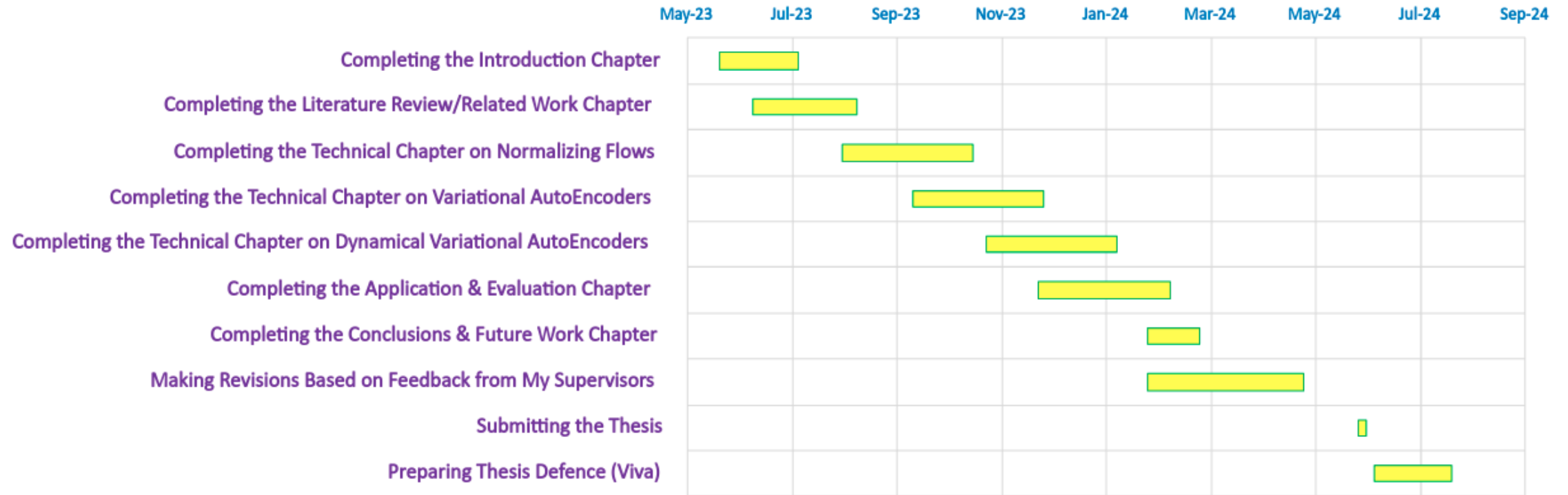
## PLAN OF ACTIVITY

Jun-22 Sep-22 Dec-22 Mar-23 Jun-23 Sep-23 Nov-23 Feb-24 May-24 Aug-24 Nov-24



# Timeline of Completing PhD Thesis

## Timetable for PhD Thesis Submission





Thank  
you



# Turnitin Originality Report

## Confirmation Assessment Written Report *by Xin Cai*

Submission date: 07-Jun-2022 12:12PM (UTC+0100)  
Submission ID: 182519476  
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Word count: 12371  
Character count: 69280

### Confirmation Assessment Written Report

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Autoregressive Models", IEEE Transactions on  
Pattern Analysis and Machine Intelligence,  
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transformation  $T$  of a real vector  $u$  sampled from  $p_u(u)$ :  $x = T(u)$  where  $u \sim p_u(u)$ . (1) We refer to  $p_u(u)$  as the base distribution of the flow-based model. The transformation  $T$  and the base distribution  $p_u(u)$  can have parameters of their own (denote them as  $\phi$  and  $\psi$  respectively); this induces a family of distributions over  $x$  parameterized by  $(\phi, \psi)$ . The defining property of flow-based models is that the transformation  $T$  must be invertible and both  $T$  and  $T^{-1}$  must be differentiable. Such transformations are known as diffeomorphisms and require that  $u$  be  $D$ -dimensional as well (Milnor and Weaver, 1997). Under these conditions, the density of  $x$  is well-defined and can be obtained by a change of variables (Rudin, 2006; Bogachev, 2007):  $p_x(x) = p_u(u) |\det JT(u)|^{-1}$  where  $u = T^{-1}(x)$ . (2) Equivalently, we can also write  $p_x(x)$  in terms of the Jacobian of  $T^{-1}$ :  $p_x(x) = p_u(T^{-1}(x)) |\det JT^{-1}(x)|$ . (3) The Jacobian

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... results of our proposed TV-PTST on DENETHOR test dataset and make comparisons with state-of-the-art models. As shown in Tab. 5, PTST improves O.A. by around 3 points but with a lower F1 score (-1.98) compared to PSE+L-TAE. TV-PTST attains highest performance in all metrics, especially with a significant increase around 7 points in F1 score compared to PSE+L-TAE. Tampered VAE for Improved Satellite Image Time Series Classification 14 Table 5: Comparison of our proposed and state-of-the-art models on DENETHOR test dataset. O.A.% Precision% Recall% F1 Score% PSE+TAE [12] 64.95 -- 54.50 PSE+L-TAE [11] 67.25 -- 58.12 PTST 70.29 61.27 56.72 56.14 TV-PTST 73.78 70.37 65.96 65.50 (a) South Africa (b) Germany/DENETHOR Fig. 1: Classification performance of TV-PTST on South Africa and Germany test datasets with partially labelled

- Tampered VAE for Improved Satellite Image Time Series Classification (<https://arxiv.org/abs/2203.16149>)
- Normalizing Flows for Probabilistic Modeling and Inference (<https://arxiv.org/abs/1912.02762>)